IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14366

How the COVID-19 Pandemic Affects Job Stress of Rural Teachers

Haizheng Li
Qinyi Liu
Mingyu Ma

MAY 2021

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14366

How the COVID-19 Pandemic Affects Job Stress of Rural Teachers

Haizheng Li
Georgia Institute of Technology and IZA

Qinyi Liu
University of International Business and Economics Beijing

Mingyu Ma
Central University of Finance and Economics Beijing

MAY 2021

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

How the COVID-19 Pandemic Affects Job Stress of Rural Teachers*

This study investigates how the COVID-19 pandemic has affected teachers' job-specific stresses and their enthusiasm for the teaching occupation. We use unique data from China that cover the periods before and after the start of the pandemic and apply difference-in-differences type methods. We find that, among rural young teachers, the pandemic has caused higher teaching stress and career development stress and has reduced passion towards the teaching occupation. We investigate the working channels of the pandemic, including job-related activities and social network. After controlling for possible working channels, the COVID-19 pandemic still shows a strong direct impact on job sentiments.

JEL Classification: I18, J24, J28

Keywords: COVID-19, pandemic, job stress, enthusiasm for occupation

Corresponding author:
Haizheng Li
School of Economics
Georgia Institute of Technology
Atlanta, GA 30332-0615
USA

E-mail: haizheng.li@econ.gatech.edu

* Partial financial support is provided by YouChange China Social Entrepreneur Foundation. The authors have benefited greatly from the research team at the China Center for Human Capital and Labor Market Research, Central University of Finance and Economics, and from the Young Teacher Empowerment Program initiated by the YouChange China Social Entrepreneur Foundation. We would like to thank the participating teachers, staff, and survey team in the training program for their support. We are also grateful for helpful comments and suggestions from Justin Burkett, Daniel Dench, Belton Fleisher, Danny R. Hughes, and Karen Yan.

I. Introduction

The highly infectious nature of COVID-19 has raised substantial anxieties among people. The World Health Organization declared the COVID-19 outbreak an international public health emergency on January 30, 2020 and a pandemic on March 11, 2020. By December 31 of that year, there were 83.42 million cumulative confirmed cases and 1.82 million deaths across 191 countries and regions.[1] Coincident with the unanticipated epidemic, the COVID-19 lockdown has also significantly changed people's lives and work due to disrupted travel plans, social isolation, and media information overload (Brodeur et al., 2021). As a result, the pandemic effect on people's psychological and mental health has become an important concern (Holmes et al., 2020).

Because of its exogenous nature, the COVID-19 pandemic provides a unique opportunity to study people's reactions to extreme events. Studies have investigated physiological changes due to the COVID-19 pandemic. For example, Qiu et al. (2020b) studies the impact on the general population; Kang et al. (2020) focuses on vulnerable groups such as health professionals; Aucejo et al. (2020) studies the influence on student experiences and expectations. However, little is known about how the pandemic influences specific job-related stresses and job perceptions.

Because the COVID-19 pandemic affects occupations differently, it is important to investigate its psychological impacts on certain highly affected occupations, especially those where work morale has a deep impact on society. For example, job stress for nurses during the pandemic may lower their productivity and cause them to exit the occupation, which can exacerbate the nurse shortage problem. Furthermore, teaching is considered one of the most stressful professions (see Collie et al., 2012 for a review). Teachers with high levels of stress

[1] The Johns Hopkins Coronavirus Resource Center: http://coronavirus.jhu.edu/map.html.

show a reduced sense of job satisfaction, absenteeism, and a tendency to exit the teaching profession. More importantly, teachers' work attitudes affect education quality and student performance (Harris and Adams, 2007). Therefore, the influences of the pandemic on teachers have potential consequences for the educational outcomes of the future generations.

In this study, we investigate the impact of the COVID-19 pandemic on teachers' job sentiments. We focus on how the pandemic influences teachers' job-specific stresses, including teaching stress and career development stress, and their job satisfaction as measured by enthusiasm for the teaching occupation. Due to the COVID-19 pandemic, lots of sudden changes have occurred for teachers, such as prolonged school closures and distance teaching. A recent survey of teachers in the US during August 2020 found that approximately 32% of the respondents reported low morale, and 47% considered making a major job-related change, with 17% saying they would completely change their career away from teaching.[2]

Our data come from large-scale annual surveys from approximately 7,500 elementary school and middle school teachers in rural China.[3] The surveys were conducted both before and after the breakout of the pandemic and thus allow us to estimate the total changes in job sentiments attributed to COVID-19. We apply the cross-section estimation as well as the difference-in-differences (DD) method to identify the impact of the pandemic. We further test the robustness of our results with various samples and estimation techniques.

For most studies about the psychological effect of the COVID-19 pandemic, the data were collected after the pandemic started, and they are mostly cross-sectional (e.g., Wang, et al., 2020a; Tan et al., 2020). Some longitudinal studies exist, but they only cover different time

[2] Source: https://finance.yahoo.com/news/teachers-education-system-coronavirus-140050666.html.
[3] Ministry of Education in China, more details could be found in website: http://www.gov.cn:8080/zhengce/zhengceku/2020-02/18/content_5480345.htm.

points during the pandemic (Wang et al., 2020b; Zhang and Ma, 2020), not before the pandemic. Such data can help identify the change of the psychological effect at different times during the pandemic but not the overall before-after effect of the pandemic. For example, Zhang and Ma (2020), using the data from China, find only a mild increase in stress from work between January and February 2020.

In comparison with the literature, our data have some unique features: 1) it is a longitudinal survey conducted before the pandemic and during the pandemic; 2) the survey provides detailed assessments of the respondents' job sentiments; 3) the survey focuses on young rural teachers, and thus the samples are very homogenous in representing a particular population. Additionally, as a routine annual survey of a large national training program for rural teachers, the purpose of the surveys is not directly related to the pandemic, so the responses are less likely to be induced toward a particular direction by the survey questions.

We propose a theoretical framework on how the pandemic affects job stress. We measure job stress and enthusiasm levels with both categories and scales. We further investigate the working channels of the pandemic, including behavioral changes in job-related activities and social network. Our results are robust to various model specifications and estimation methods.

The results show that the pandemic significantly increases teaching stress and career development stress. Moreover, the pandemic reduces passion toward teaching. Additionally, local pandemic severity has statistically significant effects on teachers' career development stress and job enthusiasm, but the magnitudes are very small. This result indicates that studies based on cross-sectional data during the pandemic may only reflect a smaller portion of the total COVID-19 pandemic effect. We find that work activities and social networks at work are channels through which the pandemic affects teachers' job attitudes. Moreover, teaching stress raises career development stress, and both job stresses reduce passion toward teaching. However, even after considering these channels, the COVID-19 pandemic still has a strong direct overall influence on job sentiments.

The rest of the paper is organized as follows: Section II presents a theoretical framework. Section III introduces the COVID-19 pandemic in China and relevant data. Section IV estimates the effect of the pandemic on job stress and enthusiasm via cross-section and before-after estimations. Section V discusses identification strategies and applies the DD estimation. Section VI tests the robustness of the results using various samples and estimation methods. Section VII explores the potential working channels, and Section VIII concludes.

II. A Theoretical Framework

According to Bliese et al. (2017), stress refers to "a condition or event in the situation, the person's reaction to the situation, or the relationship between the person and situation" (pp. 390). The identification of the stress process begins with identifying stressors (e.g., events that cause subsequent reactions) and associated strains as well as with the cognitive appraisal processes by which stress is perceived (e.g., psychological effects). Individual attributes and work environment can affect the strength of connections between stressors, perceived stress, and strains (Viswesvaran et al., 1999).

According to Cowan et al. (2011), individuals' stress levels are determined by their own coping ability and by positive and negative spillovers from their social contacts. In particular, an individual can reduce his/her stress through the mechanism of self-control. The physiological role of the stress response is to activate an individual to deploy the resources to deal with emerging demands. Stress activates coping behaviors that can reduce or eliminate the stressors.

Moreover, an individual's stress level also changes due to spillovers or buffering effects from social connections. Being in a relationship generally absorbs stress and has important buffering effects to reduce stress and psychological strains (Florian et al., 2002). In this case, the stress level can be reduced by interacting with colleagues, friends, and family members.

However, relationships can also be a source of stress itself because stress spills over between persons. This phenomenon is referred to as crossover and contagion. Crossover refers to one person's psychological strain affecting the level of strain of another person in the same social environment; contagion refers to one individual's mood and/or perceptions seeming to "spread" to those in proximity (Westman, 2001). Moreover, because the internal stress system is non-specific, stress in one domain (e.g., at work) can "crossover" to another (e.g., at home) (Hammer et al., 2005).

The unexpected COVID-19 pandemic has been a strong stressor that leads to widespread anxiety, stress and even panic among the public. In general, the level of perceived risk increases with three factors: how dreaded, uncontrollable, and fatal the risk is, how unfamiliar and unknown it is, and the level of personal and social exposure to the risk (Wong, 2008). The COVID-19 pandemic is at a remarkably high level for all the above characteristics and thus directly affects an individual's stress.

Moreover, such stress can cause an overall social amplification of risks when the information is transmitted between individuals via interpersonal networks (Dryhurst et al., 2020). For example, Holmes et al. (2020) finds that daily COVID-19 related media exposure and conflicting COVID-19 information in media were associated with acute stress and depressive symptoms in the US. Therefore, the overall impact of the pandemic may not be just related to local exposure.

We develop a conceptual framework of the dynamics of individual stress based on Cowan et al. (2011). We model the change in stress over time as:

$$\frac{dY}{dt} = f(P) - a(S,X) \cdot Y - b(\theta) \cdot Y + \sum_{i=1}^{n} r_i^{w}(\theta_w) \cdot Y_i^{w} + \sum_{j=1}^{m} r_j^{f}(\theta_f) \cdot Y_j^{f}, \quad (1)$$

where total stress level is Y, and the first term $f(P)$ represents the effect of the COVID-19 pandemic P. Because the overall pandemic impact is expected to come from the overall pessimistic and depressed atmosphere as well as from local exposure, we specify the impact of the COVID-19 pandemic into two components: the overall effect P_T and the effect due to local COVID-19 severity P_L,

$$f(P) = g(P_T, P_L). \quad (2)$$

We define $a(S,X)$ as the rate at which stress levels fall due to self-coping. The ability of coping varies across seasons, for example due to weather or holidays, and the seasonal factor is represented by S. X represents the individual traits and experiences that affect the individual's ability to adjust their stress level.

