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Higher Education Expansion and Crime: New Evidence from China

Xingfei Liu
University of Alberta

Chuhong Wang
Yango University

Zizhong Yan
Jinan University

Yi Zhao
Tsinghua University

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Xingfei Liu*
University of Alberta, IZA, and GLO

Chuhong Wang
Yango University and GLO

Zizhong Yan
Jinan University

Yi Zhao
Tsinghua University

Abstract

In this paper we present causal evidence on the impact of higher education expansion on crime by exploiting a massive expansion of college enrollment in China since 1999, using data from multiple sources. Our identification strategy exploits regional variation in the intensity of the higher education expansion with partially identified difference-in-differences models. We explore various assumptions to account for the potential unparallel trends over years and find that college expansion causally reduces crime rates and the effect changes over time. Moreover, the crime reducing effect extends beyond the post-secondary educational level and into the senior high schools. Our findings document an important yet overlooked positive externality associated with higher education expansion.

JEL classification: I2, K42

Keywords: Higher education expansion; Crime; China; Partial identification

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* Corresponding author. E-mail address: xingfei@ualberta.ca (X. Liu).

1 Introduction

Education is one of most important ways to improve human capital and skills that are rewarded in the labor market. The economics literature has generated numerous studies on the private returns to schooling. In addition to improving productivity, education also provides other important positive externalities to the society, such as health enhancement, and crime reduction. The economics literature has recently provided interesting causal evidence on how education helps to reduce criminal activity in various countries and different settings. So far, most of the studies have focused on mandatory schooling or compulsory schooling and its impact on crime for youths. Evidence on how expansion of higher education has affected crime is still sparse with the exception of Machin et.al. 2012.[1] Still little is known on how higher level of education empirically affects criminal activity not only for youth but also for the general population. We intend to fill this gap by providing new evidence on how expansion of university/college education causally affects the incidence of criminal offenses among the general population in China.

Since 1999, China has undergone massive expansion and reforms in higher education (HE), resulting in an unprecedented surge in college enrollment throughout the country. The year 1999 witnessed 1.59 million university admitted students, which is more than 47 percent from the previous year. The freshmen enrollment of higher education institutions reaches 9.15 million in 2019 according to official statistics from the Chinese Ministry of Education. The higher education expansion initiated in 1999 is not only large in magnitude but also unexpected by the population as well as local governments, therefore, it serves as an excellent natural experiment to estimate causal relationship between higher education and crime.

In the economics literature, scholars have primarily focused on the impact of China's higher education expansion on educational outcomes such schooling, returns to education, labour market outcomes as well as marriage and fertility decisions for college students *per se* (Li, Whalley, & Xing, 2014; Wu & Liu, 2014; Knight, Deng, & Li, 2017; Xing, Yang, & Li, 2018). Better education opportunities clearly influence the person who takes advantage of it, but there are external benefits

[1] In Machin, Marie, and Vujic (2012), an expansion of higher education in UK is explored. The paper shows that higher education expansion significantly reduces the youth crime in UK and that the impact is brought through productivity related variables such wages on top of the incapacitation effect. Similarly, using variations in post-compulsory education in Norway, Brugard and Falch (2013) shows that the number of semesters in high school education has diminishing effect on imprisonment of young adults.

or costs beyond *private* returns at the individual level, for example a society with a higher level of education produces spillover effects (or externalities). There is a sparse but burgeoning body of literature that estimates the *social* returns to higher education expansion in China. At the micro level, research reveals that college enrollment expansion has a positive externality and raises the average college wage premium in the Chinese labor market (see, for example, Li *et al.*, 2017). A handful of fairly recent studies have provided evidence on the impact of education expansion on firm's innovation and emissions behaviors (Che & Zhang, 2018; Rong & Wu, 2020; Chen, Song, & Wu, 2021). There are also a number of studies documenting the importance of Chinese higher education reforms at the macro level, such as its effects on productivity, global economy, and so forth (Li *et al.*, 2011; Yao, 2019). Little attention has been paid, however, to the questions of whether and how crime has been affected by the higher education expansion in China.

In this paper, we would like to answer the question: whether the large-scale higher education expansion in China has causally impacted crime in the entire country, and if so, how large is such impact and what are the dynamics of it over time? Our empirical strategy exploits exogenous variation in the intensity of HE expansion across provinces and over time. We first estimate a classical DID model and compare provincial crime rates between provinces that experience higher intensity of higher education expansion and provinces that experience relatively low level of higher education expansion. We then move away from the traditional parallel trends assumption and perform a partial identification DD analysis under alternative plausible settings. We thus can provide upper and lower bounds for the treatment effects under different pre-trend assumptions. We consistently find that the higher education expansion in China significantly reduces the crime rates across provinces regardless of the assumed pre-trend pattern. Furthermore, we show that the higher education expansion starts to demonstrate significant deterring effects on crime after 4 or 5 years of its implementation, and the effects prolong for more than a decade. The negative dynamic effects are quite robust across alternative treatment intensity measures and model specifications. Given the sequential nature of higher education, we also document large expansion on senior high school enrolment and show its negative causal effects on crime. Interestingly, the deterring effects from senior high school enrolment expansion are immediate after the implementation of higher education expansion policy, providing indirect evidence on incapacitation effect on crime.

Our empirical analysis is based on a variety of data sources at provincial level. For example, the crime rate is derived from China Law Yearbook (1989-2013), and Procuratorial Yearbook of China (1989-2013). The intensity of higher education expansion is calculated with China Statistical Yearbook (1989), and Educational Statistics Yearbook of China (1989-2012). Other important demographic information is drawn from various sources with details presented in the data section.

The existing literature highlights four main channels through which education might affect criminal activity: income effects (Lochner 2004, Lochner and Moretti 2004), incapacitation effects (Jacob and Lefgren 2003; Luallen 2006), patience or risk aversion (Baker and Mulligan 1997), and psychic costs of committing crime. Given the large quantitative negative effects identified by this paper, it is natural to think about potential channels/mechanisms behind the effects. Our results are based on general crime rates defined over the entire age distribution and including all types of criminal activity that results in arrestment. Detailed data limitations on this information prevent us from performing in-depth analysis on disentangling the various channels, however, we do show with micro-data that the higher education expansion in China helps to positively influence individual personality traits, which in turn, as an important channel, influence criminal behavior.

This study makes three important contributions to the literature. First, to our knowledge, it is among the first to establish the causal relationship between expansion of higher education at college level and criminal activity for all age groups. Second, we provide the first empirical evidence on causal impacts of higher education expansion on crime in China, one of the largest developing countries in the world. Lastly, our identification strategy is based on less restrictive parallel assumptions and provides quantitative bounds on the causal relationship between education and crime. This paper provides additional new causal evidence on higher education and its impact on crime by linking several economic literatures on education and crime, and policy evaluation, therefore it further deepens our understanding of the role of higher education in general.

The remainder of the paper is structured as follows. In Section 2, we provide the institutional background of the Chinese higher education reforms in the late 1990s and briefly discuss the potential effects of education expansion on crime. Section 3 introduces the data used and Section 4 discuss some important issues in higher education expansion. Section 5 formally lays out the identification strategy. Empirical results are discussed in detail in Section 6. Section 7 offers further discussions of the results. This paper concludes in Section 8.

2 Background

2.1 Higher education expansion in China

Since the beginning of a series of major economic reforms and economic opening-up in 1978, China's post-secondary educational system has undergone an unprecedented transformation, changing from elite access only to a more generally accessible higher education. From 1978 to 1998, Chinese higher education developed gradually with gross enrollment ratio (GER) among 18–22 year-olds consistently below 10%, far below the 15% criterion for a deemed mass higher education (see Figure 1 below). The Asian financial crisis of 1997–98 caused China's economy to slow down. At the same time, millions of workers lost their secured jobs (also known as "the iron rice bowl") as a result of massive state-owned enterprises (SOEs) reforms, which further increased the unemployment rate in China. The situation would have been aggravated if over three million high school graduates mostly entered the labor market instead of universities. Against this backdrop, the Chinese government adopted the proposal put forward by two economists who advocated for doubling the enrollment in higher educational institutions.[2] This historic decision was made in response to the need to stimulate domestic spending and to meet the growing demand for highly skilled talent. The central government took a series of corresponding actions to implement the expansion policy. In January 13, 1999, the State Council ratified the "Action Plan for Invigorating Education Towards the 21st Century" promulgated by the Chinese Ministry of Education (MOE), with the stated objective of achieving a gross enrolment rate of 11% by 2000 and 15% by 2010. Shortly after, the MOE announced plans to enroll 1.31 million students in college programs, a 0.23 million (21%) increase relative to the previous year. On June 16, 1999, three weeks before China's National College Entrance Examination (*Gaokao*), the former State Development Planning Commission and the MOE jointly announced the decision to admit another 0.33 million freshmen, in addition to the 0.23 million increased admission quota previously announced in January, into higher education institutions.[3] The expansion of college enrollment, especially the last minute notice in mid-June, was sudden, dramatic, largely unanticipated, and

[2] In November 1998, Dr. Min Tang, then chief economist of the Asian Development Bank Mission in China, and his wife Xiaolei Zuo sent a three-page letter titled "Effective ways to stimulate Chinese economy – double the college enrollment" to the leader of the National Congress and their idea gained extensive attention of policymakers and the public. In the letter, they pointed out five reasons why China should expand the higher education sector: 1) China has much fewer college students than other countries at a similar level of development; 2) there would be fierce competition between laid-off SOE workers and young high school graduates; 3) education is an ideal stimulus for domestic spending; 4) with the 7:1 student-teacher ratio, Chinese colleges have good capacity of absorbing new students; and 5) HE popularization is essential to the rejuvenation of the Chinese nation.

[3] Please refer to the memoir "60 Years of Glory: A Historic Leap in the Popularization of Higher Education" via the Chinese central government's official web portal: http://www.gov.cn/jrzg/2009-09/06/content_1410276.htm.

arguably exogenous (Wang, 2014). Because the National College Entrance Examination of 1999 was held on July 7 and 8, high school graduates and their families were almost unable to adjust their decisions within such a short period of time. This exogenous and unexpected policy shock thus provides a nice "natural experiment" that can be exploited to investigate the impact of college expansion on crime.

From 1999 onwards, the scale of higher education had been expanded tremendously before slowing down in 2012, when the MOE announced that "the enrollment scale of higher education needs to be held constant." Figure 2 illustrates the time trends in the numbers of college students, college entrants, and college graduates from 1993 to 2019. Prior to 1999, the scale of higher education remained relatively stable. In only two decades, total enrollment in regular post-secondary institutions increased sharply from 3.41 million in 1998 to 30.32 million in 2019 with an annual growth rate of 11.4% (upper panel of the figure). The number of newly admitted college students jumped by 47.4% in 1999 and continued to surge in the subsequent years, reaching 9.15 million freshmen in 2019 from 1.08 million in 1998. Similarly, the number of college graduates grew more than nine-fold from 0.83 million to 7.59 million during this period (lower panel of the figure). With the dramatic expansion, the Chinese higher education entered the mass stage in 2002 (with a gross enrolment rate of 15%) and the universal stage in 2019 (with a gross enrolment rate of 51.6%), fulfilling the enrollment targets earlier than planned, as shown in Figure 1.

After determining the aggregate quota of higher education at the national level, the MOE assigns different admission quotas to different provinces (Yang, 2014). Regional quotas in college admissions mainly follow the historical patterns of the allocation, but local government and HEIs can negotiate with the central government over their own quotas on the basis of provincial admission rates in the previous year, provincial population growth, the capacity of teachers and school facilities, government financial support, and other criteria. However, given the unexpected changes in college enrollment, we believe that there was limited room for provinces or colleges to negotiate with the MOE about their admission quotas in 1999. Our empirical strategy exploits the differential magnitude of the college expansion across provinces to identify the causal impact of education policy changes on crime.

2.2 Conceptual framework

The higher education expansion in 1999 significantly boosted the number of college students and enhanced the average level of educational attainment in China. In theory, there are a variety of channels through which higher educational attainment might affect crime. The first channel relates to the income effect of education. That is, education increases the expected returns to legitimate work and raises the opportunity costs of illegal behavior, thereby making crime less attractive to would-be offenders (Lochner, 2004; Lochner & Moretti, 2004; Machin, Marie, & Vujić, 2011). Abundant empirical evidence supports this argument and demonstrates a negative relationship between wage levels and crime rates (Grogger, 1998; Gould, Weinberg, & Mustard, 2002; Machin & Meghir, 2004). Clearly, the loss of potential income is greater for better educated workers, who earn higher wages. Meanwhile, education can trigger white collar crimes (such as fraud, forgery, and embezzlement) that require higher levels of skills, yielding somewhat contradictory findings (Lochner, 2004).

Second, education may affect criminal participation by directly affecting individual time constraint. On the one hand, receiving education at schools squeezes out the time that a person can otherwise allocate to criminal activities (a so-called "incapacitation effect"). In line with this hypothesis, Anderson (2014) shows that higher school attendance reduces arrest rates in the United States. On the other hand, being in school potentially increases social interactions and thus conflicts among students, especially fights and physical altercations, which may eventually turn into certain types of crime (a so-called "concentration effect"). Indeed, Jacob & Lefgren (2003) and Luallen (2006) find that property crime rates decrease while violent crime rates increase on school days, suggesting that both incapacitation and concentration play a role in juvenile crime.

Third, the psychic costs of committing crimes may increase with education if more years of schooling are more likely to instill in people good moral values and ethics. In addition to tangible monetary costs (e.g., forgone earnings, fines, litigation expenses, etc.), there are also intangible psychic costs arising from breaking the law, such as feelings of guilt, anxiety or fear, all of which discourage potential criminals from engaging in crime. By improving moral standards, education makes such psychic losses more serious for the more highly educated.

Finally, education may exert a subtle influence on personality traits associated with crime, for example on patience and risk aversion, which in turn will impact upon criminal decisions. This is consistent with numerous studies emphasizing the role of education in shaping time and risk preferences (see, e.g., Becker & Mulligan, 1997; Oreopoulos, 2007) and the voluminous literature on the determinants of criminal behavior highlighting that a high rate of time discounting or a high degree of risk tolerance predicts subsequent criminal involvement (e.g., Becker, 1968; Lee & McCrary, 2005; Åkerlund *et al.*, 2016). Education is found to teach people to be less impulsive, more future oriented and more risk averse. Individuals with a lot of patience (i.e., low discount rates) tend to have long time horizons and value the future consequences of their actions highly. Similarly, more risk averse individuals typically attach more weight to possible punishments in the future. This implies that more educated individuals would be more likely to care about expected future disutility, and thus less likely to be involved in crime as compared to the general population.

Overall, Higher enrolment from the college expansion can be expected to have a deterrent effect on most types of crime through income effects, incapacitation effects, psychic penalties as well as alteration of preferences, though they may have the opposite effect in some cases due to crime skill premium or concentration effects. In this paper, we do not attempt to rigorously disentangle the various channels underlying the education-crime nexus. Instead, we employ a partial identification approach that imposes different bounded variations to estimate the causal impact of college expansion on crime rates. In so doing, the relationship between higher education expansion and crime is explored in a rather transparent manner.

3 Data

We draw data from various statistical yearbooks to create a province-year panel dataset of 30 provinces between 1988 and 2012.[4] Information on crime is extracted from the China Law Yearbook (1989–2013) and the Procuratorial Yearbook of China (1989–2013), which provide annual aggregate crime statistics for all provinces. Unfortunately, we have no information from our data to identify the age of perpetrators or to distinguish between different types of crime. Following the definition of crime in Edlund *et al.* (2013), we define the crime rate as arrests for criminal offences per 10,000 inhabitants. As shown in Figure 3, China's overall crime rate nearly doubled from 3.72 in 1988 to 7.15 in 2012.[5] Moreover, crime rates vary considerably across provinces, ranging from 0.81 (Tibet, 1988) to 15.40 (Zhejiang, 2012).

[4] The year 1988 is the year for which provincial crime statistics first became publicly available. Of the 31 provincial-level administrative divisions, Chongqing was separated from Sichuan province and became a municipality under the direct administration of the central government in 1997. Therefore, we merge Chongqing into Sichuan province to promote data comparability.

[5] The fluctuations in the crime rate may be partly due to changes in relevant laws or the "Yan Da" campaigns. For example, the drop in 1997 could be explained by amendments to the Criminal Law and the Criminal Procedure Law, while the rise in 2001 might be the consequences of the "Yan Da" campaigns that took severe measures against grave illegal and criminal activities.

Educational measures are constructed primarily using data from the China Statistical Yearbook (1989) and the Educational Statistics Yearbook of China (1989–2012), including statistics on annual number of new student enrollment, total student enrollment and graduates in regular post-secondary institutions and regular senior high schools for all provinces. As can be seen from Figure 4, new student enrollment started to grow rapidly not only for colleges, but also for senior high schools, after the 1999 expansion of higher education. In 1999, the number of students newly enrolled into senior high schools was 31.5 per 10,000 population. A decade later, in 2009, this number increased to 62.2 per 10,000 population. This is consistent with the findings of Xing (2013) that higher education expansion encourages educational investment for rural residents, leading to an increase in the proportion of the population with a high school diploma in rural areas. In the following analysis, we construct three measurements of the expansion intensity, namely, static measure, dynamic measure, and weighted measure.

To control for the impact of socioeconomic conditions on crime, we gather a rich set of provincial-level information from several other data sources. Specifically, the demographic features of the population at the province level, including population size, education level, and sex ratio, are derived from the China Population and Employment Statistical Yearbook (1989–2013). From the Comprehensive Statistical Data and Materials on 60 Years of New China (1989–2013) and the China Statistical Yearbook (1989–2013), we obtain information on employment rate, per capita income, income inequality (i.e., urban over rural per capita income), urbanization rate, openness to trade (i.e., the sum of exports, imports, and foreign direct investments as a share of GDP), and construction (in square meters). The welfare expenditures and police expenditures, both measured as the shares of provincial government expenditures, originate from the Finance Yearbook of China (1992–2013).[6] The immigration rate in each province is obtained from the China Population Statistical Yearbook (1988–1991) and the China Population Statistical Data and Material by Counties and Cities (1992–2012). Summary statistics for these variables are presented in Table 1 and data sources are detailed in Table 2. The average crime rate is 6.2 offenses per 10,000 inhabitants over the sample period we examine. On average, the degree of college expansion is 0.4 on the interval [0,1].

[6] Because the urbanization data before 2005 are not available, we use the urbanization data of 1990, 2000 and 2005 calculated from the corresponding census data to interpolate the data of other years. Similarly, the welfare and police expenditure data before 2011 are unavailable and interpolated using the data of 1991.

4 Important Issues in Higher Education Expansion

4.1 Measurement of higher education expansion

To formally investigate the impact of China's higher education expansion on crime, we start by giving the precise definition of the expansion. In this paper, we are interested in understanding how crime rates vary with the expansion of college enrollment in Chinese provinces. We focus on the relationship between higher education expansion intensity and criminal behavior at the province level for three reasons. First, as illustrated in the data section, public statistics on crime rates and college admission numbers are only accessible at the province level over selected years between 1988 and 2012. Second, the increasing decentralization of the higher education system in China allows provincial governments to have a high level of autonomy in educational decision-making such as enrollment and finance. This means that provincial governments have played a major role during the expansion process. Third, the expansion took place mostly in local higher educational institutions (including local public universities, private/Minban universities, independent colleges, and vocational institutions) at provincial, prefectural, and municipal levels, rather than national public universities that are subordinated to the ministries of the central government.

As described earlier, changes to college admission policy in 1999 are abrupt and unanticipated, and local higher education providers are the major participants of the expansion. We can thus expect that, within a short time window, provinces with more abundant higher educational resources (e.g., more HEIs, sufficient teaching resources, adequate student dormitories, and other facilities, etc.), especially those with more local higher educational institutions, would have a much better capacity to cope with the rising number of college students generated by the higher education expansion. In other words, the unequal distribution of pre-existing higher education resources makes it difficult for different provinces to benefit equally from it and significant disparities exist across regions in terms of the scale and consequences of the expansion (Xing & Li, 2011). According to Li *et al.* (2017) and Rong & Wu (2020), the magnitude of higher education expansion in a province is strongly dependent on its pre-1999 enrollment capacity. In particular, given the last-minute change in the enrollment plans, admission quotas were assigned to different provinces by the central government in 1999, in which case each province expanded its college enrollment in proportion to their pre-expansion capacity so that the historical patterns of quota allocation among provinces could be largely maintained. Nonetheless, provinces assumed greater decision-making power in the allocation of admission quotas in the subsequent years (Yang, 2014). Therefore, we first make use of the pre-expansion information on the provincial enrollment scale to construct a measure of the higher education expansion:

1) *The intensity of higher education expansion (static measure)*: The ratio of students in regular post-secondary institutions to students in senior high schools. The latter is used as a standardizing factor to remove the potential confounding effect of population size on crime. The intensity of higher education expansion for province j is calculated as:

$$\mathrm{HEE}_j^{\mathrm{I}} \coloneqq \frac{U_{j,t^-}}{H_{j,t^-}}$$

where U_{j,t^-} and H_{j,t^-} stand for the total number of students enrolled in regular three or four-year colleges and universities and the total number of students enrolled in senior high schools in province j in the pre-expansion period t^- (1998),[7] respectively. This definition is also referred to as the *static measure* of the higher education expansion.

One implicit assumption behind $\mathrm{HEE}^{\mathrm{I}}$ is that the *ex-post* expansion intensity of a province is predetermined by its *ex-ante* capacity in higher education. This seems plausible for a short period of time since the sudden policy changes would not allow local governments and higher educational institutions to adjust their enrollment capacities promptly. Besides, there was little room for provinces and colleges to bargain over their assigned quotas in college admissions immediately after the announcement of enrollment expansion decisions. In the long run, however, they would be able to boost their enrollment capacities and vie for higher admission quotas for their own students. After accounting for the dynamic trends in the higher education expansion rates, we can derive the second measure of the expansion, which exploits enrollment information through the entire expansion period (1999–2012):

2) *The intensity of higher education expansion (dynamic measure)*: The sum of additional students enrolled in regular higher educational institutions per 100 population in the post-expansion period, relative to the pre-expansion period. For province j, it is:

$$\mathrm{HEE}_j^{\mathrm{II}} \coloneqq \sum_{t^+=1999}^{2012} \left(\frac{U_{j,t^+}}{P_{j,t^+}} - \frac{U_{j,t^-}}{P_{j,t^-}} \right)$$

[7] The baseline pre-expansion period is defined as the most recent year, i.e., 1998, prior to the education expansion. We have also tried to set the pre-expansion period to be 1997, 1996, or use the average enrollment numbers from 1995 to 1998. Using these alternative ways to construct the first measure, we find our results to be largely unchanged.

where $U_{j,t}$ denotes the number of students enrolled in regular three or four-year colleges and universities (as defined above) and $P_{j,t}$ represents the population size of province j in the year t. Here when performing standardization, we rely on the count of total population, instead of the size of senior high students adopted in the first definition. This is because the expansion policy is also found to impact upon high school enrollment and hence the number of senior high students in the post-expansion period suffers from endogeneity. The second definition is also referred to as the *dynamic measure* of the expansion.

An important consideration in any studies focusing on the Chinese context relates to the mobility and migration of the population. Although provincial governments tend to give admission priorities to local students, they are required to admit a certain large proportion of students from other provinces. In China, migration from one place to another is subject to harsh restrictions due to the *hukou* system. As a result, more and more college students become "internal temporary migrants" after the expansion – without converting their *hukou* status even though college degree makes them more likely to obtain a local *hukou* through high skills. After graduation, a large number of students from less developed regions and attending colleges in more developed regions will return to their hometown and their subsequent criminal behavior, if any, will appear in crime statistics in their province of birth. Others are likely to stay and work in the more developed region or move to an even more affluent region, and in this case crime is committed in the province of residence. Therefore, we construct the third measure of the higher education expansion that takes into account of the possibility of inter-province migration of students:

3) *The intensity of higher education expansion (weighted measure)*: The weighted average of the dynamic measure of the expansion. For province j at post-expansion year t^+, it is

$$\mathrm{HEE}_j^{\mathrm{III}} \coloneqq \sum_i \frac{M_{ij}}{M_j} A_i \,/P_{j,t^+} = \sum_i \frac{M_{ij}}{\sum_i M_{ij}} A_i \,/P_{j,t^+}$$

where M_{ij} denotes the number of college graduates born in province i and residing in province j. P_{j,t^+} denotes the provincial population size as before. A_i represents the increase in the number of enrolled college students born in province i from year t^- to t^+. It takes the following weighted-average form:

$$A_i = \sum_k \frac{L_{ik}}{\sum_i L_{ik}} \left(U_{k,t^+} - U_{k,t^-}\right)$$

in which L_{ik} stands for the number of college students born in province i and currently studying in province k. The term in parentheses reflects changes in the number of students enrolled in regular higher educational institutions between the pre- and post-expansion periods for province k. We refer to this definition as the *weighted measure* of the expansion.

Since our study period spans from 1998 to 2012, we employ the decennial census of 2000 and 2010 to project the inflows and outflows of non-local college students and college graduates in a similar way to Edlund *et al.* (2013). Both censuses contain information on the birthplace and level of education of the respondents, and ask whether they are studying in a regular college or university.[8] In the third definition, $U_{k,t}$ is directly observed from the Provincial Educational Statistics Yearbooks, while both M_{ij} and L_{ik} are obtained from the decennial census of 2000 and 2010 and interpolated linearly.

For instance, consider only two regions, Shanghai and Beijing, and the year 2010. If we assume that the sum of additional new students enrolled in HEIs of Beijing (Shanghai) in 2010 is 40,000 (50,000), of whom 30% (40%) are born in Beijing and 70% (60%) are born in Shanghai. The expected number of college graduates from Shanghai in 2014 would then be 42,000 (40,000×0.3+50,000×0.6), and that from Beijing is 48,000 (40,000×0.7+50,000×0.4). We further assume that 70% of college graduates born in Shanghai and 10% of college graduates born in Beijing would reside in Shanghai after graduation. Finally, *the weighted HE expansion intensity* of Shanghai is calculated as the ratio of 34,200 (42,000×0. 7+50,000*0.1) to the total population of Shanghai in 2014.

4.2 Senior high school expansion

The enormous expansion of college enrollment has not only exerted influences on college students, but also greatly increased the number students enrolled in regular senior high schools (see Figure 4). This corroborates the findings of Xing (2013) that the higher education expansion policy encourages rural residents to invest in high school education. In other words, the impact of the higher education expansion extends beyond the higher education sector as the expansion has led to high school expansion – to some extent. To investigate how the expansion of senior high schools

[8] The 1990 census provides no information on the birthplace of the respondents.

affect crime rates, we construct a measure analog to the second definition of higher education expansion.[9] Algebraically, it is defined as:

4) *The intensity of high school expansion*: The sum of additional students enrolled in regular senior high schools per 10,000 population in the post-expansion period, relative to the pre-expansion period. For province j, it is:

$$\mathrm{HSE}_j^{\mathrm{IV}} \coloneqq \sum_{\mathrm{t}^+=1999}^{2012} \left(\frac{S_{j,t^+}}{P_{j,t^+}} - \frac{S_{j,t^-}}{P_{j,t^-}} \right)$$

where $S_{j,t}$ denotes the number of students entering regular senior high schools in province j at time t. Again, $P_{j,t}$ is the population size of province j in the year t.

4.3 Treatment status: high-intensity vs. low-intensity groups

To identify the causal effect of higher education expansion on criminal behavior, we build up a standard DID framework and compare the crime rates in provinces experiencing a high level of expansion with those in provinces experiencing a low level of expansion before and after the expansion. By a slight abuse of the causal inference terminology, we refer to the former as the high-intensity (or more treated) group and the latter as the low-intensity (or less treated) group.

For each measure of the higher education expansion defined above, we apply two methods to identify the two groups. The first method – called the "median cutoff" – is to divide the 30 provinces into two equal-sized groups, and attribute provinces whose levels of higher education expansion above (below) the median to the high-intensity (low-intensity) group. The second method – called the "extreme cutoff" – is to draw a distinction between the most and least affected provinces by dropping provinces with a relatively mild degree of the expansion. Specifically, we only consider provinces at the top and bottom quantiles (defined as the 0.75th and 0.25th percentiles) of the distribution of the intensity of the higher education expansion. In so doing, we have a total of six different definitions of treatment status. See Table 3 for the full list of the high-intensity provinces under various definitions of the treatment status.

We observe from the table that treatment status changes over definition. For instance, the 4 provinces (Shandong, Shanxi, Zhejiang, and Hainan) in the low-intensity group under definition I

[9] This measure is not reweighted using census information. Before 2013, promising high school students were not allowed to take the college entrance exam outside the province of their *hukou* registration. As a result, the majority of high school students are native students in our sample period, and migration is not a big concern when studying the effect of high school expansion on crime.

(0.5th quantile) turn into high-intensity provinces under definition II (0.5th quantile). We also observe that high-intensity provinces are mostly located in eastern and central China regardless of the definition used, where economic development is more advanced.[10] For example, the 15 high-intensity provinces defined using the static measure and the median cutoff method consist of 6 eastern region provinces (Beijing, Liaoning, Shanghai, Tianjin, Jiangsu, Fujian), 5 central region provinces (Jilin, Heilongjiang, Jiangxi, Hubei, Hunan,) and 4 western region provinces (Yunnan, Sichuan, Tibet, and Shaanxi). We find from our data that more developed regions tend to have higher crime rates.[11] Therefore, we control for the economic conditions (e.g., employment rates and urban per capita income) at the province level. Apart from economic development, more treated and less treated provinces might differ in unobservable characteristics that are also correlated with the crime rate at the province level. This raises the possibility that the treatment and comparison groups could be systematically different in terms of pre-treatment characteristics, which may invalidate the parallel trends assumption required for DID identification. We will return to this issue in the Identification section.