An individual can also reduce stress by sharing it with colleagues, friends and family members. $b(\theta)$ captures these buffering effects, where θ represents the relative strength of one's social network, and $\theta \in [0,1]$, where 0 means the social relationship is broken, and 1 represents a strong social relationship.

Additionally, stress spills over between persons. Suppose an individual interacts with *n* colleagues at work and *m* friends and family members; their stress level would be influenced by the stress level of those social contacts. In particular, $\sum_{i=1}^{n} r_i^{w}(\theta_w) \cdot Y_i^{w}$ captures the spillover effects from colleagues, and $\sum_{j=1}^{m} r_j^{f}(\theta_f) \cdot Y_j^{f}$ captures the spillover effects from friends/family members, where Y_i^{w} and Y_j^{f} denote the stress levels of colleagues and family/friends, respectively, and $r_i{}^{w}$ and $r_j{}^{f}$ represent their relative spillover rates. Similarly, θ_w represents the relative strength of the relationship with colleagues and θ_f represents that for family/friends. Note that in contrast to the spillover effect, the reduction of stress due to buffering depends on the entire social network, and $b(\theta)$ represents such an effect.[4]

In constructing an empirical model based on the above framework, we need to have detailed information on a person's social network. However, such information is rarely available in data to help disentangle the different influences of the social network. Yet, a person's social network is determined by both personal characteristics and job characteristics. For example, the social relationship at work can be represented by $n_w(X, W)$ and the network of family and friends by $n_f(X, W)$, where X represents individual characteristics, and W represents job characteristics. Therefore, in the empirical estimation, we include these characteristics to capture a person's social network.

Additionally, we model the effect of the pandemic on job passion/enthusiasm in a similar framework to job stress in Equation (1). In psychology, passion/enthusiasm is defined as a strong inclination toward an activity (such as work) that one loves and that is self-defining (Vallerand and Houlfort, 2003). Apart from individual characteristics, social recognition also represents an important determinant of passion (Tóth-Király et al., 2019). A person's passion towards work can be determined by their own "enhancing" capacity as well as by "recognitions" from their social network (just like self-coping and buffering effects for stress). Moreover, the spillover effect also exists for job passion as for job stress.

III. The COVID-19 Pandemic in China and Data

The first COVID-19 case was found in Wuhan, Hubei province in China. January 19 is the

[4] We could disaggregate the buffering effects for different members in the network, and then aggregate to get the total buffering effect. To simplify the argument, we adopt the current model structure.

first day that COVID-19 cases were reported outside of Wuhan (Qiu et al., 2020a). On January 23, the Chinese government imposed a lockdown measure on Wuhan. By January 30, almost all provinces implemented the Level 1 Response to Public Health Emergency, the highest response level.[5] Figure 1 shows the trend of the cumulative, existing, and new COVID-19 cases. The spike of cumulative cases occurred around mid-February and then flattened out afterwards.

The implementation of strict quarantine measures in China has kept many people in isolation. All schools in China were required to postpone the start of the spring semester. The government encouraged schools to provide online instruction to millions of students. Since February 17, a national online learning platform has been operated by the Ministry of Education to provide educational materials for students at primary and secondary institutions.[6] About 85 percent of students and teachers use mobile devices, such as smart phones and tablets, for online education (Huang et al., 2020). As early as the end of March, with COVID-19 under control in some less affected provinces, primary schools started to reopen. Wuhan city reopened from a citywide lockdown on April 8.[7] Other provinces began reopening primary schools between April and early June.

Different policies for teaching during the pandemic brought drastic changes in teachers' work patterns. The pandemic has forced teachers to switch to online teaching and has led to many abrupt changes at work and in life. Online teaching posed new challenges for teachers, as most of them were unfamiliar with the online teaching tools. After schools reopened, teaching did not go back to normal due to the new requirements for social distancing and the new hybrid format. Moreover, teachers' administrative workload increased substantially due to the need to

[5] National Health Commission in China, more details could be found in website: http://www.nhc.gov.cn/xcs/yqtb/202102/31fdfaf836354c76891a01c6b8f58b73.shtml.
[6] Source: https://www.chinadaily.com.cn/a/202003/23/WS5e781ad2a310128217281290.html.
[7] Source: https://global.chinadaily.com.cn/a/202008/29/WS5f499baca310675eafc5636f.html.

prevent the COVID-19 from spreading in school and amongst students. Further, rural teachers usually work in less-developed, remote areas, and online teaching is new especially for them. Therefore, they are more vulnerable to direct exposure of the pandemic's influence.

Our data are a by-product of the routine survey of a large scale online annual training program for young teachers in rural China, the Young Teacher Empowerment Program (hereafter as "YTEP"). The YTEP was initiated in 2017 through the sponsorship of non-profit organizations, universities, and corporations in China.[8] It aims to help young rural teachers better fit into rural environments and improve their teaching skills and work morale. The YTEP is a year-long training program starting in September and ending in the following June, and it provides various online training courses synchronously via a specially designed broadcast platform. Participants watch the program videos online, either live or recorded, via a computer or cell phone.

YTEP participants are selected by the local government and their schools. They are two types of teachers: permanent teachers (regular teachers) and special-term teachers. Special-term teachers work via a national program in which college graduates are recruited to teach in rural areas for three years to improve education quality.[9] After three years of service, teachers who pass the assessment can become permanent teachers, or they can choose other jobs.[10] Teachers work in various types of rural schools, including 1) rural schoolhouses, usually located in remote rural areas, which have the smallest school size and which only offer primary school level education, 2) village schools, larger than schoolhouses, and 3) rural district schools, the largest among all three school types, which may offer both primary and middle school education.

---

[8] It was mainly initiated by the YouChange China Social Entrepreneur Foundation. More details could be found in website: http://www.youcheng.org/news_detail.php?id=645.

[9] Source: https://www.chinadaily.com.cn/opinion/2012-10/04/content_15796923.htm.

[10] Ministry of Education in China, more details could be found in website: http://www.moe.gov.cn/srcsite/A10/s7151/202005/t20200511_452739.html?from=timeline.

Our data come from the annual surveys of the YTEP participants as a routine evaluation of the program. One survey was conducted for the Class of 2018-19 (starting in September 2018 and ending in June 2019, hereafter as "Class-2019"). The other survey was for the Class of 2019-20 (hereafter as "Class-2020"). All surveys were administered online via the administrative team of the YTEP.[11] The survey of Class-2019 was conducted at the end of the program in June 2019. For Class-2020, the administrative team conducted two surveys; Wave-1 was added in the middle of the program in January 2020, and Wave-2 was conducted regularly at the end of the program in June 2020. They sent the survey links to participants during live-class times, and the survey was usually live for about one week. During the period that the survey was live, the administration team sent 2-3 reminders to training participants to fill out the survey. As a result, the respondents in each survey are not selected in any non-random way. A total of 7,502 rural teachers participated in all three surveys.

The Wave-1 survey of Class-2019 started on January 2, 2020 and was completed by January 20, before COVID-19 became public in China.[12] In June 2020, the pandemic was mostly under control in China but was spreading rapidly all over the world. Therefore, those who participated in Wave-2 in June were influenced by the pandemic for approximately half a year. Details of the three surveys are shown in Appendix Table A1.

The initial purpose of the surveys is not related to the pandemic but is instead just a program evaluation. There is no question related to the pandemic in the surveys. Therefore, the surveys could have the advantage of receiving more accurate responses because there are no hints toward the pandemic. Given the nature of the homogenous sample, i.e., young rural teachers, the data

[11] The data were collected by the YouChange China Social Entrepreneur Foundation. Researchers at the China Center for Human Capital and Labor Market Research were invited to do the third-party evaluation for the YTEP.

[12] The public in China was not yet informed about the new coronavirus during the Wave-1 survey. For example, according to Fang et al. (2020), on January 18, 2020, more than 10,000 families gathered for the annual Wuhan Lunar New Year banquet in Wuhan. There were 6 participants that responded after January 20, and they were deleted from the sample.

provide a unique opportunity to study the changes of job stress and job enthusiasm due to the pandemic. In order to represent more accurately the same population, we restrict our samples to permanent teachers and special-term teachers. Temporary teachers are excluded from the sample as their job attitudes can be very different. We also keep teachers aged 35 or below and with no more than 5 years' teaching experience to focus on relatively inexperienced young teachers (dropped 3.5% of the sample outside this range). The final sample size used in the analysis is 5,767 after eliminating those with incomplete information.

Because one objective of the YTEP is to help develop better morale amongst rural teachers, one part of the surveys specifically assesses job-specific stresses and attitudes toward the teaching occupation. The related survey questions are listed in Table 1. In the literature, different sources have been cited as causes of teacher stress, e.g., stress related to workload or related to students' behavior and discipline (Klassen and Chiu, 2010). Teachers may have different concerns and stress at different stages of career development (Holmes, 2005). We classify related survey questions into three aspects pertaining to job attitudes, each aspect consisting of two questions. They are: 1) Teaching stress, 2) Career development stress, and 3) Job passion/enthusiasm for the teaching occupation. The measure of teaching stress focuses on stress from students, such as helping them graduate and maintaining discipline. The measure of career development stress concerns career advancements, including receiving promotions and awards. These stresses represent different aspects of job-related pressure.

Job passion/enthusiasm represents a teacher's job attitude and is measured by questions like "I will not feel tired of being a teacher." In general, passion is associated with determination, motivation, and a high degree of self-control. When work is highly valued, it will be internalized in the person's identity in an autonomous fashion, leading to a harmonious passion (Vallerand et al., 2014). Research shows that passion for work is positively related to work satisfaction (Carbonneau et al., 2008) and will lower turnover intentions (Houlfort et al., 2014).

For the above survey questions, the choices are divided into different categories, such as “no,” “unsure,” and “yes,” as listed in Appendix Table A2. We first classify those choices into two categories to indicate the stress status for a particular measure: high (as 1) and low (as 0). For example, the survey questions related to teaching stress are “I feel great pressure to help students graduate and enroll in the next level of education” and “I feel great pressure to maintain students’ discipline.” A respondent is considered to have a high value of stress if he/she chooses “completely agree,” “agree,” or “mostly agree” among all seven possible choices listed in the survey. If the high value of stress occurs for either of the two questions, we define an individual as having high teaching stress with a value of 1, and 0 otherwise. The detailed classifications for various choice sets are presented in Appendix Table A2.