We next examine the time trends in provincial crime rates for the treatment and comparison groups (under the static definition) over the period 1988–2012. Figures 5 reveals several interesting patterns. Before the implementation of the expansion policy, high-intensity and low-intensity provinces exhibit similar crime trends, with the former group having higher rates of criminal offences. This is the case regardless of whether we use the median cutoff method or the extreme cutoff method to define the two groups. After the higher education expansion, crime rates in both groups increase, and the increase is larger in low-expansion provinces. This is especially true when we compare between the most and least affected provinces – we find that the crime rate of provinces below the 25th percentile exceeds that of provinces above the 75th percentile, as shown in Figure 5A.

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[10] Chinese provinces are typically classified into three economic regions: the eastern, central and western regions of China. Specifically, the eastern group includes 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central group consists of 8 provinces: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the western group consists of 11 provinces: Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Ningxia, Qinghai, Xinjiang, Guangxi, and Inner Mongolia.

[11] Taking the year 1998 as an example, the GDP values of high-intensity and low-intensity provinces were 282 billion and 268 billion, respectively. In our data, the correlation coefficient between GDP and crime rates is 0.3, which is statistically significant at the 1 percent level. We also regress the crime rate on GDP as well as controlling for province fixed effects and year fixed effects, which yields a positive and significant slop estimate with a R-squared of 0.80, consistent with the findings based on unconditional correlations. It is worth noting that Tibet and Shanxi are classified as the more treated group despite the fact that their GDP values are below the average of all provinces.

5 Identification

In this section, we formulate our empirical strategy and illustrate how to move away from relying on traditional parallel trends assumption and perform the partial identification DID analysis under plausible settings.

5.1 Empirical specification

To identify the causal effect of college expansion on provincial crime rates, we take advantage of the HE expansion policy in 1999 that resulted in sudden and unexpected increases in college enrollment. Exploiting exogenous variation in the intensity of the higher education expansion across provinces and over time, we first estimate a standard DID model of the following form:

$$Y = \alpha + \tau 1(High\_intensity) \times Post + \theta 1(High\_intensity) + \eta Post + X\beta + \mathrm{u} \qquad (1)$$

where Y indicates a province's crime rates. $1(.)$ is an indicator function that takes the value of one for provinces with high intensity of the higher education expansion. $Post$ is a dummy variable equal to one for the post-expansion period (i.e., 1999 and later years) and zero otherwise. X contains a set of observable confounders such as employment and income inequality to control for regional characteristics that may affect the crime rate in a province. The policy effect is captured by the point estimate of parameter τ on the interaction between $1(High\_intensity)$ and the $Post$ indicator. We expect τ to be negative if the higher education expansion has a deterrent effect on crime. The validity of the DID estimate relies on the assumption that in the absence of the the higher education expansion, high-intensity and low-intensity provinces would have experienced the same change in crime rates during the expansion period. In other words, controlling for observable determinants of crime, there should be no omitted time-varying, province-specific effects correlated with both the higher education expansion intensity and crime rates.

There are some concerns with the plausibility of this parallel trends assumption. For instance, the estimated policy effect can be biased by reverse causality, in which case the provincial governments adjust the scale of college enrollment in response to an increasing crime rate, the change in crime at the province level would then be correlated with the provincial higher education expansion intensity. In addition, there might be unobservable factors that are correlated with both the enrollment decision of the government and the intensity of the higher education expansion. The most pervasive omitted variables include other important policy changes occurring during our sample period, such as the "Yan Da" campaigns[12] that were carried out periodically since 1983 to severely crack down on crimes. It is important to note that even if we can find the proxies for the omitted variables, adding only the linear additive form of them into the model may be inappropriate. Moreover, endogeneity can arise due to the non-random nature of $High\_intensity$, i.e., the fact that provinces with different intensities of the higher education expansion might differ fundamentally in other unobservable respects that may influence criminal activities.

To credibly identify the causal impact of the higher education expansion on crime, we depart from conventional practices in the policy evaluation literature. Instead, we adopt a partial identification approach that weakens the parallel trends assumption and allows for differential trends in outcomes for the more treated and less treated groups. This is akin to Manski & Pepper (2018)'s approach, which evaluates the impact of right-to-carry laws on crime rates under a range of *bounded variation* assumptions. Similarly, we provide the bounded variation estimates of the college expansion policy on crime rates under weaker identifying assumptions. Specifically, we consider three types of restrictions (i.e., strong, middle, weak) on the possible differences in trends between the high-intensity and low-intensity groups. We also assess the sensitivity of results by calculating the minimum values of the bound parameters based on observed pre-treatment data.

5.2 Maintained assumptions

We briefly review the traditional assumptions used to address the selection problem as a starting point. To illustrate the idea in a simple setting, consider the effect of the higher education expansion on the crime rate in high-intensity provinces (defined using the static measure of the expansion and the median cutoff) in a specific year, say, 2000. The average treatment effect (ATE) can be formally written as:

$$\begin{aligned} \tau_{2000,high} &= E[Y_{2000}(1)|X = high] - E[Y_{2000}(0)|X = high] \\ &= Y_{high,2000}(1) - Y_{high,2000}(0) \qquad (2) \end{aligned}$$

[12] "Yan Da", also known as "Strike Hard" or "Severe Crackdown", is a nation-wide campaign launched by the central government to crack down on street crimes and punish dangerous and chronic offenders with long prison sentences. The campaigns were carried out four times – in 1983, 1996, 2001, and 2010.

In equation (2) the first term can be computed using available data, and it is $Y_{high,2000}(1) = Y_{high,2000} = 5.51$. Since the higher education expansion began in 1999, the second term, $Y_{high,2000}(0)$, is counterfactual and cannot be revealed by observed data. However, the pre-treatment data on crime rates for the more treated group are available, so are the post-treatment crime data for the less treated group. Thus, we can compute three simple but different findings on the counterfactual crime rate in high-intensity provinces in 2000, $Y_{high,2000}(0)$, under alternative *invariance* assumptions:

Time invariance:

$$Y_{high,2000}(0) = Y_{high,1998}(0) = 4.90 \tag{3}$$

Intergroup invariance:

$$Y_{high,2000}(0) = Y_{low,2000}(0) = 5.52 \tag{4}$$

DID invariance (parallel trends):

$$\begin{aligned} Y_{high,2000}(0) &= \left[Y_{low,2000}(0) - Y_{low,1998}(0)\right] + Y_{high,1998}(0) \\ &= \left(Y_{low,2000} - Y_{low,1998}\right) + Y_{high,1998} \\ &= (5.52 - 4.61) + 4.90 = 5.81 \end{aligned} \tag{5}$$

These, in turn, imply treatment effects of 0.61, –0.01, and –0.3 respectively. Hence, the policy effects of interest differ in both direction and magnitude under various *invariance* assumptions in equations (3), (4), and (5).

Next, we relax the traditional *invariance* assumptions maintained above. Specifically, we impose *bounded variation* assumptions under a given treatment *t* as follows:

Bounded time variation:

$$\left|Y_{high,a}(t) - Y_{high,b}(t)\right| \leq \delta_{h(ab)} \tag{6}$$

Bounded intergroup variation:

$$\left|Y_{high,a}(t) - Y_{low,a}(t)\right| \leq \delta_{(hl)a} \tag{7}$$

Bounded DID variation:[13]

$$\left|[Y_{high,a}(t) - Y_{high,b}(t)] - [Y_{low,a}(t) - Y_{low,b}(t)]\right| \leq \delta_{(hl)(ab)} \tag{8}$$

[13] The bounded DID variation assumption is equivalent to the DID invariance assumption when $\delta = 0$.

where $(h,\ l)$ respectively indicates the more treated group and the less treated group, (a, b) are specified years, and the bound parameters ($\delta_{h(ab)}$, $\delta_{(h\ l)a}$, $\delta_{(hl)(ab)}$) are specified positive constants which can easily be calculated using data prior to the implementation of the expansion policy. To simplify the notation, we suppress the dependence of δ on the treatment t.

The bounded DID variation assumption restricts the absolute difference in the crime rate between high-intensity and low-intensity provinces over two years to be less than $\delta_{(hl)(ab)}$. Letting $\delta_{(hl)(ab)} \geq 0$ weakens the traditional parallel trends assumption by supposing that the differences in outcomes between the two groups before and after the expansion may differ by no more than $\delta_{(hl)(ab)}$. The bound parameter $\delta_{(hl)(ab)}$ determines the extent of violations to the parallel trends assumption. The larger the selected value of the parameter $\delta_{(hl)(ab)}$, the weaker the assumption.[14] In the next section, we will demonstrate in detail how to select the values of the bound parameters δ based on observed pre-1999 data in our study setting.

Figure 6 displays the estimated bounds on policy effects for different values of $\delta_{(hl)(ab)}$, where $a = 2000$ and $b = 1998$. It reveals that the effect is point identified under the traditional DID invariance assumption ($\delta = 0$), with a 25.6 percentage point decrease in the crime rate in high-intensity provinces after the HE expansion. We also see that ambiguity regarding the sign of the estimated treatment effect increases with $\delta_{(hl)(2000,1998)}$. For example, when $\delta_{(hl)(2000,1998)} = 0.5$, we obtain $Y_{high,2000}(1) = 5.51$ and $Y_{high,2000}(0) \in [5.31, 6.31]$. Thus, $\tau_{2000,high} \in [-0.8, 0.2]$.

In this paper we report empirical findings under three types of DID assumptions that have different levels of identifying power – from strong, middle to weak. Specifically, the strong DID assumption is exactly the conventional parallel trends assumption (i.e., $\delta = 0$ in equation (8)). The weak DID assumption corresponds to the bounded DID variation assumption (equation (8)). There is an inevitable trade-off between the strength of assumptions and the precision of findings. The strong DID assumption enables point identification of the policy effect on crime, while the weak one sometimes does not identify even the sign of the effect. Between these two extremes, we

[14] The bounded time variation assumption restricts the absolute difference in the crime rate in high-intensity provinces between two years to be less than $\delta_{h(ab)}$. Letting $\delta_{h(ab)} \geq 0$ weakens the traditional time invariance assumption by allowing the temporal differences in outcomes to differ by no more than $\delta_{h(ab)}$. The larger the selected value of $\delta_{h(ab)}$, the weaker the assumption. Likewise, the bounded intergroup variation assumption restricts the contemporaneous absolute difference in the crime rate in the year *a* between high-intensity and low-intensity provinces to be less than $\delta_{(hl)a}$. Letting $\delta_{(hl)a} \geq 0$ weakens the traditional intergroup invariance assumption by allowing the intergroup differences in outcomes to differ by no more than $\delta_{(hl)a}$. The larger the selected value of $\delta_{(hl)a}$, the weaker the assumption.

consider middle-ground assumption that relaxes the strict invariance assumption but strengthens the bounded variation assumption. More detailed descriptions of these three assumptions are discussed below.

The confidence sets under various coverage notions can be computed using methods prevalent in the econometric literature on partial identification (e.g., Imbens & Manski, 2004; Chernozhukov, Hong, & Tamer, 2007; Rambachan & Roth, 2020). However, existing methods for computing such confidence bands are built on the implicit assumption that the data are a random sample drawn from an infinite population. Manski & Pepper (2018) and Manski & Molinari (2021) raise concerns about the sampling process in their state-level analyses. Similarly, the random sampling assumption may not be credible in our setting. Above all, it is cumbersome to assume that the realized population of a region/province is a random sample of individuals drawn from some superpopulation. Moreover, criminal behavior involves complex social interactions and it is difficult to assume that crimes are committed independently by members of the population. Therefore, we do not report standard errors that reflect sampling variability.[15]

5.3 Bounded DID variation parameters

In this section, we adopt a rather transparent way to calculate the minimum values of the bound parameters based on observed pre-policy data between 1988 and 1998. We start with the crime rates in 1997 and 1998. Again, we rely on the static measure of the higher education expansion and the median cutoff to define the treatment and comparison groups. The 1998 crime rate in high-intensity provinces is 4.90, and the rate in low-intensity provinces is 4.61, while the corresponding rates for 1997 are 4.31 and 3.97, respectively. Importantly, the validity of the bounded variation assumptions depends on the choices of the bound parameters. Recall from equation (6) that the bounded time variation assumption is consistent with the 1988 crime rate in high-intensity provinces if $\delta_{h(1998,1997)} \geq 0.59\ (4.90 - 4.31)$. Similarly, the bounded intergroup variation assumption in equation (7) is valid in 1998 if $\delta_{(hl)1998} \geq 0.29\ (4.90 - 4.61)$, and the bounded DID assumption in equation (8) is valid if $\delta_{(hl)(1998,1997)} \geq 0.05$. Imposing reasonable restrictions

[15] Abadie *et al.* (2014) advocate for the use of randomization-based standard errors in the experimental setting; unfortunately, their approach does not apply to observational studies.

on the bound parameters ensures that the bounded variation assumptions are consistent with the 1997 and 1998 data.

We then extend this approach and conduct comparisons for the whole pre-expansion period of 1988–1998. We compute a set of the minimum values of the bound parameters that ensure the various bounded variation assumptions are consistent with the observed pre-1999 data, and then select the maximum of these minimum values. To find the minimum valid parameter value required for the bounded intergroup assumption, we calculate the difference in crime rates between the two groups in each year prior to 1999. To ensure the validity of the bounded time assumption, we compute the minimum valid parameter value for each pair of adjacent years from 1988 to 1998 (1988 to 1989, 1989 to 1990, and so forth).

It is worthwhile to mention that there might be pre-existing trends in outcomes, and we hope to set up a flexible framework that allows for the possibility that changes in crime rates by treatment status can be explained by extrapolating different trends for the high-intensity and low-intensity groups. As a robustness check, we also calculate the minimum valid parameter for each pair of nonadjacent years, i.e., compare observed crime rates separated by 2, 3, 4 or 5 years, from 1988 to 1998 (e.g., 1988 and 1990, 1988 and 1991, 1988 and 1992, 1988 and 1993, and so forth). Our bound parameter thus takes into account the changes in crime rates between the two groups two years after and one to five years before the 1996, when the largest "Yan Da" campaign was carried out. In so doing, we to some extent employ the pre-treatment information to control for potential differences in crime rates between the two groups after the policy change.

Table 3 presents the minimum bound parameters under various definitions of treatment status. We first focus on the static definition of HE expansion. When we compare provinces with above median expansion intensity to those with below median expansion intensity, the intergroup variation parameter needs to be at least 1.073, the time variation parameter at least 1.261, and the DID variation parameter at least 0.849, in order to make the models consistent with the data prior to 1999; when only provinces at the top and bottom 0.25th quantiles are considered, the intergroup and time variation parameters turn larger (2.803 and 1.589, respectively), while the DID variation parameter becomes smaller (0.831). As for the dynamic definition, the corresponding parameters are 0.545, 1.304, and 0.574 when using the median cutoff method, and 2.09, 1.244, and 1.542 when using the extreme cutoff method. In the case of the weighted measure, the corresponding parameters are 1.882, 1.172, and 1.154 when using the median cutoff method, and 2.758, 1.097, and 1.067 when using the extreme cutoff method. The table also reports the 0.75th quantile of the minimum valid parameters for the DID assumption (DID_0.75). We see from the last column that the DID parameter decreases, for example, from 0.849 to 0.557 with static definition and median cutoff.

6 Results

This section reports point and set estimates of the impact of college expansion on crime under different assumptions.