The advantage of this approach is that the categories were directly obtained from the survey responses. However, such a measure can only capture large changes across measured categories. Therefore, we assign a scale for each category of survey responses so that we can measure the continuous changes of job sentiments. Based on the different choice sets for the related questions, we construct scale measures by assigning a value of 0-10 for each choice. For example, we assign a value of 0 for “no”, a value of 10 for “yes”, and a value of 5 for “unsure”. Some values assigned to a particular choice may be subject to individual judgement. To ensure the scaling was assigned as representatively as possible, all 10 survey team members assigned a scale value to each choice independently in three rounds at different times during a period of one month. Their average values are then used in our analysis. Appendix Table A2 shows the assigned values in more detail. Because each measure of job attitudes is based on two questions in the survey, we take the average of the values.

Table 1 shows the distribution of job stress and enthusiasm in the three surveys. It seems that a lower percentage of individuals indicate high job stress in Wave-2 compared to Wave-1. However, comparing with Class-2019, Class-2020 displays higher proportions of job stress during the pandemic. Similar results are found based on the scale measures, i.e., job stress levels are higher in June 2020 compared to those in June 2019, and job enthusiasm is also much lower.

Table 2 shows the summary statistics of individual and job characteristics across the three surveys. As expected, the statistics between Wave-1 and Wave-2 of Class-2020 are almost identical. The samples from Class-2019 and Class-2020 surveys are comparable, except some differences in married and ethnic groups, as well as in the share of special-term teachers. The largest difference occurs for regional distribution, with 68% of the Class-2019 sample from non-western regions compared to approximately 25% for Class-2020.

IV. Cross-section and Before-After Estimation

Based on Equation (1) and (2) in the theoretical framework, we have several options to estimate the effect of the COVID-19 pandemic. We first estimate the effect of local pandemic severity with only the cross-sectional sample from the Wave-2 survey conducted in June 2020. The identification comes from the fact that individuals have different amounts of exposure to COVID-19 due to local severity. However, the limitation is that it can only capture the marginal effect of the local severity on job sentiments, not the total effect of the pandemic.

Local severities vary substantially, as measured by the number of cumulative COVID-19 cases at the provincial level. As of June 5, 2020, when the Wave-2 survey was conducted, the number of cumulative cases confirmed was the lowest in Qinghai province (18 cases) and the highest in Hubei province (68,135 cases).[13] In addition to local cumulative cases as a measure of pandemic severity, other potential measures include the number of new cases or existing cases. However, as seen in Figure 1, because of the dramatic restrictions adopted by the Chinese government to control the COVID-19 pandemic, these numbers became almost zero for almost all provinces when the Wave-2 survey was conducted. Additionally, the numbers of cases are too small compared to the population of the province, and thus their ratio is not used as a measure.

A potential concern is that the cumulative cases may also capture provincial effects that affect teachers' job sentiments. For rural elementary and middle school teachers, their job sentiments may be related to the social status of the teaching occupation in the local area and to the competitiveness of the job in the local labor market. Therefore, their job sentiments are likely to be affected by different stages of economic development. Thus, we add a regional dummy in the model to distinguish the relatively less developed western region from other regions to control for such effects.

The empirical model using only the cross-section sample to estimate the effect of the local pandemic severity is specified as follows:

$$Y_i = \alpha + \varphi P_{Li} + X_i \lambda + \varepsilon_i, \qquad (3)$$

where Y_i represents measures of job stress or enthusiasm for individual i, P_{Li} is the number of cumulative COVID-19 cases in the province where individual i lives. X_i includes a set of individual characteristics and job characteristics, and ε_i is individual-specific error term.

We use both measures for job stress and enthusiasm: (i) categorial measures (high or low) and (ii) scale measures. The results are reported in Table 3. For the stress measures, the local severity has no significant impact on teaching stress but increases career development stress

[13] We have done regressions without the Hubei sample to test the sensitivity due to the extreme value, and the results are similar.

based on the scale measure. However, an increase of local COVID-19 cumulative cases has a statistically significant effect on lowering job enthusiasm based on both categorical and scale measures, but the marginal effect of the local severity is very small. For example, an increase of 100 cumulative cases at the provincial level increases career development stress by 0.002 points, with the average value of the stress at around 6.1 points.[14]

To estimate both overall effect P_T and local effect P_L, we use data before and during the pandemic by applying the before-after estimator (Smith and Todd, 2005). In our data, the Wave-1 sample was collected in January 2020 before the pandemic became public. During the period between the Wave-1 and Wave-2 surveys, the pandemic unfolded. However, between Wave-1 and Wave-2, some other effects overlapped with COVID, including 1) the YTEP training effect and 2) the seasonal patten of stresses.

Regarding the YTEP training effect, the first half of the program ends in January, and the entire program ends on June. Thus, the program may alter participants' job attitudes in the second half of training given its design. For the seasonal effect, people's feelings are affected by cold (January) or hot (June) weather. According to Nelson and Martin II (2010), seasonal changes in the quality and quantity of stress are common, and the stress response is stronger during the winter. Cooke et al. (2007) compares the seasonal (winter and summer) effectiveness of aromatherapy massage on the stress and anxiety levels of emergency nurses and finds pre-massage anxiety was significantly higher in winter than summer. Conversely, January represents the beginning of a new year, which may bring more hope and inspiration and thus may contribute to higher job morale.

The training effect and seasonal impact on job sentiments results in a time-specific intercept

[14] We use the increment of 100 cases because the average cumulative case count as of June 2020 is 345, as shown in Table 2.

common across individuals which causes the before-after estimation to break down (Smith and Todd, 2005). One way to avoid the time-specific intercept is to use samples from Class-2019 and the Wave-2 of Class-2020 surveys. Because both surveys were conducted at the end of the YTEP training program and in summertime, there will be no difference in seasonal and training effects between those two samples, assuming that seasonal patterns do not vary across years and the YTEP training effect is similar in different years. Therefore, we use Class-2019 as counterfactual in the same period and apply the before-after estimation to the following models by pooling Class-2019 and Class-2020 Wave-2 samples together:

$$Y_{it} = \alpha + \delta P_T + \varphi P_{Lit} + X_{it}\lambda + \varepsilon_{it}, \quad (4)$$

where P_T is a dummy variable that equals 1 if surveyed in 2020, and δ measures the overall effect of the pandemic. Other variables have the same definitions as above in Model (3).

The results are reported in Table 4. The estimated pandemic effects are consistent using both categorical and scale measures. The pandemic increases both teaching stress and career development stress and reduces passion for the teaching occupation. All estimated overall effects are statistically significant. In contrast, the effects of the local severity are either statistically insignificant or economically insignificant. The estimated total effects are much larger than the marginal effects of local severity. Given that the pandemic had been spreading already, the effect of local confirmed cases is relatively smaller compared to the overall pandemic effect. Additionally, for most people, the major impact on attitudes comes via various preventative measures rather than experiences of or awareness of the direct pandemic illness on individuals around them. This result also shows that cross-sectional data during the pandemic can only capture a very small part of the total impact of COVID-19.

We also report the estimates for control variables in Table 4. These variables may influence an individual's stress coping abilities as well as their social network. The estimated parameters generally have the expected sign and significance. In particular, teachers with more experience feel less teaching stress, probably because they are better trained for teaching. Female teachers are more likely to feel higher teaching stress. Compared to schoolhouse teachers, those who work in larger schools have higher teaching stress, possibly due to higher instructional expectations at their schools. Compared to the relatively less developed western region, rural teachers in other regions feel less teaching stress. However, those with more years of teaching experience have higher career development stress. Special-term teachers have less career development stress, likely because they are less concerned about their future career as a teacher.

As for job passion, being married and having children are both positively associated with the teacher's job enthusiasm. Those who work in larger schools have lower enthusiasm towards the occupation compared to teachers at small schoolhouses, possibly due to the fact that a teaching job is highly respected in a remote village. Special-term teachers indicate higher job enthusiasm.

V. Difference-in-Differences Estimation

One issue with pooling only the samples of Class-2019 and Wave-2 of Class-2020 in the above estimation is that the Wave-1 sample is not used. This sample provides additional information about job sentiments and their variations. Therefore, applying the DD estimation allows us to use all data to improve the estimation efficiency. We define the treatment group as survey participants who took the survey in both January and June of 2020 and who experienced the COVID-19 pandemic ("treatment") for five months. Ideally, we need a control group who took the January survey but did not go through the pandemic. However, such data cannot exist because everyone experienced the pandemic one way or another. Therefore, we consider one potential control group, the Class-2019 who participated in the survey conducted in June 2019. This group was not under any pandemic influences but participated in similar YTEP training and did the survey at the end of the training in the summer. Additionally, both the 2019 and 2020 surveys asked similar questions and were implemented in the same way. Given the homogenous nature of the samples, i.e., young rural teachers, it is reasonable to assume that the training effect and the seasonal influence are similar for the 2019 and 2020 cohorts. Therefore, we can difference out the seasonal and training effects and identify the net effect of the pandemic.

Our DD framework is illustrated in Figure 2. The survey respondents in January 2020 are divided into two groups, a treatment group and a control group. The treatment group went through the pandemic "treatment" and was surveyed again in June. The control group did not go through the treatment but were "as if" a counterfactual represented by Class-2019. As shown in Figure 2, a total of 3,076 samples took the survey in January 2020 (Wave-1), and 2,155 of them took the survey again in June (Wave-2). There are two different ways to specify the control group before the treatment for participants in Wave-1. One way is to include only those who did not participate in Wave-2 (921 observations); the other way is to include all participants in Wave-1 (total 3,076 observations). The first option is closer to the standard DD estimation. However, the advantage of the second option is that the sample size is larger. Therefore, we adopt the second approach and use all observations of Wave-1 as control group for January.[15]

Based on Duflo (2001), Bertrand et al. (2004), Hansen (2007), and Imbens and Wooldridge (2009), we specify the DD empirical model as below:

$$Y_{igt} = \alpha + \delta P_{Tgt} + \beta T_g + \gamma S_t + X_{igt}\lambda + \varepsilon_{igt}, \qquad (5)$$

where Y_{igt} represents measures of job stress or enthusiasm for individual *i* in group *g* surveyed

[15] As a robustness check, we did the estimation using the first option for the control group which includes only those that did not participate in Wave-2 survey. The results are generally consistent.

at time t, and T_g is a dummy variable equal to 1 for the treatment group and 0 for the control group. S_t is a dummy variable that equals 1 if surveyed in summer. The variable $P_{Tgt} = T_g \cdot S_t$, and δ represents the overall effect of the pandemic. X_{igt} includes a set of individual and job characteristics, and ε_{igt} is an individual-specific idiosyncratic error term.[16]

Table 5 presents the DD regression results based on both probit and Ordinary Least Square (OLS) estimations.[17] Based on the probit estimation, the pandemic increases an individual's probability of having high teaching stress by 7.9 percentage points (marginal effect), which is statistically significant. The estimated marginal effect for career development stress is 5.3 percentage points. The DD estimation results based on a scale are consistent with those based on categorical measures. The pandemic increases an individual's teaching stress level by 0.302 points, which is approximately 6% of its mean value. The pandemic also shows a positive effect on career development stress level with an increase of 0.393 points. The teaching stress due to the pandemic is possibly caused by drastic changes in the teaching format, such as switching to online teaching or teaching in a socially distanced manner (MacIntyre et al., 2020). The influence of the pandemic on career development stress is possibly due various uncertainties that may negatively affect a teacher's career plan.

Additionally, the pandemic has a statistically significant effect on job enthusiasm. In particular, it reduces a young rural teacher's job enthusiasm by approximately 1.04 points in the scale model, which is about 15% of its mean. This result is consistent with Alves et al. (2020), which finds that the pandemic has reduced the perception of well-being in the profession. The

[16] One option is the Seemingly Unrelated Regression Equations model. Because the explanatory variables included in each equation are the same, individual regression models will produce the same results.

[17] Including local pandemic severity produces results that are very similar to those reported in Table 5. However, the marginal effect of the local severity is very small compared to the direct effect of the pandemic. For example, an increase of 100 cumulative cases increases the effect of the pandemic on career development stress by 0.002 points compared to the direct pandemic effect of 0.385 points. The relative effect of local severity on job enthusiasm is also small (0.002 vs 1.033). Therefore, we do not include local pandemic severity in the regressions below.

coefficient of the treatment group dummy is statistically insignificant for all models. It supports our assumption that there is no systematic difference between the treatment and control group.

The key assumption in the DD approach is that participants in all three surveys are representative samples from the same population. Given the design of the YTEP training program is for young rural teachers and the way the participants are selected, the assumption is likely to hold. One issue is that, as seen in Table 2, the much higher proportion of non-western participants in 2019 could imply this cohort has better access to resources and social networks that reduce stress.

To test this assumption, we estimate the above model using subsamples from different regions. Results are reported in Table 6. The estimated COVID effects are comparable for the west and non-west samples, except that the pandemic's effect on teaching stress becomes statistically insignificant for the western sample.[18] Therefore, the potential regional difference does not alter the estimated results due to the pandemic.

VI. Matched Samples and Differenced Estimation

In this section, we further test the robustness of the findings reported above. In particular, given that for the control group, those before and after the treatment are not the same individuals, we adopt a matching process to select individuals who are similar. We match the sample of Class-2019 with the Wave-1 of Class-2020 using multiple matching (Stuart, 2010). Because individuals in the samples are similar, we can exactly match multiple variables, including demographic characteristics and job characteristics that may influence job stress and enthusiasm. The matching process involves: 1) matching exactly demographic and job characteristics; 2)

[18] Since the proportions of special-term and permanent teachers between Class-2019 and Class-2020 differ by more than 10 percentage points, we have estimated the effects using separated samples. The results are very robust.

doing nearest neighbor matching with age and years of teaching experience.

Importantly, to focus on potential regional differences in job sentiments, we construct the control groups to have similar sample proportions between western and non-western regions as that of the treatment groups. Because the proportion of participants from the west is 72% in the treatment group but only 32% in Class-2019, we retain all the western samples in Class-2019 and match those with western samples in Wave-1 of Class-2020; we then match non-western participants. There are more non-western observations than needed in Class-2019 because of matching the regional proportion. We then randomly select a sample from the matched non-western observations. This process results in matched control group samples between Class-2019 and Class-2020 Wave-1, with the western vs. non-western ratio of 62:38, which is closer to that of 72:28 for the treatment group.[19]

Moreover, we estimate a differenced DD model to show the control for observed heterogeneity between "matched" samples. The Model (5) is restructured as below:

$$Y_{igt} - Y_{igt'} = \gamma + \delta P_{Tg} + \lambda(X_{igt}) - \lambda(X_{igt'}) + \varepsilon_{igt} - \varepsilon_{igt'}, \qquad (6)$$

where Y_{igt} and $Y_{igt'}$ represent measures of job sentiments after and before the treatment. This model shows that any imperfect matching in observed heterogeneity has been accounted for in the model due to X_{igt} before and after the pandemic. More specifically, Equation (6) shows that differences in job sentiment before and after treatment are caused by: 1) time trend γ; 2) the treatment effect δ; 3) observed heterogeneity; and 4) unobserved heterogeneity. The treatment effect of the pandemic is consistently identified if the unobserved heterogeneity satisfies that $E(\varepsilon_{igt} - \varepsilon_{igt'}) = 0$. The estimation based on Equation (5) and (6) is asymptotically identical but

[19] To balance the western vs. non-western sample ratio and sample size, we cap the difference in the regional sample ratio to within 10 percentage points.

may differ in finite samples (e.g., due to changes in degrees of freedom).

In Table 7, we report the results based on the matched sample using both the regular DD estimation (Equation 5) and the differenced DD estimation (Equation 6). The estimated effects in both models are very close, and moreover they are consistent with those in Table 5. For example, in the differenced DD estimation, the pandemic increases an individual's teaching stress and career development stress levels by 0.264 points and 0.431 points, respectively, and the effects are significant at the 5% level. The pandemic also shows a significantly negative effect on job enthusiasm, approximately 0.983 points. Therefore, the results are robust to different samples used and to different estimations.

Another potentially more difficult issue with our DD estimation is that, if the seasonal and/or training effects differ between 2019 and 2020, the estimated pandemic effect may still capture some of those influences. In this case, the expected value of the error terms in Equation (6) is not 0, i.e., $E(\varepsilon_{igt} - \varepsilon_{igt'}) \neq 0$. However, our assumption that the seasonal patten is constant across years is commonly used in techniques for seasonal adjustment. Additionally, the YTEP training effect is likely to be constant across years due to its design.

We further investigate those assumptions to get additional information about the pandemic effect. One possible way to investigate the effect of unobserved differences in the seasonal pattern and training effects is to find another measure that could reflect such differences so that we can remove them in the estimation. Based on the data availability, a potential candidate is the stress of social interaction in rural areas. The YTEP program is to help teachers who work and live in rural areas improve their social interactions, and thus the stress of social interactions may be influenced by the YTEP training. Additionally, stress of social interaction may also fluctuate seasonally.

The DD model for social interaction stress can be written as:

$$W_{igt} - W_{igt'} = \kappa + \psi P_{Tg} + \lambda_W(X_{igt}) - \lambda_W(X_{igt'}) + v_{igt} - v_{igt'}, \qquad (7)$$

where W_{igt} measures social interaction stress. If the difference in the social interaction stress between Class-2019 and Wave-2 of Class-2020 captures the unobserved differences between those two groups, it could help difference out the bias in estimating the effects of the pandemic. This approach works similarly to the difference-in-difference-in-differences (hereafter "DDD") estimation (Wooldridge, 2010). We specify our model as:

$$\left(Y_{igt} - Y_{igt'}\right) - \left(W_{igt} - W_{igt'}\right) =$$

$$(\gamma - \kappa) + (\delta - \psi)P_{Tg} + [h(X_{igt}) - h(X_{igt'})] + [(\varepsilon_{igt} - \varepsilon_{igt'}) - (v_{igt} - v_{igt'})]. \qquad (8)$$

In Equation (8), the first term of the model $\gamma - \kappa$ represents the difference in time trends between job sentiments and social stress. The coefficient $\delta - \psi$ is the "DDD" estimate of the pandemic's effect on job sentiments netting out of the pandemic's effect on social stress. In the model, $h(X) = \lambda(X) - \lambda_W(X)$, and the third term $h(X_{igt}) - h(X_{igt'})$ represents the difference by observed heterogeneity. For the unobserved heterogeneity, if $E[(\varepsilon_{igt} - \varepsilon_{igt'}) - (v_{igt} - v_{igt'})] = 0$, then the unobserved difference due to the training effect and seasonal pattern will be differenced out. Even if the expectation of the unobserved difference is not zero, Model (8) can still reduce the bias.

One particular issue in the above model is whether the stress of social interaction is affected by the pandemic. As shown in the second term of Equation (8), if the pandemic has no effect on social interaction stress, then the estimate of $\delta - \psi$ represents the total pandemic effect on job sentiments; otherwise, it is a relative pandemic's effect on job sentiments netting out the pandemic's impact on social interaction stress. The pandemic causes various restrictions on social interactions. It might increase people's anxiety about communicating with others, or it might reduce stress by reducing the need to interact with each other. In other words, the hypothetical direction of the potential impact is mixed. We estimate the DD model for the social interaction stress and the results are reported in Column 1 of Table 8. It appears that the COVID-19 pandemic has no significant effect on social interaction stress for rural young teachers.

The results of the “DDD” estimation for job sentiments are shown in Column 2-4 of Table 8. Compared to the DD results in Table 7, the pandemic’s effect on career development stress and job enthusiasm are quite robust, with the former increasing by 0.413 points and the latter decreasing by approximately 1.001 points; both are highly significant. Although statistically insignificant, the pandemic increases an individual’s teaching stress level by 0.246 points, which is similar in magnitude to the previously reported DD estimates. Therefore, after differencing out the potential unobserved heterogeneity between the two samples, the estimated pandemic effects on job stress and job passion remain quite robust.

VII. Investigation of Working Channels

Given the above results that the pandemic has significant impact on rural teachers’ job sentiments, in this section, we investigate some working channels underlying the effect. The YTEP surveys provide some information on rural teachers’ work activities, which can help identify working channels of the pandemic on their job stress and passion.

The COVID-19 has changed work patterns and workload because teachers need to learn new teaching formats, conduct instruction via various online platforms, manage students’ learning online, etc. For example, Yang (2020) finds that around 63% of teachers find using online education platforms difficult. The reasons include factors such as instability of internet connections and online platforms, unfamiliarity with relevant technology, difficulty in controlling the progress of the course, and limited interaction with students. Moreover, after schools reopened, to be prepared for a pandemic resurgence, teachers were required to get ready to switch between face-to-face and online teaching modes at any time. In many places, schools offer hybrid classes with both in-person and online formats. In addition, teachers are also responsible for additional administrative work, such as epidemic prevention for the school and students and regular data reporting, etc.[20]

Therefore, even if hours worked may not increase, the changes due to the pandemic create additional work responsibilities for teachers. As shown in Table 9, rural young teachers taught a relatively larger number of classes across time, for example, 14.92 in June 2019 vs. 18.83 in June 2020. They also gave students many more weekly homework assignments in Class-2020 than in Class-2019.