6.1 Conventional DID estimates

Before conducting partial identification analysis, we first report the conventional DID estimation results under the strong assumption of parallel trends, which serves as a benchmark for comparison purposes. The DID estimates using the static higher education expansion measure and the median cutoff are presented in Table 4.[16] From specification (1), we know little about the dynamics of the policy effects, i.e., how crime rates have changed after the expansion policy was announced and whether such policy impact grows, stabilizes, or fades over time due to changing enforcement costs. Therefore, we also estimate a multiple-period DID by replacing the *Post* dummy with a series of year dummies, which permits the policy effect to be expressed as annual changes relative to the reference period (from 1988 to 1998). Columns 1 and 2 report estimates of the baseline DID specification and columns 3 and 4 present the multiple-period DID estimates. The even-numbered columns report estimates for each of the models with a set of controls at the province level. We do find a negative, but not significant effect of the higher education expansion on crime rates – the estimated coefficient of interest on the interaction term is strictly negative, no matter whether covariates are added or not. The crime reducing effect becomes larger and more significant at -1.10(in 2009), -1.03(in 2010) -1.20(in 2011), and -1.14(in 2012) per 10,000 population, implying that the expansion policy effectively deterred crime in the long run.

6.2 Bounded DID variation estimates

We next use bounded variation assumptions with the parameter values shown in Table 3 to draw inferences on the impact of the higher education expansion on crime. As previously mentioned, we

[16] Results using alternative definitions are presented in the Discussion section.

perform partial identification analysis without providing measures of statistical precision. There are three types of DID assumptions worthy of consideration. The strong DID assumption is the traditional DID invariance assumption where δ = 0. The weak DID assumption is the bounded DID variation assumption using the bound parameters in the DID column of Table 3. The middle-ground assumptions are a combination of the bounded DID variation assumption and bounded time and intergroup variation assumptions that are suitable for this application:

Middle-ground assumption 1:

$|[Y_{high,a}(0) - Y_{high,b}(0)] - [Y_{low,a}(0) - Y_{low,b}(0)]| \leq \delta_{(hl)(ab)}$, where $\delta_{(hl)(ab)} =$ DID_0.75 in Table 3 for $a \in [1999, 2012]$ and $b = 1998$ (9)

Middle-ground assumption 2:

$0 \leq Y_{low,a}(0) - Y_{high,a}(0) \leq \delta_{(hl)a}$, where $\delta_{(hl)a}$ = intergroup in Table 3 for $a \in [1999, 2012]$ (10)

Middle-ground assumption 3:

$Y_{high,a}(0) \geq Y_{high,1998}(0)$ for $a \in [1999, 2012]$ (11)

The first assumption is the bounded DID variation assumption in equation (8) with the value of the bound parameter δ set to the 75th percentile of the distribution of the minimum valid parameters required for the assumptions to be consistent with the observed pre-1999 data. This assumption relaxes the stringent DID invariance assumption but strengthens the weak assumption using the DID parameters suggested in Table 3. The second assumption is the one-sided bounded intergroup variation assumption in equation (7), which requires that the crime rate in low-intensity provinces in the year *a* is no less than the counterfactual crime rate in high-intensity provinces in the year *a* by $\delta_{(hl)a}$. The last assumption is the bounded time variation assumption in equation (6) asserting that crime rates have started to rise since 1999.

6.2.1 The impact of higher education expansion on crime

Tables 5 and 6 display findings on annual treatment effects subject to different identifying restrictions using the static the higher education expansion measure. The year 1998 is used as the anchor year. Table 5 shows the results from comparing between provinces with expansion intensity above and below the provincial median, and Table 6 shows the results from comparing provinces with the highest expansion intensity to those with the lowest expansion intensity. In each table, bounds in bold identify the sign of the treatment effect to be negative, and those in bold and italics identify the sign to be positive. Bounds in italics are infeasible as the lower bound is above the upper bound. Column 1 of Tables 5 shows that high expansion intensity is negatively correlated with criminal activities, and the effect size has changed over time – mildly decreasing in early years of the policy intervention but strongly decreasing in later years. For example, the expansion policy is found to reduce crime rates by 0.265 in 1999, 0.65 in 2006, and 1.013 in 2012. Given that the strong DID assumption is imposed, these effects are point identified.

We then apply the parameter values in Table 3 to relax the conventional DID assumption. To do this, we add and subtract the DID parameters in Table 3 (δ = DID) to the estimates obtained with the strong assumption. For example, the effect of HE expansion on the 2012 crime rate is bounded between [–1.013 – 0.849, –1.013 + 0.849] = [–1.862, –0.163], as can be seen from columns 2 and 3 of Table 5. The results from the weak DID assumption indicate that high levels of HE expansion reduced crime rates in almost every year since 2007 except 2010, but the crime reducing effect was absent in the early years. This largely confirms the long-term negative effects of the expansion policy on crime previously found in columns 3 and 4 of Table 4.

Table 5, columns 4 and 5, as well as Figure 7A reports the bounds under middle-ground DID assumptions. We see that the widths of the bounds are substantially tighter under these alternative assumptions. Considering again the year 2012, the new lower and upper bounds on the crime rate are respectively –0.721 and –0.456. It is notable that the upper bounds slightly exceed zero during the first few years after the policy change, from 1999 to 2003, after which the sign of the bounds is unambiguously negative. Again, we find that the deterrent effect of the expansion policy on crime fluctuates over time. The largest effect seems to take place in 2007, as reflected by the bound of [–1.064, –0.799].

The results focusing on the comparison between the most and least affected provinces, summarized in Table 6 and Figure 7B, convey a similar and stronger story on the negative effect of HE expansion on crime. It is reassuring to find that we are able to identify the negative sign of the policy effect for every year after 2003 – even under the weak assumption, which gives us greater confidence in our findings. Similar results are obtained with middle-ground assumptions, again, with narrower bounds.

To sum up, both the conventional and partial DID results are consistent with the hypothesis that expanding college enrollment has imposed a negative effect on overall criminal behavior.

Moreover, we find that this policy did not affect the crime rate in the short run, but the crime rate began to decline at least five years after its implementation.

6.2.2 The impact of senior high school expansion on crime

So far, we have examined the impact of the expansion policy within the higher education sector. As highlighted by Xing (2013), college enrollment increases have acted also on the supply side to increase the number of senior high school students. Recall from Figure 4 that the expansion occurred very strongly in high school education as new student enrollment in senior high schools grew at an even faster rate than that in colleges and universities since 1999.

While the higher education expansion caused a decline in criminal behavior among college students, the relative increase in the number of high school students could further reduce crime rates among teenagers. There are mainly three reasons why we are interested in understanding the impact of senior high school expansion on criminal behavior. The first reason being that high school education is generally more affordable and easier to access than higher education – primarily due to lower tuition fees[17] and fewer entry requirements. This may imply different adjustment costs in response to the policy shock. Second, and more importantly, we intend to paint a more complete picture of the impact of education expansion on crime by separately considering its effects from the the higher education sector and the high school sector. The first cohort of students directly affected by college expansion is the cohort of young adults turning 19 in 1999.[18] However, the spillover effects of the expansion policy associated with increased high school participation seem to be concentrated on the younger cohort of students who are immature juveniles (mostly between 15 and 18 years old). It is thus likely that younger age cohorts play a significant role in reducing crime rates. Finally, since most high school students are local students in our study period, the estimated impact of high school expansion is more straightforward and does not encounter potential migration issues (see also the earlier discussion in Section 4.2).

We now turn to the estimation results. We rerun the DID regressions of Table 4 by using the variable HSE^{IV} defined before to measure the scale of high school expansion. As reported in Appendix A Table A1, the coefficient on the interaction term remains negative without and with covariates (columns 1 and 2). The relevant point estimates of –0886 and –0.332 are insignificantly

[17] According to data from the China Education Finance Statistical Yearbook (2013), the average cost of tuition for HE was about 7,803 yuan per year, while the annual cost for high school education was only 1,734 yuan.
[18] The Gaokao exams are taken at the end of the last year of senior secondary schools (i.e., around age 19).

different from zero at conventional levels. Nevertheless, columns 3 and 4 indicate that senior high school expansion significantly decreased crime rates in the short and medium run, but the crime reducing effect mostly disappeared after six years. The immediate effects from senior high school enrolment in the short-run clearly suggests indirect evidence on incapacitation effect on crime by younger cohorts.

Tables 7 and 8 display results from partial identification analysis using the static measure of HE expansion intensity. The results in columns 4 and 5 of the tables show that, under our preferred middle-ground assumptions, the bounds of the effect are unanimously below zero throughout the expansion period (except empty bounds in 1999 and 2000 when looking at the most and least affected provinces). This indicates that crime was adversely affected by high school expansion. Meanwhile, parallel to the results in Tables 5 and 6, we find that the effects in the high school sector emerged much earlier than those in the higher education sector, where the crime reducing effect was absent in the first few years. Figure 7 visualizes the bounds under these assumptions. A comparison of the set estimates in Figure 6 and Figure 7 reveals that the signs of the treatment effects are more definite and the magnitudes of the effects are larger for high school expansion. Yet we are unable to identify the sign of the policy impact when imposing the weak assumption, no matter whether treatment status is defined according to the median cutoff (Table 7, columns 2 and 3) or the extreme cutoff (Table 8, columns 2 and 3).

We thus conclude that college expansion imposed a negative effect on crime not only through the higher educational level but also via the high school level. One possible explanation is that the expansion in senior high schools offer more opportunities for teenagers to continue their education and keep more youth off the street, thereby reducing juvenile crime rates at the province level.

7 Discussions

7.1 Alternative definitions of HE expansion

In the main analysis, our treatment variable is a static measure that captures the intensity of HE expansion based on 1998 enrollment information. The conventional DID estimates from using the dynamic and weighted measure of HE expansion are shown in Tables A2 and A3 of Appendix A. Consistent with the earlier findings, the negative relationship between expansion intensity and crime rates persists when using these two alternative definitions. Interestingly, after taking into account population mobility across regions, the results are strikingly similar to those of our benchmark analysis (Tables 4), and the coefficient on the interaction term, which is not statistically significant at any conventional level before, becomes significantly negative (column 2 of Table A3). Although far from conclusive, these results point to the possibility that a larger scale of HE expansion has led to crime falls.

The results of the bounded DID variation analysis, using alternative definitions of HE expansion, are reported in Tables A4-A7 of Appendix A. Tables A4 and A6 are the analog to Table 5, and Tables A5 and A7 are the analog to Table 6. Figures A1 and A2 depict the bounds under the middle-ground assumptions, respectively for the dynamic measure and the weighted measure. Figures A1 and A2 are the analog to Figure 7. Let us first focus on the dynamic measure. The first column of Tables A4 and A5 shows that no matter whether median cutoff or extreme cutoff is used, the strong DID assumption findings are invariably negative for almost all years. If we relax this strict invariance assumption and compare between above- and below-median provinces, most of the bounds appear to include zero. This means that we cannot generally identify the sign of the policy impact under the weak and middle-ground assumptions (columns 2-5, Table A4). However, comparing the highest- and lowest-intensity provinces delivers expected negative consequences of the policy on crime under the middle-ground assumptions (columns 2-5, Table A5), which are more pronounced and lasting as compared with those obtained using the static measure (columns 2-5, Table 6). We then look at the results from using the weighted measure. Results based on this alternative definition largely support our previous findings – even though there are some differences. Unlike the situation with the dynamic measure, when comparing the most and least affected provinces we cannot econometrically identify the bounds of the policy effect for certain years even under our favored middle-ground assumptions; but when the direction of treatment effects can be partially identified, we obtain similar insights of the impact of HE expansion on crime rates (columns 3 and 4, Table A7). These findings suggest that the negative expansion effect on crime is robust to different definitions of college expansion.

7.2 Mechanisms

As discussed in Section 2, increased education may affect crime through a variety of channels including income effects, incapacitation effects, psychic costs, and personality traits. The most obvious channel is through an incapacitation effect. This is because the expansion policy transformed potential unemployed young workers to high school graduates or college graduates, and more students remained in school longer than they would have without this policy. In this paper, we do not attempt to rigorously disentangle the underlying channels. To provide suggestive evidence that incapacitation is not the only mechanism at work, we employ micro-level survey data to investigate how education influences individual personality traits, which, in turn, influence criminal behavior.

Specifically, we draw on data from the 2010 wave of the China Family Panel Studies (CFPS).[19] We focus on individuals aged between 20 and 49, who are economically active. Following Wang & Zhang (2019), we map the questions in the CFPS questionnaire into the Big Five Factors of personality, i.e., openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism. Table A8 in the Appendix provides a detailed description of the relevant questions. To ensure the internal consistency among the questions in each dimension, we standardize all variables describing the Big Five questions by converting them into z-scores and calculate an aggregate measure by averaging over z-score values. We examine whether the Big Five personality traits are associated with schooling years in Table 9. In all instance we find that educational attainment shapes individual personality traits. An additional year of schooling is associated with a 0.018 standard deviation increase in the conscientiousness score, 0.028 in the agreeableness score, 0.034 in the extroversion score, and 0.036 in the openness score. By contrast, one extra year of schooling leads to a 0.018 standard deviation decrease in the neuroticism score. All these effects are statistically significant at the 1 percent level. In the literature, neuroticism is found to be positively related to criminal activities (Egan, 2009), whereas extroversion, conscientiousness, and openness are negatively correlated with criminal activities (Cameron, 2019). We are thus fairly confident that this implicit aspect of the education expansion – through the reshaping of personality – is of great importance, and we can rule out the notion that the only mechanism underpinning the crime reducing impact of education is incapacitation. Clearly, more research is needed to better understand the mechanisms behind the negative education expansion effect on crime.

8 Conclusion

[19] The CFPS is a biennial survey designed to be complementary to the Panel Study of Income Dynamics in the United States. It is one of the largest and most comprehensive national panel surveys in China, covering 25 of 31 provinces/regions and 95% of the total population of China. The CFPS questionnaires collect information on communities, households, household members, adults, and children.

This paper presents new evidence on the negative causal effects of higher education on crime in a fast-growing economy, China. Utilizing a large scale post-secondary educational expansion as a natural experiment, our methodology relies on a partial identification DID approach recently suggested by Manski and Pepper (2018). Although the partial identification analysis might not directly generate informative conclusions, our study is based on a set of maintained assumptions specified according to the context of our study. We define various bounded-variation DID assumptions that flexibly restrict the variation of two groups of treated provinces across multiple years. It becomes rather transparent to see how our specified assumptions yield the conclusions. The DD point estimates and three sets of boundary estimates all show consistent evidence on deterring effects of higher education on crime and that such effects are more pronounced several years after the implementation of the university expansion program. The estimated quantitative negative effects are large and significant. Taking 1999 as a reference year and the average crime rate of 4.9/10000 for provinces with larger higher education expansion, the DD point estimates suggest a decrease in crime rate by 21 to 24 percent between 2009 and 2012. Our preferred boundary estimates based on middle-ground assumptions indicate the effects in a range of 5 to 10 percent reduction in 2004, 9 to 15 percent in 2012, and maximum of 16 to 22 percent in 2007. The results are consistent and robust after accounting for the contemporary population movements and the proportion of non-local students admitted by local universities.