Besides the above channel of workloads, we also look at social network. Based on the theoretical framework, the social network can have both buffering effects and spillover effects on an individual's stress. We use the information reported by the teachers about how many close colleagues they have in the school. Table 9 shows that the proportion of teachers with some close colleagues is smaller for Class-2020. Additionally, job-related training programs may enhance an individual's stress coping ability. Data in Table 9 shows that the proportion of samples participating in other job training programs also declines across time.

Based on the discussion about potential working channels on job sentiments, we first estimate the same DD model on these channel variables to assess how they are affected by the pandemic. The results are reported in Table 10.[21] It shows that the COVID-19 pandemic has a significant effect on increasing the number of weekly classes taught for rural young teachers, as

[20] Source: https://www.sohu.com/a/378302780_260616.
[21] We have also done all estimations with working channels using the matched sample and the results are consistent.

well as on increasing the homework assigned, and both effects are statistically significant. A possible reason for the increasing teaching load is due to online teaching. Teachers can record instruction videos and share the same materials to students in more classes. For homework, due to the difficulty in controlling online teaching quality, teachers thus gave homework assignments more frequently.

On rural teacher's social network, the pandemic displays a statistically significant effect in reducing close colleagues in school. Additionally, it also reduced the rural young teachers' participation in other training programs outside the YTEP, and the effect is statistically significant. The results in Table 10 show that all those potential channel variables are affected by the pandemic in the DD estimation. Therefore, they could be the working channels of the pandemic on teachers' job sentiments.

In order to investigate these working channels, we add them in the DD model for the pandemic. The results are reported in Table 11. The results show that teaching load and homework generally result in higher job stresses and lower job passion. The estimated effects of average number of classes taught per week are much stronger and are statistically significant in affecting all three job sentiments, based on both categorical and level measures. The amount of homework assignments has a significant effect on teaching stress but mixed effects on career development stress and passion for the teaching job, as perhaps assigning and grading homework represents a smaller part of work compared to teaching classes.

Additionally, having close colleagues shows a statistically significant effect of reducing both teaching stress and career development stress, for both the category- and scale-based models. This result indicates that the buffering effects for stress from the colleague network exceed that of the spillover effects, and thus help reduce the stress. On the other hand, other training programs do not show a statistically significant effect on job sentiments.

Comparing Table 11 to Table 5, we find that, with the inclusion of the channel variables, the magnitude of the total pandemic effect is reduced in all the models. For example, based on the scale measures, the total effect of the pandemic on teaching stress reduces by nearly half from 0.302 to 0.163 points. The amount of change is smaller for career development stress, from 0.393 to 0.281 points, a drop of 28%. The effect on job enthusiasm also changes from -1.040 to -0.925 points, a drop of 11%. Overall, the change in magnitude indicates that a significant portion of the pandemic effect on job sentiments operates through the potential channel of work activities and social network in workplace.

Besides work activities, another possible working channel of the pandemic is that a higher teaching stress during the pandemic may transfer to higher career development stress. Therefore, we add the teaching stress to the model. The results reported in Table 12 indicate that teaching stress is strongly related to career development stress. More specifically, it reduces the direct effect of the pandemic for the career development stress from 0.393 to 0.226 points, a drop of 42%. If the teaching stress measure is influenced by other factors such as difference in seasonality and YTEP training between the two years, this model will also help offset such influences on career development stress and mitigates the potential bias.

Additionally, as discussed in the conceptual framework, it is possible that teachers' teaching stress and career development stress affect their passion toward the teaching occupation. Stressful feelings at work might make job activities less enjoyable and thus reduce an individual's work satisfaction and job passion. We further estimate the model of job passion by including job stress measures. We find that both teaching stress and career development stress negatively affect job enthusiasm and are statistically significant (Table 12). More specifically, approximately 2.7% of the pandemic effect on job enthusiasm is accounted for by the increase in teaching and career development stresses. Interestingly, the total effect of both stress measures is -0.088 (by adding -0.064 and - 0.024), which is much larger than the decline in the direct effect of the pandemic (i.e., from -1.040 in Column 6 of Table 5 to -1.012 in Column 2 of Table 12).

All the estimation results show that, even after taking out the impact due to behavioral changes or other potential effects, we still find a statistically significant direct effect of COVID-19 on job sentiments. It appears that a part of the change in job sentiments is not directly related to behavioral changes on the job or changes at the local level but is likely caused by subtle anxieties and fears about the uncertainties and risks all over the world due to the COVID-19 pandemic.

VIII. Conclusion

The COVID-19 pandemic has greatly changed the way people work and live. In this study, we use the unique survey data to investigate the pandemic's effects on teachers' job-specific stresses and their enthusiasm for the teaching profession. Unlike some other professions, teachers' work moral will have a deep impact on a society. Our data come from young rural teachers in China and cover the time before and during the pandemic.

We propose a theoretical framework on the dynamics of an individual's stress. The pandemic has a direct effect on job attitudes due to changes of work format as well as an overall depressed atmosphere. It also has an indirect effect through an individual's social networks via buffering and spillover.

We apply both cross-section and difference-in-differences type estimations. Our results show that the COVID-19 pandemic increases a young rural teacher's teaching stress and career development stress with the effects being statistically significant. Specifically, the pandemic increases the probability of high teaching and career development stress by 8-9 and 5-7 percentage points, respectively. When both are measured by the 10-point scales, the pandemic increases teaching and career development stress by approximately 0.3 and 0.4 points, respectively, representing an increase of 5-7% from their average values.

Moreover, for job passion, the pandemic reduces the probability a teacher's high enthusiasm towards teaching by 17-24 percentage points, and reduces the scale of enthusiasm by 0.9-1.0 points, which is about 13-15% of the average values.

The local severity of COVID-19 affects job sentiments, but its relative magnitudes are much smaller than the overall pandemic effect. Therefore, studies based on data collected after the pandemic may identify only a small portion of the total pandemic effect. We conduct robustness checks using matched samples as well as other estimations to better control for the effects caused by observed and unobserved heterogeneity. The results are quite robust to these checks.

We also investigate the channels through which COVID-19 affects teachers' job attitudes. Work-related activities can help explain 28-46% of the pandemic effect on job stresses and approximately 11% of the reduction in job enthusiasm due to the pandemic. Additionally, higher teaching stress contributes to higher career development stress, and both lead to a reduction in enthusiasm felt for teaching. The COVID-19 pandemic still displays a strong direct influence on teachers' job sentiments even after controlling for those channels. This result sheds light on the ways that the pandemic fosters overall anxiety and a pessimistic social atmosphere, thereby exerting a direct impact on job sentiments.

The takeaway from this study is that COVID-19 has a significant impact on teachers' job-related stresses and on their job enthusiasm. Because teachers' morale affects education outcomes for the next generations, their mental health and psychological changes during the COVID-19 pandemic should be carefully addressed. Governments at various levels can provide teachers with better online teaching tools, carefully designed training programs for online teaching technology and teaching methods, and targeted services to reduce the mental and psychological influences of the pandemic to improve teaching morale. It is also important to create more certainties in alternative teaching arrangements to reduce the burden of frequent switches between instructional formats. Additionally, it is helpful to provide timely and scientifically based information to calm the pandemic-related anxiety of the population at large.

References

Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics*, 189.

Alves, R., Lopes, T., and Precioso, J. (2020). Teachers' well-being in times of Covid-19 pandemic: factors that explain professional well-being. *International Journal of Educational Research and Innovation*, (15), 203-217.

Aucejo, Esteban M., Jacob French, Maria Paola Ugalde Araya, Basit Zafar (2020). The impact of COVID-19 on student experiences and expectations: Evidence from a survey. *Journal of Public Economics*, 191.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates?. *The Quarterly Journal of Economics*, 119(1), 249-275.

Bliese, P. D., Edwards, J. R., and Sonnentag, S. (2017). Stress and well-being at work: A century of empirical trends reflecting theoretical and societal influences. *Journal of Applied Psychology*, 102(3), 389–402.

Brodeur, Abel, Andrew E. Clark, Sarah Fleche, Nattavudh Powdthavee. (2021). COVID-19, lockdowns and well-being: Evidence from Google Trends, *Journal of Public Economics*, 193.

Carbonneau, N., Vallerand, R. J., Fernet, C., and Guay, F. (2008). The role of passion for teaching in intrapersonal and interpersonal outcomes. *Journal of Educational Psychology*, 100(4), 977.

Collie, R. J., Shapka, J. D., and Perry, N. E. (2012). School climate and social–emotional learning: Predicting teacher stress, job satisfaction, and teaching efficacy. *Journal of Educational Psychology,* 104*(*4), 1189–1204.

Cooke, M., Holzhauser, K., Jones, M., Davis, C., and Finucane, J. (2007). The effect of aromatherapy massage with music on the stress and anxiety levels of emergency nurses: comparison between summer and winter. *Journal of Clinical Nursing*, 16(9), 1695-1703.

Cowan, R., Sanditov, B., and Weehuizen, R. (2011). Productivity effects of innovation, stress and social relations. *Journal of Economic Behavior and Organization*, 79(3), 165-182.

Dryhurst, S., Schneider, C. R., Kerr, J., Freeman, A. L., Recchia, G., Van Der Bles, A. M., ... & van der Linden, S. (2020). Risk perceptions of COVID-19 around the world. *Journal of Risk Research*, 1-13.

Duflo, E. (2001). Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment. *The American Economic Review*, 91(4): 795–813.

Fang, Hanming, Long Wang, Yang Yang. (2020). Human mobility restrictions and the spread of the Novel Coronavirus (2019-nCoV) in China, *Journal of Public Economics*, 191.

Florian, V., Mikulincer, M., Hirschberger, G. (2002). The anxiety-buffering function of close relationships: evidence that relationship commitment acts as a terror management mechanism. *Journal of Personality and Social Psychology,* 82 (4), 527–542.

Gagné, M. Ed. (2014). The Oxford handbook of work engagement, motivation, and self-determination theory. Oxford University Press, USA.

Hammer, L.B., Cullen, J.C., Neal, M.B., Sinclari, R.R., Shafiro, M.V. (2005). The longitudinal effects of work-family conflict and positive spillover on depressive symptoms among dual-earner couples. *Journal of Occupational Health Psychology*, 10, 138-154.

Hansen, C. B. (2007). Generalized least squares inference in panel and multilevel models with serial correlation and fixed effects. *Journal of Econometrics*, 140(2), 670-694.

Harris, Douglas N., Scott J. Adams. (2007). Understanding the level and causes of teacher turnover: A comparison with other professions. *Economics of Education Review*, 26(3), 325-337.

Holmes, E. A., O'Connor, R. C., Perry, V. H., Tracey, I., Wessely, S., Arseneault, L., ... and Ford, T. (2020). Multidisciplinary research priorities for the COVID-19 pandemic: a call for action for mental health science. *The Lancet Psychiatry*.

Holmes, E. (2005). Teacher well-being: Looking after yourself and your career in the classroom. *Psychology Press.*

Houlfort, N., Philippe, F. L., Vallerand, R. J., and Ménard, J. (2014). On passion and heavy work investment: personal and organizational outcomes. *Journal of Managerial Psychology*, 29(1), 25-45.

Huang, R. H., Liu, D. J., Tlili, A., Yang, J. F., and Wang, H. H. (2020). Handbook on facilitating flexible learning during educational disruption: The Chinese experience in maintaining undisrupted learning in COVID-19 Outbreak. Beijing: Smart Learning Institute of Beijing Normal University.

Imbens, G. W., and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1), 5-86.

Kang, L., Ma, S., Chen, M., et al. (2020). Impact on mental health and perceptions of psychological care among medical and nursing staff in Wuhan during the 2019 novel coronavirus disease outbreak: a cross-sectional study. *Brain, Behavior, and Immunity*.

MacIntyre, P. D., Gregersen, T., and Mercer, S. (2020). Language teachers' coping strategies during the COVID-19 conversion to online teaching: Correlations with stress, wellbeing and negative emotions. *System*, 102352.

Nelson, R. J., and Martin II, L. B. (2010). Seasonal changes in stress responses. *Stress Science: Neuroendocrinology*, 440.

Qiu, Y., Chen, X., and Shi, W. (2020a). Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *Journal of Population Economics*, 1.

Qiu, J., Shen, B., Zhao, M., Wang, Z., Xie, B., and Xu, Y. (2020b). A nationwide survey of psychological distress among Chinese people in the COVID-19 epidemic: implications and policy recommendations. *General Psychiatry*, 33(2).

Smith, J. A., and Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. *Journal of Econometrics*, 125(1-2), 305-353.

Stuart, Elizabeth A. (2010). Matching methods for causal inference: a review and a look forward. *Statistical Science*, 25(1), 1-21.

Tan, W., Hao, F., McIntyre, R. S., Jiang, L., Jiang, X., Zhang, L., and Zhang, Z. (2020). Is returning to work during the COVID-19 pandemic stressful? A study on immediate mental health status and psychoneuroimmunity prevention measures of Chinese workforce. *Brain, Behavior, and Immunity*.

Tóth-Király, I., Bőthe, B., Jánvári, M., Rigó, A., and Orosz, G. (2019). Longitudinal trajectories of passion and their individual and social determinants: A latent growth modeling approach. *Journal of Happiness Studies*, 20(8), 2431-2444.

Vallerand, R. J., and Houlfort, N. (2003). Passion at work: Toward a new conceptualization. In S.W. Gilliland, D. D. Steiner, and D. P. Skarlicki (Eds.), Emerging perspectives on values in organizations (pp. 175-204). Greenwich, CT: Information Age Publishing.

Vallerand, R. J., Houlfort, N., and Forest, J. (2014). Passion for work: Determinants and outcomes. InM. Gagné (Ed.), The Oxford handbook of work engagement, motivation, and self-determination theory (pp. 85-105). Oxford: Oxford University Press.

Viswesvaran, C., Sanchez, J. I., & Fisher, J. (1999). The role of social support in the process of work stress: A meta-analysis. *Journal of Vocational Behavior*, 54(2), 314-334.

Wang, C., Pan, R., Wan, X., et al., (2020a). Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in China. *Int. J. Environ. Res. Public Health* 17, E1729.

Wang, C., Pan, R., Wan, X., Tan, Y., Xu, L., McIntyre, R. S., ... and Ho, C. (2020b). A longitudinal study on the mental health of general population during the COVID-19 epidemic in China. *Brain, Behavior, and Immunity*.

Westman, M. (2001). Stress and strain crossover. *Human Relations,* 54, 557-591.

Wong, G. (2008). Has SARS infected the property market? Evidence from Hong Kong. *Journal of Urban Economics*, 63(1), 74-95.

Wooldridge, Jeffrey M. (2010). Econometric analysis of cross section and panel data, MIT press.

Yang, X. (2020). Teachers' perceptions of large-scale online teaching as an epidemic prevention and control strategy in China. *ECNU Review of Education*.

Zhang, Y., and Ma, Z. F. (2020). Impact of the COVID-19 pandemic on mental health and quality of life among local residents in Liaoning Province, China: A cross-sectional study. *International Journal of Environmental Research and Public Health*, 17(7), 2381.

Table 1 Summary Statistics of Job Stress and Job Enthusiasm

Variable	Questionnaire items	Proportion in High Category			Average Scale		
		Class-2019	Class-2020		Class-2019	Class-2020	
			Wave-1	Wave-2		Wave-1	Wave-2
		06/2019	01/2020	06/2020	06/2019	01/2020	06/2020
Teaching stress	I feel pressure to help students graduate and enroll in the next level of education; I feel pressure to maintain students' discipline	0.520	0.691	0.647	5.247	5.790	5.694
		(0.500)	(0.462)	(0.478)	(2.001)	(2.270)	(2.260)
Career development stress	I feel pressure to get a promotion; I feel pressure to receive merit awards	0.483	0.620	0.554	5.682	6.310	6.073
		(0.500)	(0.486)	(0.497)	(2.510)	(2.480)	(2.397)
Passion for occupation	I will not feel tired of being a teacher; I would still choose to be a teacher if given a second chance	0.880	0.778	0.673	7.541	7.113	6.546
		(0.325)	(0.416)	(0.469)	(2.227)	(2.152)	(2.234)
Social interaction stress	I feel pressure to interact with others in rural areas	0.167	0.242	0.252	4.216	3.951	4.232
		(0.373)	(0.428)	(0.434)	(2.362)	(2.901)	(2.781)
Obs.		1,543	3,076	3,303	1,543	3,076	3,303

Notes:

1. The sample are restricted to full-time employed rural teachers at age 35 or below and within 5 years' teaching experience.
2. The values on the left panel represent the proportion of the category of high-level stress or passion in the sample. The values on the right panel indicate the average scale of stress or passion of the sample. See details in Appendix Table 2.
3. Estimated standard errors are in parentheses.

Table 2 Variable Definition and Summary Statistics

Variable	Definition	Class-2019 06/2019	Class-2020 Wave-1 01/2020	Class-2020 Wave-2 06/2020
Female	1 if female	0.849	0.816	0.801
Age	Age	26.63	25.31	25.68
Han-ethnicity	1 if Han ethnic group	0.853	0.684	0.697
Married	1 if married	0.356	0.243	0.269
Children	1 if having children	0.204	0.152	0.159
College or above	1 if college degree or above	0.826	0.825	0.820
Teaching degree	1 if graduated with a teaching degree	0.723	0.685	0.674
Exp	Teaching experience	1.923	1.465	1.571
Permanent teacher	1 if permanent teacher	0.252	0.351	0.357
Special-term teacher	1 if special-term teacher	0.748	0.649	0.643
Schoolhouse	1 if rural schoolhouse	0.339	0.398	0.431
Village school	1 if village school	0.266	0.257	0.226
Rural district school	1 if rural district school	0.395	0.345	0.343
Non-western	1 if central or eastern region	0.680	0.274	0.245
Local severity P_L	Cumulative number of confirmed COVID19 cases (in 100) in the province as of June 5, 2020	0	0	3.452
Obs.		1,543	3,076	3,303

Notes:

1. The samples are full-time employed rural teachers at age 35 or below and within 5 years' teaching experience.
2. Non-western region includes Fujian, Jiangsu, Zhejiang, Shandong, Beijing, Guangdong, Liaoning, Jilin, Heilongjiang, Hubei, Hunan, Anhui, Jiangxi, Shanxi, and Henan. Western region includes Chongqing, Sichuan, Guangxi, Inner Mongolia, Guizhou, Gansu, Xinjiang, Ningxia, Qinghai, and Yunnan.

Table 3 Effect of Pandemic on Job Sentiment: Cross-section Estimation

	Cross-section Estimation with Class-2020 Wave-2 sample $Y_i = \alpha + \varphi P_{Li} + X_i\lambda + \varepsilon_i$					
	Probit Estimation Based on Category			Estimation Based on Scale		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Teaching stress	Career development stress	Passion for occupation	Teaching stress	Career development stress	Passion for occupation
Local severity P_L	-0.001	0.004	-0.015***	0.001	0.002***	-0.003**
	(0.001)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2/R2	0.016	0.007	0.024	0.028	0.009	0.036
Chi2/F	67.700***	30.884***	101.775***	7.413***	3.079***	10.408***
N	3,303	3,303	3,303	3,303	3,303	3,303

Notes:

1. The dependent variable of the probit estimation is defined as 1 for high value and 0 otherwise.
2. The marginal effects of the probit model are reported and are calculated using the average marginal effects.
3. Other control variables included are the same as those listed in Table 4.
4. Robust standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4 Effect of Pandemic on Job Sentiment: Before-After Estimation