We also document causal effects of senior high school expansion on crime induced by a massive expansion on college/university enrolment. The empirical evidence shows that relative to the effects of higher education, senior high school expansion generated significant negative impact on crime shortly after the policy has been implemented rather than the deferred effects from the higher education expansion. This may suggest that the mechanism behind the deterring effects of the two levels of education might differ. The senior high school expansion could involve more incapacitation effects, while the university expansion may also generate effects through other channels such as income effects and increased patience or risk aversion. Our complimentary analysis shows with micro level data, that the higher educational expansion in China also helps to improve positive personality traits, which then presents one possible channel to reduce crime. The focus of the paper is not to disentangle the various channels through which education can affect criminal behavior in society, but rather to offer more complete picture on causal evidence on negative effects of higher education on crime for the entire population in China. If economists were able to access suitable micro-level data in which the criminal or delinquent behavior of individuals from different regions can be observed, a micro-level analysis would then allow for more in-depth explorations on the role of higher education in affecting the crime rate. This will be our future research agenda.

Our empirical findings speak to the policy maker that higher education has nontrivial positive externalities on crime reduction, and it should be considered in the educational policy design. For example, for countries with lower rates of higher education attainment, setting a higher quota in college admissions could subsequently bring improvement to public security. For senior high schools, lowering the entry requirements to admit more teenage students is likely to reduce the local crime rate directly.

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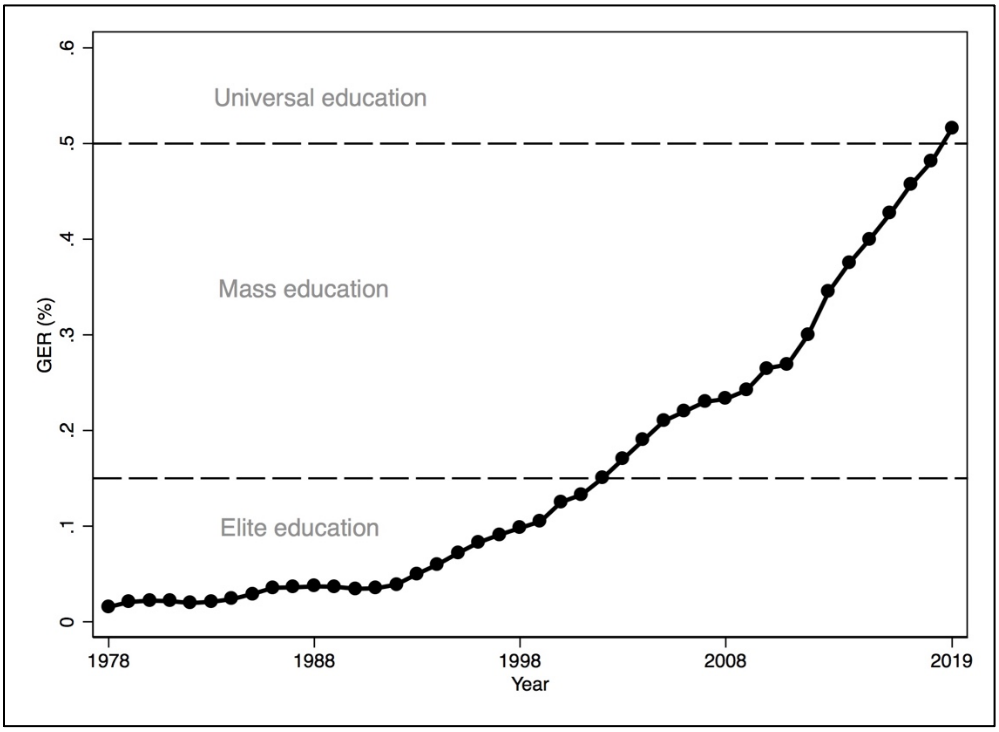
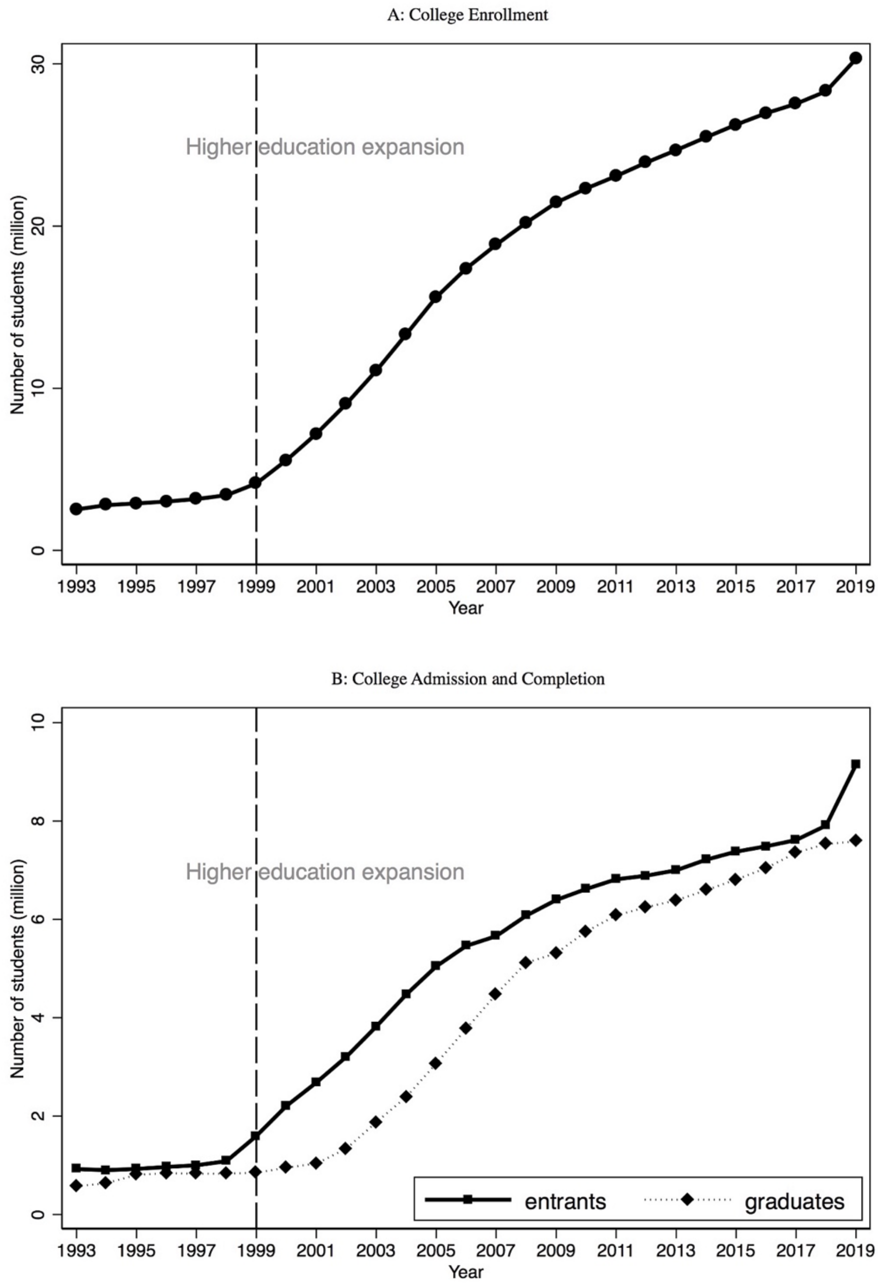
Figures and Tables

Figure 1 Gross Enrollment Ratio of Higher Education in China, 1978–2019.



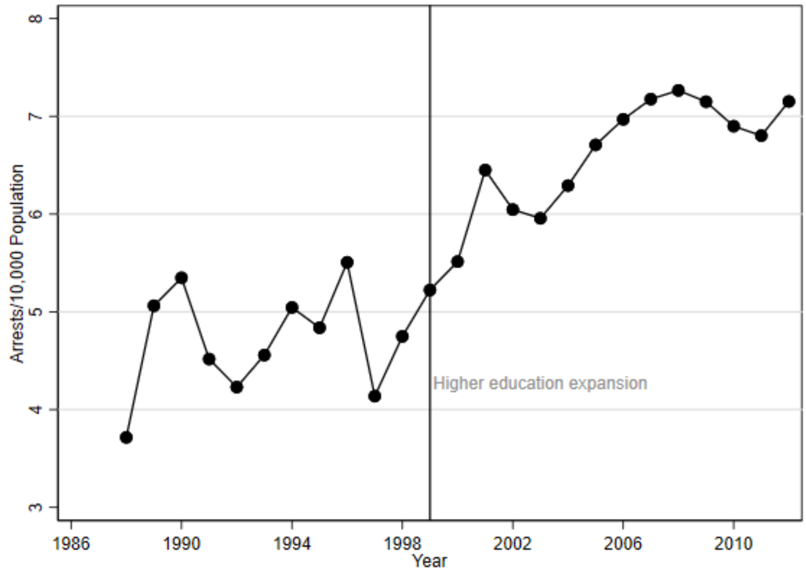
Notes: The figure depicts the percentage of 18 to 22 year-olds enrolled in Chinese regular institutions of higher education between 1978 and 2019.
Source: Educational Statistics Yearbook of China (1978–2002), Statistical Bulletin of the National Education Development (2003–2019).

Figure 2 College Enrollment, College Admission and College Completion, 1993–2019.



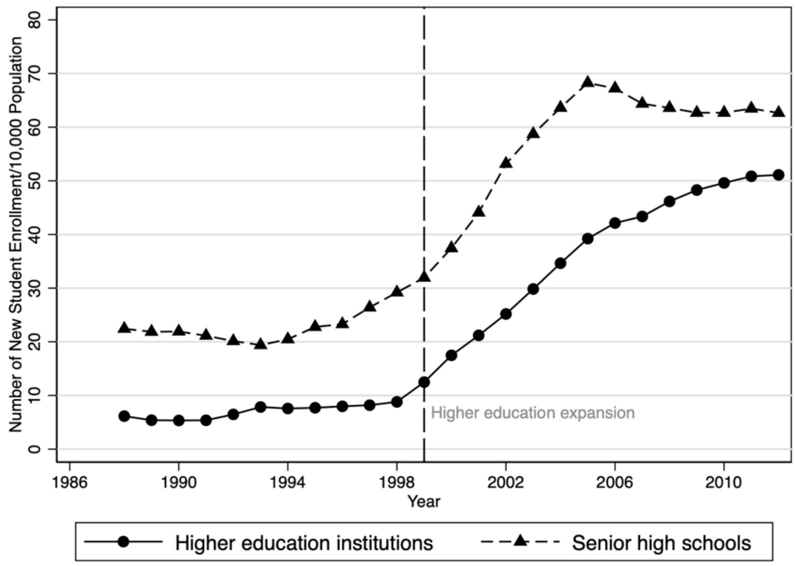
Notes: Panel A plots the total number of students (including undergraduates and graduates) enrolled in Chinese regular institutions of higher education for the years 1993–2019. Panel B reports the number of new students admitted to regular institutions of higher education and the number of students graduating from regular institutions of higher education each year from 1993 to 2019.
Source: China Statistical Yearbooks (1994–2020).

Figure 3 Arrests for Criminal Offences, 1988–2012.



Source: China Law Yearbook (1989–2013), Procuratorial Yearbook of China (1989–2013).

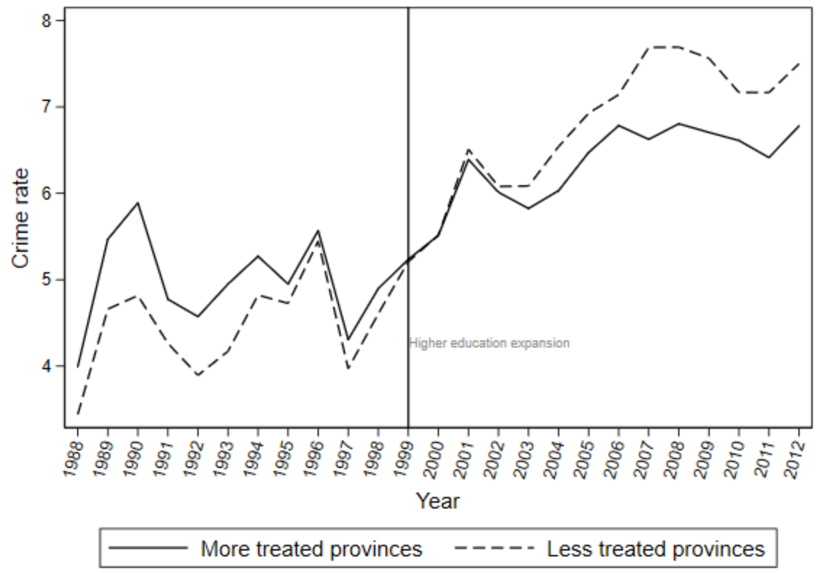
Figure 4 New Student Enrollment in Regular Higher Education Institutions and Regular Senior High Schools, 1988–2012.



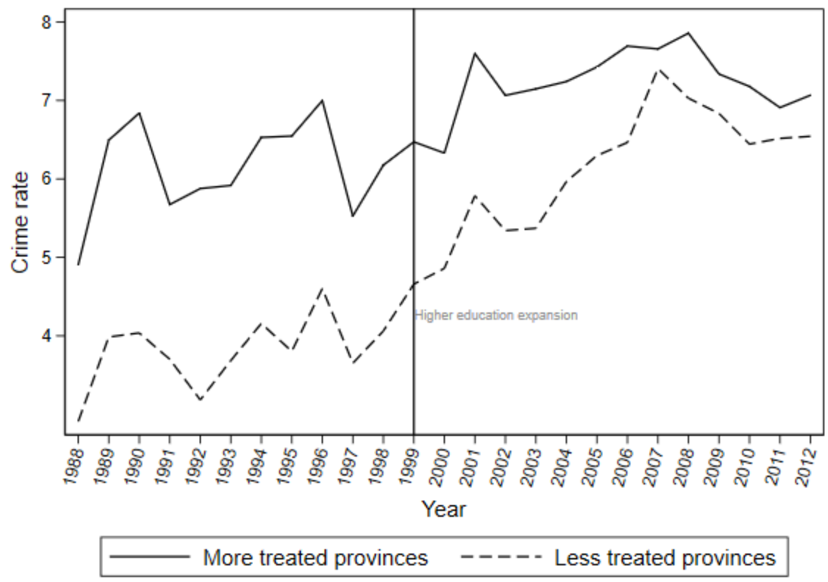
Source: China Statistical Yearbook (1989), Educational Statistics Yearbook of China (1989–2012).

Figure 5 Crime Rate by Year and Treatment Status.