	Before-After Estimation with Class-2019 & Class-2020 Wave-2 $Y_{it} = \alpha + \delta P_T + \varphi P_{Lit} + X_{it}\lambda + \varepsilon_{it}$					
	Probit Estimation Based on Category			Estimation Based on Scale		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Teaching stress	Career development stress	Passion for occupation	Teaching stress	Career development stress	Passion for occupation
Overall effect P_T	0.093***	0.073***	-0.171***	0.311***	0.440***	-0.916***
	(0.016)	(0.019)	(0.021)	(0.076)	(0.085)	(0.077)
Local severity P_L	-0.000	0.001	-0.011***	0.002	0.003	-0.003
	(0.000)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Female	0.116***	-0.004	0.025	0.538***	0.088	-0.073
	(0.018)	(0.019)	(0.016)	(0.081)	(0.091)	(0.083)
Age>=30	0.013	0.028	0.025	-0.080	0.209	0.195
	(0.026)	(0.028)	(0.026)	(0.119)	(0.134)	(0.121)
Exp	-0.028***	0.030***	-0.003	-0.165***	0.103***	-0.020
	(0.007)	(0.007)	(0.007)	(0.032)	(0.036)	(0.033)
Han-ethnicity	0.018	0.005	0.035**	0.084	-0.064	0.176**
	(0.017)	(0.017)	(0.014)	(0.075)	(0.085)	(0.077)
Married	0.024	0.035	0.065***	-0.029	0.174*	0.369***
	(0.021)	(0.022)	(0.019)	(0.094)	(0.106)	(0.096)
Children	-0.026	0.023	0.040	-0.097	-0.075	0.329***
	(0.026)	(0.027)	(0.024)	(0.116)	(0.131)	(0.118)
College or above	-0.001	-0.017	-0.011	0.033	-0.053	-0.158*
	(0.019)	(0.019)	(0.017)	(0.084)	(0.095)	(0.086)
Teaching degree	-0.008	-0.005	-0.027**	-0.100	-0.022	-0.135*
	(0.015)	(0.016)	(0.013)	(0.068)	(0.077)	(0.069)
Special-term teacher	0.001	-0.051***	0.017	0.111	-0.156**	0.439***
	(0.015)	(0.016)	(0.014)	(0.069)	(0.077)	(0.070)
Village school	0.017	0.028	-0.013	0.200**	0.182**	-0.087
	(0.018)	(0.019)	(0.016)	(0.082)	(0.092)	(0.083)
Rural district school	0.028*	0.015	-0.035**	0.357***	0.089	-0.241***
	(0.016)	(0.017)	(0.014)	(0.073)	(0.082)	(0.075)
Non-western	-0.079***	-0.015	0.008	-0.295***	0.008	-0.075
	(0.017)	(0.019)	(0.019)	(0.078)	(0.088)	(0.079)
_cons				5.048***	5.473***	7.334***
				(0.156)	(0.176)	(0.159)
Pseudo-R2/R2	0.024	0.013	0.063	0.036	0.013	0.069
Chi2/F	155.707***	82.821***	304.900***	12.811***	4.655***	25.704***
N	4,846	4,846	4,846	4,846	4,846	4,846

Notes:

1. The marginal effects of the probit model are reported and are calculated using the average marginal effects.
2. Robust standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Effect of Pandemic on Job Sentiment: DD Estimation

	$Y_{igt} = \alpha + \delta P_{Tgt} + \beta T_g + \gamma S_t + X_{igt}\lambda + \varepsilon_{igt}$					
	Probit Estimation Based on Category			Estimation Based on Scale		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Teaching stress	Career development stress	Passion for occupation	Teaching stress	Career development stress	Passion for occupation
Overall effect P_T	0.079***	0.053**	-0.243***	0.302***	0.393***	-1.040***
	(0.021)	(0.022)	(0.019)	(0.096)	(0.109)	(0.096)
S	-0.129***	-0.141***	0.117***	-0.414***	-0.694***	0.345***
	(0.015)	(0.016)	(0.015)	(0.069)	(0.082)	(0.071)
T	0.014	0.013	0.014	0.066	0.068	0.065
	(0.013)	(0.014)	(0.012)	(0.063)	(0.069)	(0.059)
Female	0.118***	0.021	0.007	0.569***	0.214***	-0.094
	(0.013)	(0.014)	(0.011)	(0.066)	(0.073)	(0.062)
Age>=30	0.004	0.047**	0.028	-0.090	0.131	0.147
	(0.020)	(0.022)	(0.020)	(0.097)	(0.112)	(0.094)
Exp	-0.020***	0.040***	-0.008	-0.109***	0.151***	-0.037
	(0.006)	(0.006)	(0.005)	(0.027)	(0.030)	(0.027)
Han-ethnicity	-0.002	0.006	0.019*	-0.029	-0.083	0.140**
	(0.012)	(0.012)	(0.010)	(0.055)	(0.061)	(0.055)
Married	-0.024	0.021	0.060***	-0.251***	0.054	0.426***
	(0.015)	(0.016)	(0.014)	(0.072)	(0.084)	(0.071)
Children	0.016	-0.005	0.053***	0.083	-0.000	0.262***
	(0.019)	(0.020)	(0.018)	(0.091)	(0.103)	(0.086)
College or above	-0.002	-0.024*	-0.021*	-0.014	-0.170**	-0.224***
	(0.014)	(0.014)	(0.012)	(0.063)	(0.069)	(0.061)
Teaching degree	-0.042***	-0.007	-0.012	-0.183***	-0.002	-0.099**
	(0.011)	(0.011)	(0.010)	(0.051)	(0.057)	(0.049)
Special-term teacher	0.013	-0.045***	0.060***	0.126**	-0.169***	0.479***
	(0.011)	(0.012)	(0.010)	(0.053)	(0.059)	(0.051)
Village school	0.008	-0.022*	-0.023**	0.099*	-0.040	-0.137**
	(0.013)	(0.013)	(0.011)	(0.060)	(0.068)	(0.058)
Rural district school	0.040***	0.011	-0.054***	0.345***	0.138**	-0.348***
	(0.012)	(0.012)	(0.010)	(0.055)	(0.061)	(0.054)
Non-western	-0.068***	-0.039***	-0.029***	-0.206***	-0.009	-0.049
	(0.012)	(0.013)	(0.011)	(0.057)	(0.063)	(0.057)
_cons				5.528***	6.163***	7.106***
				(0.110)	(0.123)	(0.107)
Pseudo-R2/R2	0.029	0.018	0.047	0.033	0.018	0.056
Chi2/F	329.072***	208.658***	408.610***	21.258***	11.231***	34.496***
N	8,929	8,929	8,929	8,929	8,929	8,929

Notes:

1. The marginal effects of the probit model are reported and are calculated using the average marginal effects.
2. Robust standard errors in parentheses and * p < 0.1, ** p < 0.05, *** p < 0.01

Table 6 Effect of Pandemic on Job Stress and Job Enthusiasm (Non-western & Western Samples)

	Non-western Sample			Western Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Teaching stress	Career development stress	Passion for occupation	Teaching stress	Career developmen t stress	Passion for occupation
Overall effect P_T	0.271*	0.435**	-1.005***	0.129	0.341**	-1.078***
	(0.157)	(0.180)	(0.156)	(0.128)	(0.147)	(0.132)
S	-0.529***	-0.702***	0.391***	-0.183*	-0.656***	0.356***
	(0.101)	(0.119)	(0.102)	(0.100)	(0.120)	(0.107)
T	0.063	0.030	0.065	0.063	0.080	0.064
	(0.114)	(0.128)	(0.109)	(0.075)	(0.082)	(0.070)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.043	0.031	0.071	0.028	0.014	0.053
F	9.945***	7.390***	16.202***	11.870***	5.819***	23.132***
N	3,101	3,101	3,101	5,828	5,828	5,828

Notes:

1. The dependent variables are the scales of stress and passion.
2. Other control variables included are the same as those listed in Table 4.
3. Robust standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7 Effect of Pandemic on Job Sentiment: DD Estimation with Matched Samples

	DD Model with Matched Sample $Y_{igt} = \alpha + \delta P_{Tgt} + \beta T_g + \gamma S_t + X_{igt}\lambda + \varepsilon_{igt}$			Differenced DD Model with Matched Sample $Y_{igt} - Y_{igt'} = \gamma + \delta P_{Tg} + \lambda(X_{igt}) - \lambda(X_{igt'}) + \varepsilon_{igt} - \varepsilon_{igt'}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Teaching stress	Career development stress	Passion for occupation	Teaching stress	Career development stress	Passion for occupation
Overall effect P_T	0.284**	0.439***	-1.006***	0.264**	0.431***	-0.983***
	(0.128)	(0.146)	(0.127)	(0.117)	(0.136)	(0.120)
S	-0.390***	-0.731***	0.304***			
	(0.109)	(0.126)	(0.109)			
T	0.049	-0.005	0.022			
	(0.096)	(0.105)	(0.089)			
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
_cons	5.636***	6.351***	7.131***	-0.378***	-0.712***	0.311***
	(0.154)	(0.171)	(0.152)	(0.104)	(0.125)	(0.111)
R2	0.031	0.018	0.064	0.007	0.009	0.033
F	12.850***	7.084***	26.791***	5.654***	2.403***	6.733***
N	5,842	5,842	5,842	2,921	2,921	2,921

Notes:

1. The dependent variables are the scales of stress and passion.
2. Other control variables included are the same as those listed in Table 4.
3. Robust standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8 Effect of Pandemic on Job Sentiment: "DDD" Estimation with Matched Samples

	DD Model with Matched Sample	"DDD" Model with Matched Sample $Y_{igt}-Y_{igt'}-(W_{igt}-W_{igt'})=(\gamma-\kappa)+(\delta-\psi)P_{Tg}+[h(X_{igt})-h(X_{igt'})]+(\varepsilon_{igt}-\varepsilon_{igt'})-(v_{igt}-v_{igt'})$		
Dependent variable	(1) Social interaction stress	(2) Teaching stress	(3) Career development stress	(4) Passion for occupation
Overall effect P_T	0.018	0.246	0.413**	-1.001***
	(0.151)	(0.156)	(0.166)	(0.213)
Other variables	Yes	Yes	Yes	Yes
_cons	0.236*	-0.614***	-0.947***	0.076
	(0.136)	(0.137)	(0.150)	(0.196)
R2	0.004	0.003	0.008	0.013
F	1.230	0.737	2.257***	2.871***
N	2,921	2,921	2,921	2,921

Notes:

1. The dependent variables are the scales of stress and passion.
2. Other control variables included are the same as those listed in Table 4.
3. Robust standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9 Variable Definition of Working Channels and Summary Statistics

Variable	Definition	06/2019	01/2020	06/2020
Classes taught	Average number of classes taught per week	14.92	17.88	18.83
		(9.417)	(6.807)	(7.964)
Homework	Average number of homework assignments per week	3.803	4.219	4.208
		(2.085)	(2.137)	(2.071)
Close colleagues	1 if have some close colleagues	0.895	0.714	0.731
		(0.306)	(0.452)	(0.443)
Job training	1 if participate in any other job training program	0.572	0.523	0.489
		(0.495)	(0.500)	(0.500)
Obs.		1,384	3,059	3,256

Notes:

1. The variable "Close colleagues" is defined as 1 if the respondents report having some or many close colleagues in the Class-2019 survey; and as 1 if the respondents reported having three or more close colleagues in the Class-2020 surveys.
2. Estimated standard errors are in parentheses.

Table 10 Effect of Pandemic on Job Activities

	(1)	(2)	(3)	(4)
Dependent variable	Classes taught	Homework	Close colleagues	Job training
Overall effect P_T	2.876***	0.430***	-0.220***	-0.200***
	(0.354)	(0.094)	(0.019)	(0.023)
S	-1.905***	-0.409***	0.202***	0.118***
	(0.288)	(0.073)	(0.013)	(0.017)
T	0.039	-0.071	0.000	0.011
	(0.175)	(0.058)	(0.013)	(0.014)
Other variables	Yes	Yes	Yes	Yes
R2	0.179	0.076	0.045	0.043
F	113.703***	47.996***	34.705***	27.868***
N	8,701	8,701	8,701	8,701

Notes:

1. Other control variables included are the same as those listed in Table 4.
2. Robust standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11 Working Channels of Pandemic through Job Activities

	Probit Estimation Based on Category			Estimation Based on Scale		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Teaching stress	Career development stress	Passion for occupation	Teaching stress	Career development stress	Passion for occupation
Overall effect P_T	0.056***	0.039*	-0.230***	0.163*	0.281**	-0.925***
	(0.021)	(0.023)	(0.020)	(0.099)	(0.114)	(0.099)
S	-0.113***	-0.128***	0.109***	-0.306***	-0.606***	0.262***
	(0.016)	(0.017)	(0.016)	(0.072)	(0.087)	(0.074)
T	0.016	0.013	0.014	0.074	0.069	0.065
	(0.013)	(0.014)	(0.012)	(0.063)	(0.069)	(0.059)
Classes taught	0.003***	0.002**	-0.002***	0.021***	0.017***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.003)
Homework	0.021***	0.005**	-0.000	0.092***	0.014	-0.004
	(0.003)	(0.003)	(0.002)	(0.012)	(0.013)	(0.011)
Close colleagues	-0.030***	-0.040***	0.070***	-0.219***	-0.314***	0.535***
	(0.012)	(0.012)	(0.010)	(0.054)	(0.060)	(0.054)
Job training	-0.001	0.011	0.007	0.053	0.041	-0.011
	(0.010)	(0.011)	(0.009)	(0.048)	(0.054)	(0.047)
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2/R2	0.038	0.019	0.056	0.048	0.024	0.071
Chi2/F	427.310***	225.679***	524.399***	23.658***	11.529***	34.656***
N	8,701	8,701	8,701	8,701	8,701	8,701

Notes:

1. The marginal effects of the probit model are reported and are calculated using the average marginal effects.
2. Other control variables included are the same as those listed in Table 4.
3. Robust standard errors in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

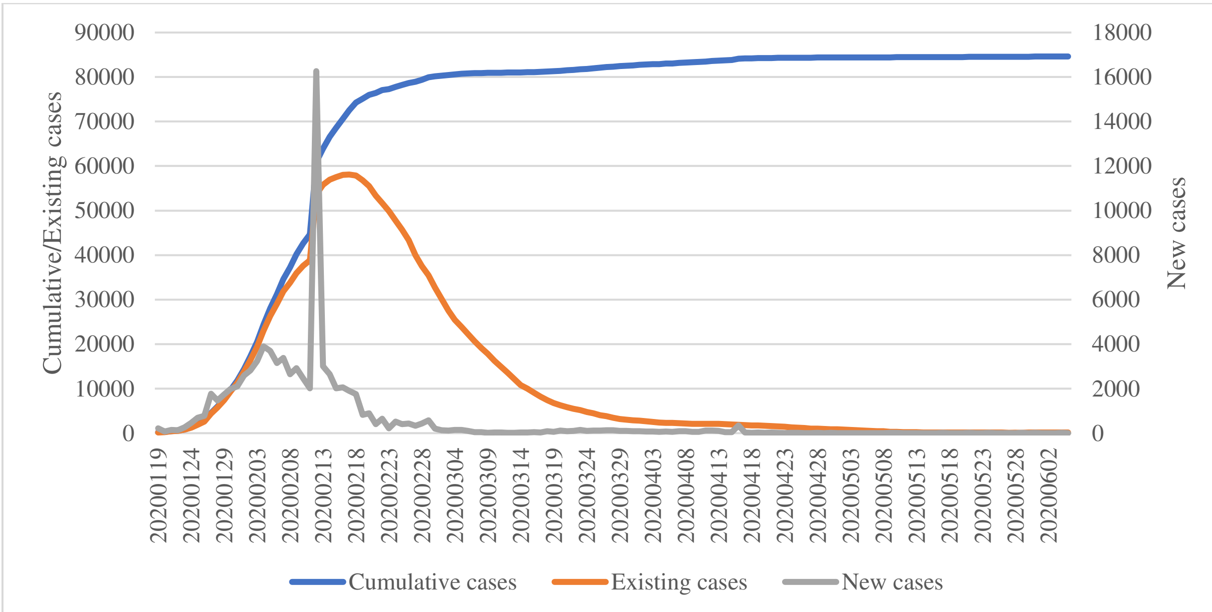
Table 12 Working Channels of Pandemic through Different Job Stresses

	Estimation Based on Scale	
	(1)	(2)
Dependent variable	Career development stress	Passion for occupation
Overall effect P_T	0.226**	-1.012***
	(0.096)	(0.096)
S	-0.465***	0.302***
	(0.072)	(0.071)
T	0.031	0.071
	(0.058)	(0.059)
Teaching stress	0.551***	-0.064***
	(0.012)	(0.013)
Career development stress		-0.024**
		(0.011)
Other variables	Yes	Yes
R2	0.258	0.062
F	164.230***	34.549***
N	8,929	8,929

Notes:

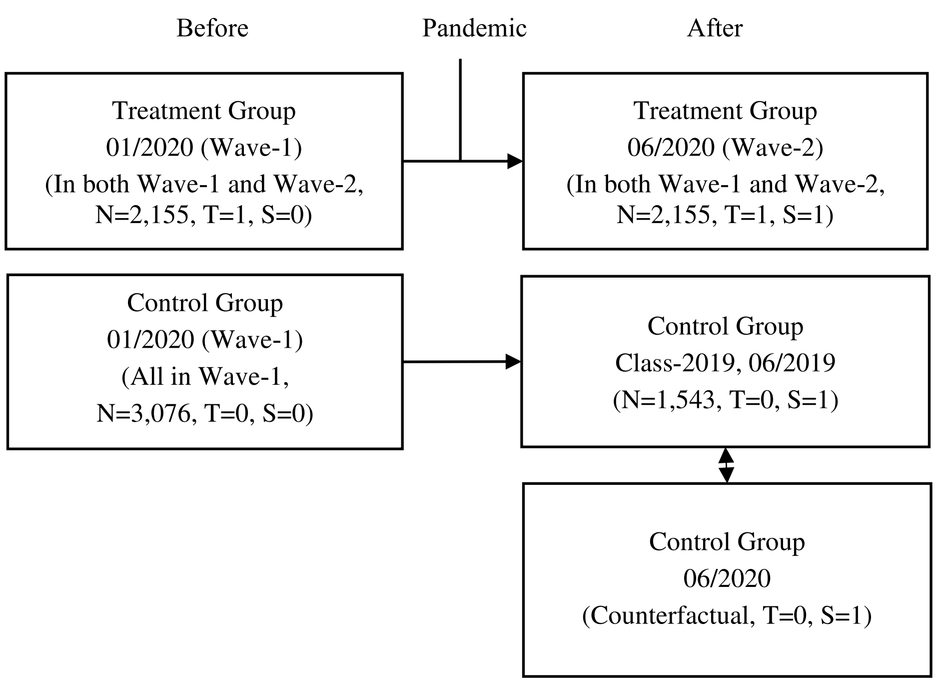
1. The dependent variables are the scales of stress and passion.
2. Other control variables included are the same as those listed in Table 4.
3. Robust standard errors in parentheses and * p < 0.1, ** p < 0.05, *** p < 0.01

Figure 1 The COVID-19 Pandemic Trend in China



Notes: "Cumulative cases" represents the cumulative number of confirmed cases in China since the outbreak. "Existing cases" is the current number of confirmed cases. "New cases" is calculated as the change in the number of cumulative cases compared to the previous day.

Figure 2 The Pandemic Influence and the DD Estimation Design



Appendix Table A1 Three Online Surveys on YTEP Evaluation

Class	Survey	Sample size	Time	Note
Class-2019	06/2019	2,099	May 22–June 20, 2019	
Class-2020	01/2020 (Wave-1)	3,649	January 2-January 20, 2020	2,869 individuals participated in both Wave-1 and Wave-2; 780 individuals only participated in Wave-1
	06/2020 (Wave-2)	4,623	June 5–June 25, 2020	2,869 individuals participated in both Wave-1 and Wave-2; 1,754 individuals only participated in Wave-2

Appendix Table A2 Rules for Categorizing Choices and for Assigning Scale Values

Survey class	Choice set	Question	Option	Category (high=1, low=0)	Scale (0-10)
Class-2019	Choice set 1	Would you still choose to be a teacher if given a second chance?	No	0	0.17
			Unsure		4.70
			Yes	1	9.90
	Choice set 2	Do you feel tired of being a teacher?	Often	0	1.03
			Sometimes		3.77
			Seldom		6.90
			Never	1	9.93
	Choice set 3	1. Do you have great pressure to help students graduate and enroll in the next level of education? 2. Do you have great pressure to maintain students' discipline? 3. Do you have great pressure to get promotion? 4. Do you have great pressure to receive merit awards? 5. Do you have great pressure to interact with others in the rural areas?	No	0	0.27
			A little bit		2.40
			Somewhat		4.97
			A decent amount	1	7.33
			A lot		9.80
Class-2020	Choice set 4	1. I feel great pressure to help students graduate and enroll in the next level of education 2. I feel great pressure to maintain students' discipline 3. I feel great pressure to get promotion 4. I feel great pressure to receive merit awards 5. I will not feel tired of being a teacher 6. I would still choose to be a teacher if given a second chance 7. I feel great pressure to interact with others in the rural areas.	Completely disagree	0	0.20
			Mostly disagree		1.83
			Somewhat disagree		3.23
			Indifferent		5.10
			Mostly agree	1	7.33
			Agree		8.67
			Completely agree		10.0

Notes: The scale values are the average of those from all 10 survey team members. Each team member assigned scale values in three rounds at different time and did it independently.