A：Crime Rate by Year and Treatment Status Classified by the Median Value of the Distribution of the Intensity of Provincial Higher Education Expansion

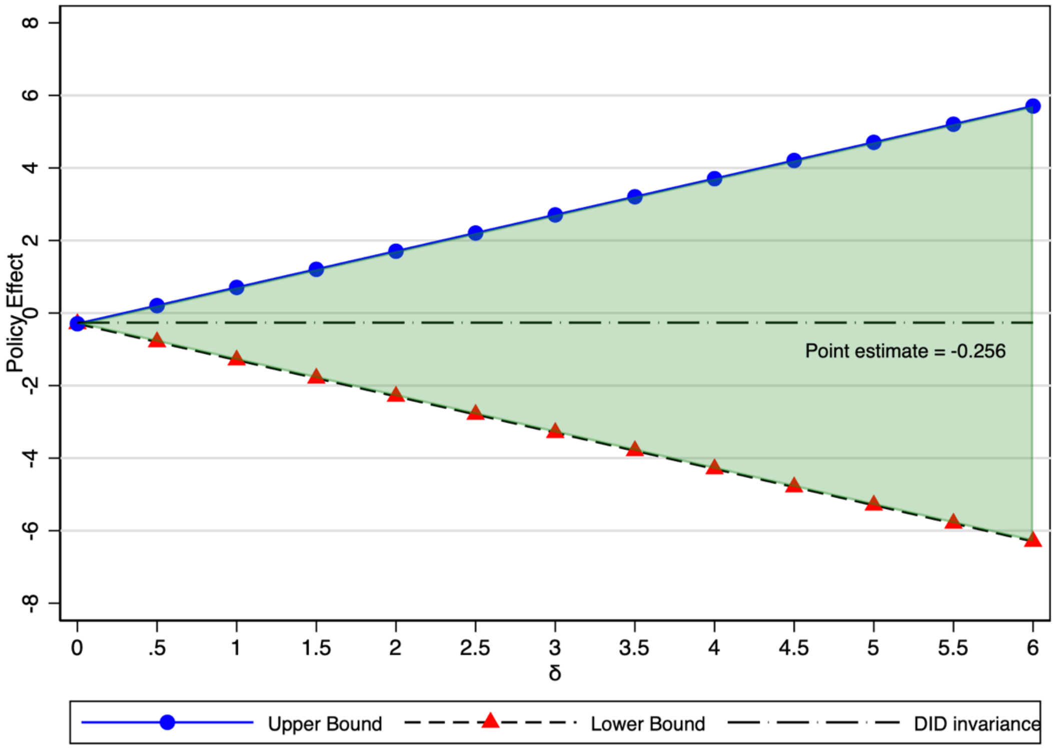


B：Crime Rate by Year and Treatment Status Classified by the 0.25th & 0.75th Quantiles of the Distribution of the Intensity of Provincial Higher Education Expansion



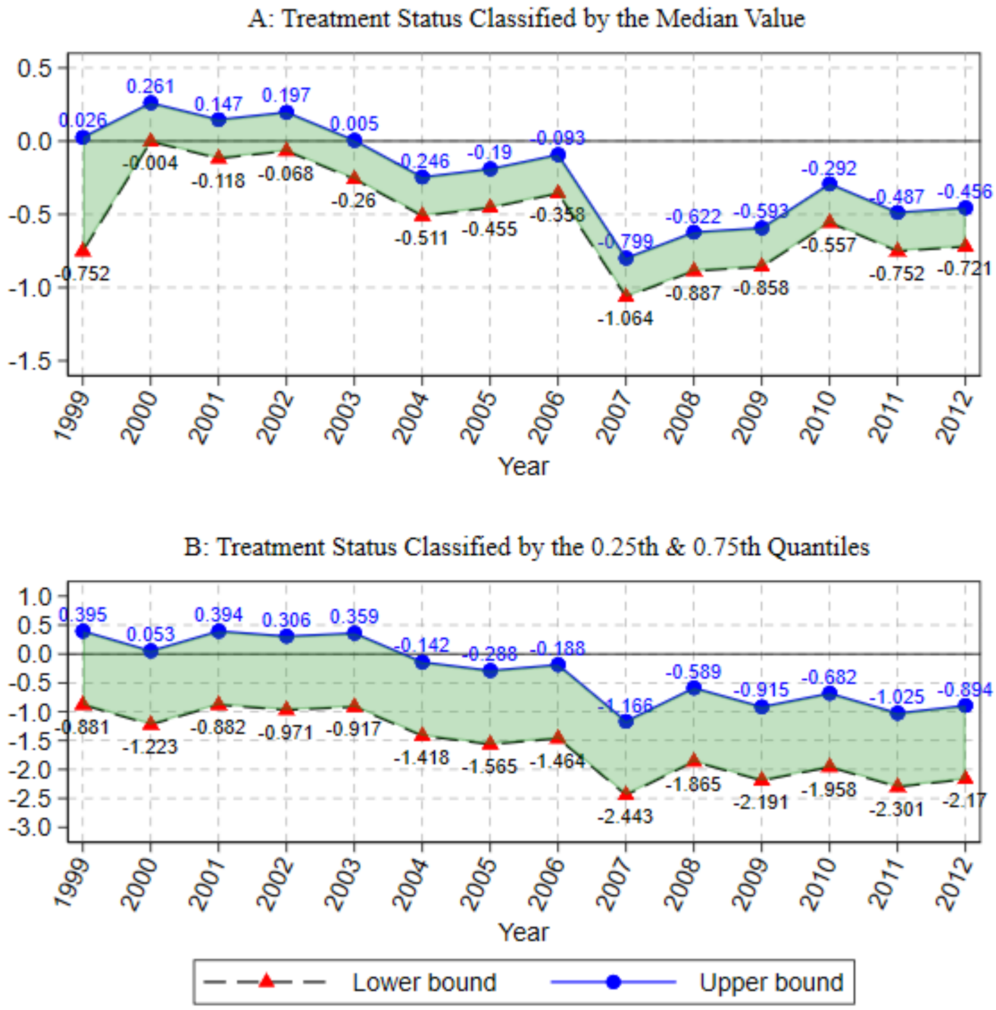
Notes: The intensity of provincial higher education expansion is defined as the ratio of the number of students in regular institutions of higher education in a province in 1998 to the number of students in regular senior high schools. The treatment status is based on the median or extreme cutoff. For example, in panel A, provinces whose expansion intensity above (below) the median value belong to the more treated (less treated) group.

Figure 6 Bounds on the the Policy Effect as a Function of δ.



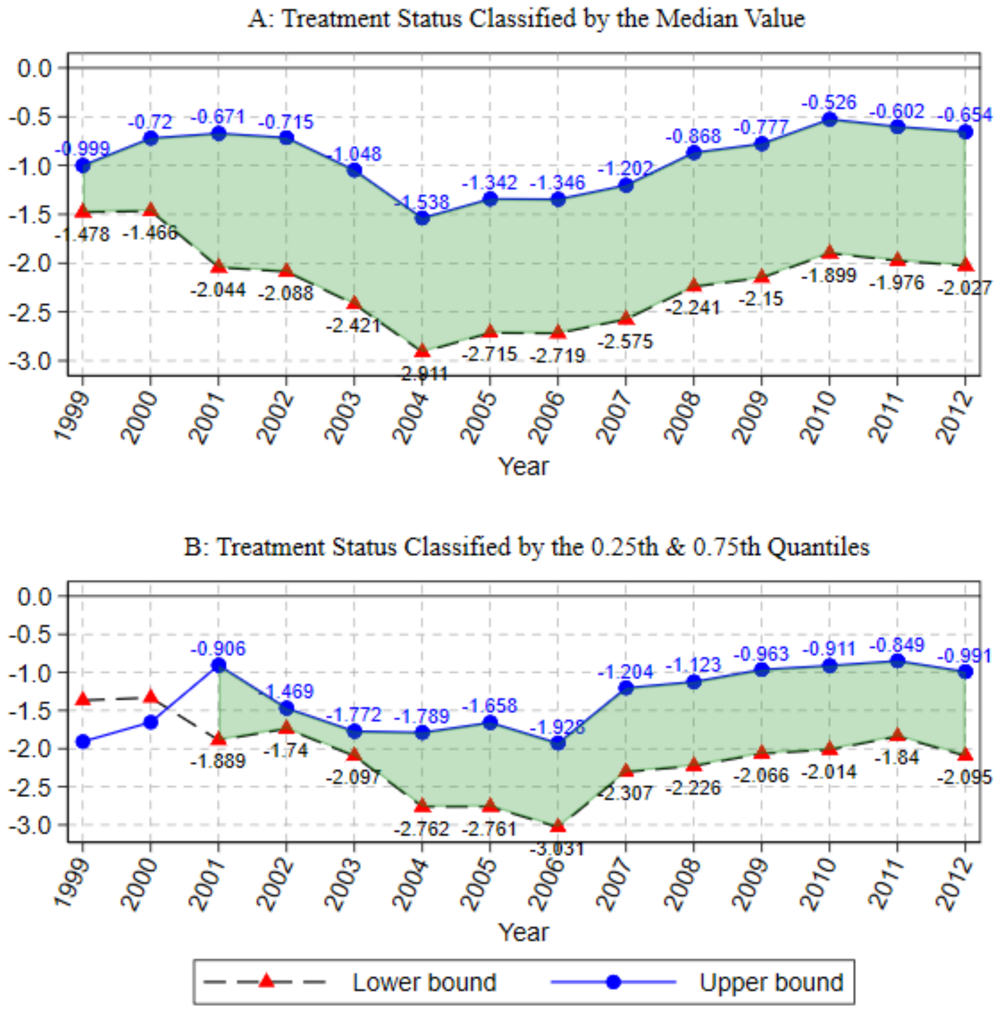
Notes: The lower and upper bounds of the policy effect for different values of δ are respectively plotted by red triangles and blue solid dots. The DID invariance estimates are plotted with a dash dotted line.

Figure 7 Bounds on the Policy Effect of Higher Education Expansion Under Middle-Ground Assumptions (Definition I).



Notes: The lower and upper bounds of the policy effect under middle-ground assumptions (δ = DID_0.75) are respectively plotted by red triangles and blue solid dots. The top panel is based on the median cutoff and the bottom panel is based on the extreme cutoff.

Figure 8 Bounds on the Policy Effect of Senior High School Expansion Under Middle-Ground Assumptions.



Notes: The lower and upper bounds of the policy effect under middle-ground assumptions (δ = DID_0.75) are respectively plotted by red triangles and blue solid dots. The top panel is based on the median cutoff and the bottom panel is based on the extreme cutoff. Green area and bound values are not attached for invalid bounds.

Table 1 Descriptive Statistics.

Variable	Mean	Std. Dev.	Maximum	Minimum
Dependent Variable				
Crime rate (arrests/10,000 population)[a]	6.20	2.34	15.40	0.81
Higher education expansion				
Intensity of HE expansion	0.40	0.25	1.46	0.19
Covariates				
Population (10,000)	4,140	2,814	11,847	212
Education (% without a high school degree)	0.80	0.09	1.00	0.40
Sex ratio (males/females)	1.04	0.03	1.15	0.90
Employment (% employed, 15–64 years old)	75.99	9.27	97.79	51.25
Urban per capita income (RMB)	7,715	4,884	30,088	2,177
Inequality (urban/rural per capita income)	2.76	0.71	5.16	1.24
Urbanization (% living in urban areas)	40.28	17.32	89.30	12.59
Economic openness $\frac{\text{Export+Import+FDI}}{\text{GDP}}$	0.33	0.43	2.76	0.03
Immigration rate (‰ born outside province)[b]	1.63	0.70	7.44	0.20
Construction (10,000 m^2)	9,505	17,941	166,969	22
Welfare (% of government expenditures)	4.90	4.77	28.83	0.10
Police (% of government expenditures)	5.76	1.39	10.79	3.00

Notes: There are 750 observations: annual data from 30 provincial-level administrative divisions, 1988—2012. Table 2 provides a description of data sources.

[a] Criminal offenses include homicide, assault, robbery, rape, abduction of women and children, larceny, fraud, smuggling, and so on.

[b] Change to *hukou* status.

Table 2 Data Sources.

Variables	Data sources
Crime rate	China Law Yearbook, 1989–2013; Procuratorial Yearbook of China, 1989–2013
Intensity of HE expansion	China Statistical Yearbook, 1989; Educational Statistics Yearbook of China, 1989–2012
Population, education, sex ratio	China Population & Employment Statistical Yearbook, 1989–2013
Employment, urban per capita income, inequality, urbanization, (Export + Import + FDI)/GDP, construction.	Comprehensive Statistical Data and Materials on 60 Years of New China, 1989–2013; China Statistical Yearbook, 1989–2013
Welfare and police expenditures	Finance Yearbook of China, 1992–2013
Immigration rate	China Population Statistical Yearbook, 1988–1991; China Population Statistical Data and Material by Counties and Cities, 1992–2012

Table 3 List of Pronvinces and Bounded Variation Parameters by Various Definitions of Treatment Status.

		Bounded Variation Parameters			
Definition	More Treated Provinces	Inter-group	Time	DID	DID_0.75
	(1)	(2)	(3)	(4)	(5)
Definition I (0.5th quantile)	Beijing, Shanghai, Tianjin, Yunnan, Jilin, Sichuan, Jiangsu, Jiangxi, Hubei, Hunan, Fujian, Tibet, Liaoning, Shaanxi, Heilongjiang	1.073	1.261	0.849	0.557
Definition I (0.25th & 0.75th quantiles)	Beijing, Shanghai, Tianjin, Jilin, Tibet, Liaoning, Shaanxi, Heilongjiang	2.803	1.589	0.831	0.697
Definition II (0.5th quantile)	Beijing, Shanghai, Tianjin, Jilin, Shandong, Shanxi, Jiangsu, Jiangxi, Zhejiang, Hainan, Hubei, Fujian, Liaoning, Shaanxi, Heilongjiang	0.545	1.304	0.574	0.471
Definition II (0.25th & 0.75th quantiles)	Beijing, Tianjin, Jilin, Jiangsu, Jiangxi, Hubei, Liaoning, Shaanxi	2.09	1.244	1.542	1.28
Definition III (0.5th quantile)	Tianjin, Jilin, Anhui, Shandong, Shanxi, Jiangsu, Jiangxi, Hebei, Henan, Zhejiang, Hubei, Hunan, Liaoning, Shaanxi, Heilongjiang	1.882	1.172	1.154	0.831
Definition III (0.25th & 0.75th quantiles)	Shandong, Shanxi, Jiangsu, Jiangxi, Hebei, Henan, Hubei, Shaanxi	2.758	1.097	1.067	0.682
Definition IV (0.5th quantile)	Inner Mongolia, Sichuan, Ningxia, Anhui, Shanxi, Jiangxi, Henan, Hainan, Hubei, Hunan, Gansu, Fujian, Tibet, Guizhou, Shaanxi	1.566	1.441	1.968	1.521
Definition IV (0.25th & 0.75th quantiles)	Inner Mongolia, Anhui, Shanxi, Jiangxi, Henan, Gansu, Guizhou, Shaanxi	2.44	1.531	1.899	1.465

Notes: The bound parameters are calculated by taking the maximum of the minimum parameter values required for the assumptions to be consistent with observed data in each year prior to 1999. The DID_0.75 parameter is the 0.75th quantile of the distribution of the minimum valid parameters.

Table 4 Estimated Effects of Higher Education Expansion on Crime: Conventional DID Estimates (Definition I and 0.5th Quantile).

	(1)	(2)	(3)	(4)
High intensity	0.617	0.152	0.617	0.196
	(0.536)	(0.449)	(0.545)	(0.452)
Post	1.918***	-0.201		
	(0.474)	(0.329)		
High intensity × Post	-0.477	-0.584		
	(0.546)	(0.377)		
High intensity×1999			0.030	-0.221
			(0.379)	(0.329)
High intensity×2000			-0.301	-0.661*
			(0.376)	(0.328)
High intensity×2001			-0.232	-0.440
			(0.448)	(0.364)
High intensity×2002			-0.102	-0.323
			(0.466)	(0.374)
High intensity×2003			-0.254	-0.407
			(0.511)	(0.465)
High intensity×2004			-0.273	-0.352
			(0.714)	(0.560)
High intensity×2005			-0.266	-0.387
			(0.702)	(0.579)
High intensity×2006			0.014	0.046
			(0.748)	(0.626)
High intensity×2007			-0.633	-0.415
			(0.780)	(0.556)
High intensity×2008			-0.417	-0.276
			(0.759)	(0.536)
High intensity×2009			-1.084	-1.100**
			(0.670)	(0.484)
High intensity×2010			-0.922	-1.033**
			(0.653)	(0.494)
High intensity×2011			-1.224*	-1.199**
			(0.668)	(0.515)
High intensity×2012			-1.012	-1.143*
			(0.792)	(0.595)
Covariates	No	Yes	No	Yes
Year dummies	No	No	Yes	Yes

Notes: Treatment status is defined using the static measure and median cutoff. High intensity is a dummy variable indicating whether the level of HE expansion in a province is above the median expansion intensity. The level of HE expansion is defined as the ratio of the number of students in regular institutions of higher education in a province in 1998 to the number of students in regular senior high schools. Columns 1 and 2 present regression results from the two-period DID model without and with covariates shown in Table 1. Columns 3 and 4 present regression results from the multiple-period DID model without and with covariates. Robust standard errors in parentheses are clustered at the province level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5 Bounds on the Policy Effect of Higher Education Expansion by Year under Different Maintained Assumptions (Definition I and 0.5th Quantile).

Year	DID_Strong	LB_DID_Weak	UB_DID_Weak	LB_DID_Mid	UB_DID_Mid
	(1)	(2)	(3)	(4)	(5)
1999	-0.265	-1.115	0.584	-0.752	0.026
2000	-0.296	-1.145	0.553	-0.004	0.261
2001	-0.41	-1.259	0.44	-0.118	0.147
2002	-0.36	-1.209	0.489	-0.068	0.197
2003	-0.552	-1.401	0.297	-0.26	0.005
2004	-0.802	-1.652	0.047	**-0.511**	**-0.246**
2005	-0.747	-1.596	0.102	**-0.455**	**-0.19**
2006	-0.65	-1.499	0.199	**-0.358**	**-0.093**
2007	-1.356	**-2.205**	**-0.507**	**-1.064**	**-0.799**
2008	-1.179	**-2.028**	**-0.33**	**-0.887**	**-0.622**
2009	-1.15	**-1.999**	**-0.301**	**-0.858**	**-0.593**
2010	-0.849	**-1.698**	**0.001**	**-0.557**	**-0.292**
2011	-1.044	**-1.893**	**-0.195**	**-0.752**	**-0.487**
2012	-1.013	**-1.862**	**-0.163**	**-0.721**	**-0.456**

Notes: Bounds in bold identify the sign of the policy effect to be negative, and those in bold and italics identify the sign of the policy effect to be positive. Bounds in italics are infeasible. DID_Strong refers to the point estimates of the policy effect under the traditional DID invariance assumption ($\delta = 0$). LB_DID_Weak and UB_DID_Weak represent the lower and upper bounds of the policy effect under the bounded DID variation assumption (δ = DID for Definition I (0.5th quantile) in Table 3). LB_DID_Mid and UB_DID_Mid represent the lower and upper bounds of the policy effect under the middle-ground assumptions including the bounded DID variation assumption (δ = DID_0.75 for Definition I (0.5th quantile) in Table 3) as well as bounded time and intergroup variation assumptions suited for this application.

Table 6 Bounds on the Policy Effect of Higher Education Expansion by Year under Different Maintained Assumptions (Definition I and 0.25th & 0.75th Quantiles).

Year	DID_Strong	LB_DID_Weak	UB_DID_Weak	LB_DID_Mid	UB_DID_Mid
	(1)	(2)	(3)	(4)	(5)
1999	-0.301	-1.132	0.529	-0.881	0.395
2000	-0.643	-1.474	0.187	-1.223	0.053
2001	-0.302	-1.133	0.528	-0.882	0.394
2002	-0.391	-1.222	0.44	-0.971	0.306
2003	-0.337	-1.168	0.493	-0.917	0.359
2004	-0.839	**-1.669**	**-0.008**	**-1.418**	**-0.142**
2005	-0.985	**-1.815**	**-0.154**	**-1.565**	**-0.288**
2006	-0.885	**-1.715**	**-0.054**	**-1.464**	**-0.188**
2007	-1.863	**-2.693**	**-1.032**	**-2.443**	**-1.166**
2008	-1.286	**-2.116**	**-0.455**	**-1.865**	**-0.589**
2009	-1.611	**-2.442**	**-0.781**	**-2.191**	**-0.915**
2010	-1.379	**-2.209**	**-0.548**	**-1.958**	**-0.682**
2011	-1.721	**-2.552**	**-0.891**	**-2.301**	**-1.025**
2012	-1.59	**-2.421**	**-0.76**	**-2.17**	**-0.894**

Notes: Bounds in bold identify the sign of the policy effect to be negative, and those in bold and italics identify the sign of the policy effect to be positive. Bounds in italics are infeasible. DID_Strong refers to the point estimates of the policy effect under the traditional DID invariance assumption ($\delta = 0$). LB_DID_Weak and UB_DID_Weak represent the lower and upper bounds of the policy effect under the bounded DID variation assumption (δ = DID for Definition I (0.25th & 0.75th quantiles) in Table 3). LB_DID_Mid and UB_DID_Mid represent the lower and upper bounds of the policy effect under the middle-ground assumptions including the bounded DID variation assumption (δ = DID_0.75 for Definition I (0.25th & 0.75th quantiles) in Table 3) as well as bounded time and intergroup variation assumptions suited for this application.

Table 7 Bounds on the Policy Effect of Senior High School Expansion by Year under Different Maintained Assumptions (Definition IV and 0.5th Quantile).

Year	DID_Strong	LB_DID_Weak	UB_DID_Weak	LB_DID_Mid	UB_DID_Mid
	(1)	(2)	(3)	(4)	(5)
1999	-0.01	-1.978	1.959	**-1.478**	**-0.999**
2000	0.002	-1.966	1.971	**-1.466**	**-0.72**
2001	-0.576	-2.544	1.392	**-2.044**	**-0.671**
2002	-0.62	-2.589	1.348	**-2.088**	**-0.715**
2003	-0.953	-2.921	1.015	**-2.421**	**-1.048**
2004	-1.443	-3.411	0.525	**-2.911**	**-1.538**
2005	-1.247	-3.215	0.721	**-2.715**	**-1.342**
2006	-1.251	-3.219	0.717	**-2.719**	**-1.346**
2007	-1.107	-3.075	0.861	**-2.575**	**-1.202**
2008	-0.773	-2.741	1.195	**-2.241**	**-0.868**
2009	-0.682	-2.65	1.286	**-2.15**	**-0.777**
2010	-0.431	-2.399	1.537	**-1.899**	**-0.526**
2011	-0.508	-2.476	1.46	**-1.976**	**-0.602**
2012	-0.559	-2.528	1.409	**-2.027**	**-0.654**

Notes: Bounds in bold identify the sign of the policy effect to be negative, and those in bold and italics identify the sign of the policy effect to be positive. Bounds in italics are infeasible. DID_Strong refers to the point estimates of the policy effect under the traditional DID invariance assumption (δ = 0). LB_DID_Weak and UB_DID_Weak represent the lower and upper bounds of the policy effect under the bounded DID variation assumption (δ = DID for Definition IV (0.5th quantile) in Table 3). LB_DID_Mid and UB_DID_Mid represent the lower and upper bounds of the policy effect under the middle-ground assumptions including the bounded DID variation assumption (δ = DID_0.75 for Definition IV (0.5th quantile) in Table 3) as well as bounded time and intergroup variation assumptions suited for this application.

Table 8 Bounds on the Policy Effect of Senior High School Expansion by Year under Different Maintained Assumptions (Definition IV and 0.25th & 0.75th Quantiles).

Year	DID_Strong	LB_DID_Weak	UB_DID_Weak	LB_DID_Mid	UB_DID_Mid
	(1)	(2)	(3)	(4)	(5)
1999	0.099	-1.8	1.998	*-1.366*	*-1.908*
2000	0.133	-1.766	2.032	*-1.332*	*-1.653*
2001	-0.424	-2.323	1.475	**-1.889**	**-0.906**
2002	-0.275	-2.174	1.624	**-1.74**	**-1.469**
2003	-0.632	-2.531	1.267	**-2.097**	**-1.772**
2004	-1.297	-3.196	0.602	**-2.762**	**-1.789**
2005	-1.296	-3.195	0.602	**-2.761**	**-1.658**
2006	-1.566	-3.465	0.333	**-3.031**	**-1.928**
2007	-0.842	-2.741	1.056	**-2.307**	**-1.204**
2008	-0.761	-2.66	1.137	**-2.226**	**-1.123**
2009	-0.601	-2.5	1.298	**-2.066**	**-0.963**
2010	-0.549	-2.448	1.35	**-2.014**	**-0.911**
2011	-0.375	-2.274	1.524	**-1.84**	**-0.849**
2012	-0.63	-2.529	1.269	**-2.095**	**-0.991**

Notes: Bounds in bold identify the sign of the policy effect to be negative, and those in bold and italics identify the sign of the policy effect to be positive. Bounds in italics are infeasible. DID_Strong refers to the point estimates of the policy effect under the traditional DID invariance assumption ($\delta = 0$). LB_DID_Weak and UB_DID_Weak represent the lower and upper bounds of the policy effect under the bounded DID variation assumption (δ = DID for Definition IV (0.25th & 0.75th quantiles) in Table 3). LB_DID_Mid and UB_DID_Mid represent the lower and upper bounds of the policy effect under the middle-ground assumptions including the bounded DID variation assumption (δ = DID_0.75 for Definition IV (0.25th & 0.75th quantiles) in Table 3) as well as bounded time and intergroup variation assumptions suited for this application.

Table 9 Education and Personality Traits.

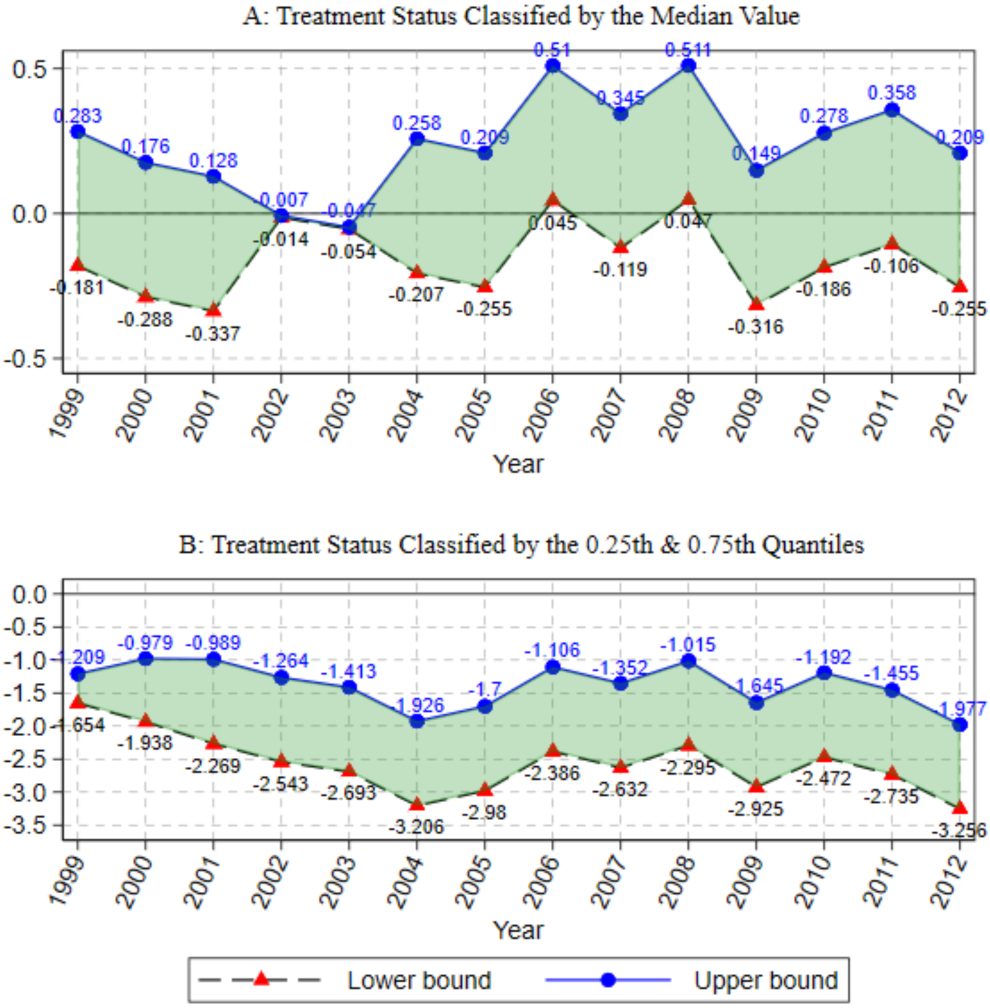
	Conscientiousness	Agreeableness	Extroversion	Openness	Neuroticism
Variable	(1)	(2)	(3)	(4)	(5)
Years of schooling	0.018***	0.028***	0.034***	0.036***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Gender	0.004	-0.019*	0.002	-0.029**	-0.108***
	(0.010)	(0.010)	(0.011)	(0.012)	(0.016)
Han ethnicity	0.030	-0.012	0.037	-0.031	0.021
	(0.022)	(0.022)	(0.024)	(0.023)	(0.031)
Urban *hukou*	-0.088***	-0.039**	0.018	0.036*	0.026
	(0.016)	(0.016)	(0.016)	(0.020)	(0.022)
Employment	0.019*	0.074***	0.037***	0.015	-0.084***
	(0.011)	(0.011)	(0.012)	(0.013)	(0.018)
Ever married	0.099***	0.113***	0.191***	-0.067***	-0.274***
	(0.017)	(0.018)	(0.020)	(0.018)	(0.027)
Education of mother	-0.005	0.006	0.011	0.022***	-0.001
	(0.007)	(0.007)	(0.007)	(0.008)	(0.010)
Education of father	0.008	0.006	0.014**	-0.001	-0.008
	(0.006)	(0.005)	(0.006)	(0.006)	(0.009)
Observations	14,874	14,829	15,208	15,208	15,127
Province dummies	Yes	Yes	Yes	Yes	Yes
Birth year dummies	Yes	Yes	Yes	Yes	Yes

Notes: The Big Five measures are based on the questions detailed in Table A8. Robust standard errors in parentheses are clustered at the province and birth year level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix to the paper:

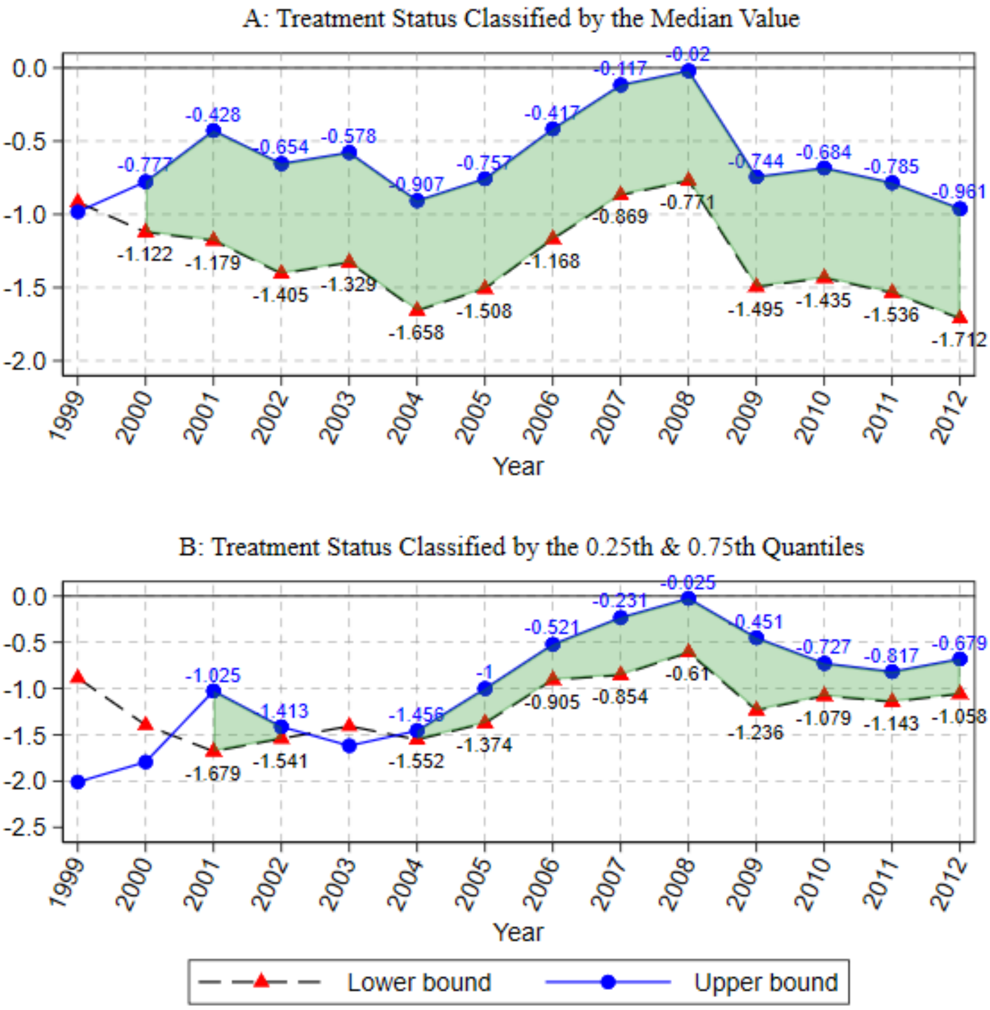
"Higher Education Expansion and Crime: New Evidence from China"

Figure A1 Bounds on the Policy Effect of Higher Education Expansion Under Middle-Ground Assumptions (Definition II).



Notes: The lower and upper bounds of the policy effect under middle-ground assumptions (δ = DID_0.75) are respectively plotted by red triangles and blue solid dots. The top panel is based on the median cutoff and the bottom panel is based on the extreme cutoff.

Figure A2 Bounds on the Policy Effect of Higher Education Expansion Under Middle-Ground Assumptions (Definition III).



Notes: The lower and upper bounds of the policy effect under middle-ground assumptions (δ = DID_0.75) are respectively plotted by red triangles and blue solid dots. The top panel is based on the median cutoff and the bottom panel is based on the extreme cutoff.

Table A1 Estimated Effects of Senior High School Expansion on Crime: Conventional DID Estimates (Definition IV and 0.5th Quantile).

	(1)	(2)	(3)	(4)
High intensity	-1.298**	-0.472	-1.298**	-0.535
	(0.492)	(0.431)	(0.500)	(0.434)
Post	2.123***	-0.189		
	(0.472)	(0.371)		
High intensity×Post	-0.886	-0.332		
	(0.528)	(0.387)		
High intensity×1999			-0.613*	-0.260
			(0.361)	(0.341)
High intensity×2000			-0.559	-0.090
			(0.365)	(0.397)
High intensity×2001			-1.207***	-0.819**
			(0.388)	(0.361)
High intensity×2002			-1.252***	-0.776**
			(0.401)	(0.371)
High intensity×2003			-1.260***	-0.871*
			(0.455)	(0.467)
High intensity×2004			-1.542**	-0.942*
			(0.654)	(0.554)
High intensity×2005			-1.330*	-0.538
			(0.657)	(0.587)
High intensity×2006			-1.324*	-0.529
			(0.705)	(0.657)
High intensity×2007			-1.164	-0.498
			(0.758)	(0.571)
High intensity×2008			-0.746	0.077
			(0.750)	(0.505)
High intensity×2009			-0.492	0.163
			(0.694)	(0.511)
High intensity×2010			-0.249	0.265
			(0.674)	(0.536)
High intensity×2011			-0.328	0.217
			(0.704)	(0.470)
High intensity×2012			-0.335	0.329
			(0.812)	(0.595)
Covariates	No	Yes	No	Yes
Year dummies	No	No	Yes	Yes

Notes: High intensity is a dummy variable indicating whether the level of senior high school expansion is above the median expansion intensity. The level of senior high school expansion is defined as the sum of additional students enrolled in regular senior high schools per 10,000 population in a province from 1999 to 2012, relative to 1998. Columns 1 and 2 present regression results from the two-period DID model without and with covariates shown in Table 1. Columns 3 and 4 present regression results from the multiple-period DID model without and with covariates. Robust standard errors in parentheses are clustered at the province level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A2 Estimated Effects of the Higher Education Expansion on Crime: Conventional DID Estimates (Definition II and 0.5th Quantile).

	(1)	(2)	(3)	(4)
High intensity	0.644	-0.036	0.644	-0.015
	(0.535)	(0.515)	(0.544)	(0.532)
Post	1.594***	-0.303		
	(0.316)	(0.369)		
High intensity×Post	0.171	-0.407		
	(0.553)	(0.367)		
High intensity×1999			0.204	0.125
			(0.377)	(0.350)
High intensity×2000			0.025	-0.106
			(0.380)	(0.389)
High intensity×2001			0.044	-0.192
			(0.450)	(0.400)
High intensity×2002			-0.015	-0.486
			(0.466)	(0.368)
High intensity×2003			-0.162	-0.632
			(0.513)	(0.460)
High intensity×2004			0.050	-0.430
			(0.716)	(0.543)
High intensity×2005			0.015	-0.694
			(0.704)	(0.529)
High intensity×2006			0.407	-0.223
			(0.744)	(0.660)
High intensity×2007			0.337	-0.313
			(0.787)	(0.554)
High intensity×2008			0.545	-0.122
			(0.756)	(0.510)
High intensity×2009			0.142	-0.636
			(0.700)	(0.503)
High intensity×2010			0.281	-0.711
			(0.674)	(0.489)
High intensity×2011			0.261	-0.622
			(0.705)	(0.537)
High intensity×2012			0.260	-0.626
			(0.813)	(0.654)
Covariates	No	Yes	No	Yes
Year dummies	No	No	Yes	Yes

Notes: Treatment status is defined using the dynamic measure and median cutoff. High intensity is a dummy variable indicating whether the level of HE expansion in a province is above the median expansion intensity. The level of HE expansion is defined as
the sum of additional students enrolled in regular institutions of higher education per 100 population in a province from 1999 to 2012, relative to 1998. Columns 1 and 2 present regression results from the two-period DID model without and with covariates shown in Table 1. Columns 3 and 4 present regression results from the multiple-period DID model without and with covariates. Robust standard errors in parentheses are clustered at the province level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A3 Estimated Effects of the Higher Education Expansion on Crime: Conventional DID Estimates (Definition III and 0.5th Quantile).

	(1)	(2)	(3)	(4)
High intensity	-1.207**	-0.840*	-1.207**	-0.835*
	(0.500)	(0.414)	(0.509)	(0.446)
Post	1.904***	-0.021		
	(0.330)	(0.341)		
High intensity×Post	-0.449	-0.631*		
	(0.547)	(0.323)		
High intensity×1999			-0.293	-0.058
			(0.375)	(0.360)
High intensity×2000			-0.380	-0.161
			(0.373)	(0.364)
High intensity×2001			-0.323	-0.183
			(0.446)	(0.381)
High intensity×2002			-0.466	-0.481
			(0.457)	(0.359)
High intensity×2003			-0.477	-0.569
			(0.506)	(0.454)
High intensity×2004			-0.945	-1.081**
			(0.693)	(0.523)
High intensity×2005			-0.822	-1.097**
			(0.687)	(0.518)
High intensity×2006			-0.569	-0.827
			(0.740)	(0.603)
High intensity×2007			-0.246	-0.401
			(0.788)	(0.575)
High intensity×2008			-0.019	-0.216
			(0.763)	(0.467)
High intensity×2009			-0.543	-0.861**
			(0.693)	(0.395)
High intensity×2010			-0.390	-0.723*
			(0.672)	(0.390)
High intensity×2011			-0.433	-0.802*
			(0.702)	(0.445)
High intensity×2012			-0.383	-0.861
			(0.811)	(0.559)
Covariates	No	Yes	No	Yes
Year dummies	No	No	Yes	Yes

Notes: Treatment status is defined using the weighted measure and median cutoff. High intensity is a dummy variable indicating whether the level of HE expansion in a province is above the median expansion intensity. The level of HE expansion is defined as the weighted average of the dynamic measure of HE expansion. Columns 1 and 2 present regression results from the two-period DID model without and with covariates shown in Table 1. Columns 3 and 4 present regression results from the multiple-period DID model without and with covariates. Robust standard errors in parentheses are clustered at the province level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A4 Bounds on the Policy Effect of Higher Education Expansion by Year under Different Maintained Assumptions (Definition II and 0.5th Quantile).

Year	DID_Strong	LB_DID_Weak	UB_DID_Weak	LB_DID_Mid	UB_DID_Mid
	(1)	(2)	(3)	(4)	(5)
1999	-0.181	-0.755	0.393	-0.181	0.283
2000	-0.288	-0.862	0.286	-0.288	0.176
2001	-0.337	-0.911	0.237	-0.337	0.128
2002	-0.478	-1.052	0.096	**-0.014**	**-0.007**
2003	-0.518	-1.092	0.056	**-0.054**	**-0.047**
2004	-0.207	-0.781	0.368	-0.207	0.258
2005	-0.255	-0.829	0.319	-0.255	0.209
2006	0.045	-0.529	0.62	***0.045***	***0.51***
2007	-0.119	-0.693	0.455	-0.119	0.345
2008	0.047	-0.527	0.621	***0.047***	***0.511***
2009	-0.316	-0.89	0.259	-0.316	0.149
2010	-0.186	-0.76	0.388	-0.186	0.278
2011	-0.106	-0.681	0.468	-0.106	0.358
2012	-0.255	-0.829	0.319	-0.255	0.209

Notes: Bounds in bold identify the sign of the policy effect to be negative, and those in bold and italics identify the sign of the policy effect to be positive. Bounds in italics are infeasible. DID_Strong refers to the point estimates of the policy effect under the traditional DID invariance assumption ($\delta = 0$). LB_DID_Weak and UB_DID_Weak represent the lower and upper bounds of the policy effect under the bounded DID variation assumption (δ = DID for Definition II (0.5th quantile) in Table 3). LB_DID_Mid and UB_DID_Mid represent the lower and upper bounds of the policy effect under the middle-ground assumptions including the bounded DID variation assumption (δ = DID_0.75 for Definition II (0.5th quantile) in Table 3) as well as bounded time and intergroup variation assumptions suited for this application.

Table A5 Bounds on the Policy Effect of Higher Education Expansion by Year under Different Maintained Assumptions (Definition II and 0.25th & 0.75th Quantiles).

Year	DID_Strong	LB_DID_Weak	UB_DID_Weak	LB_DID_Mid	UB_DID_Mid
	(1)	(2)	(3)	(4)	(5)
1999	-0.374	-1.916	1.169	**-1.654**	**-1.209**
2000	-0.659	-2.201	0.884	**-1.938**	**-0.979**
2001	-0.989	-2.532	0.553	**-2.269**	**-0.989**
2002	-1.264	-2.806	0.279	**-2.543**	**-1.264**
2003	-1.413	-2.955	0.13	**-2.693**	**-1.413**
2004	-1.926	**-3.469**	**-0.384**	**-3.206**	**-1.926**
2005	-1.7	**-3.242**	**-0.157**	**-2.98**	**-1.7**
2006	-1.106	-2.648	0.437	**-2.386**	**-1.106**
2007	-1.352	-2.895	0.19	**-2.632**	**-1.352**
2008	-1.015	-2.558	0.527	**-2.295**	**-1.015**
2009	-1.645	**-3.188**	**-0.103**	**-2.925**	**-1.645**
2010	-1.192	-2.734	0.351	**-2.472**	**-1.192**
2011	-1.455	-2.998	0.087	**-2.735**	**-1.455**
2012	-1.977	**-3.519**	**-0.434**	**-3.256**	**-1.977**

Notes: Bounds in bold identify the sign of the policy effect to be negative, and those in bold and italics identify the sign of the policy effect to be positive. Bounds in italics are infeasible. DID_Strong refers to the point estimates of the policy effect under the traditional DID invariance assumption ($\delta = 0$). LB_DID_Weak and UB_DID_Weak represent the lower and upper bounds of the policy effect under the bounded DID variation assumption (δ = DID for Definition II (0.25th & 0.75th quantiles) in Table 3). LB_DID_Mid and UB_DID_Mid represent the lower and upper bounds of the policy effect under the middle-ground assumptions including the bounded DID variation assumption (δ = DID_0.75 for Definition II (0.25th & 0.75th quantiles) in Table 3) as well as bounded time and intergroup variation assumptions suited for this application.

Table A6 Bounds on the Policy Effect of Higher Education Expansion by Year under Different Maintained Assumptions (Definition III and 0.5th Quantile).

Year	DID_Strong	LB_DID_Weak	UB_DID_Weak	LB_DID_Mid	UB_DID_Mid
	(1)	(2)	(3)	(4)	(5)
1999	-0.084	-1.239	1.07	*-0.916*	*-0.983*
2000	-0.291	-1.445	0.863	**-1.122**	**-0.777**
2001	-0.348	-1.502	0.807	**-1.179**	**-0.428**
2002	-0.574	-1.728	0.58	**-1.405**	**-0.654**
2003	-0.498	-1.652	0.656	**-1.329**	**-0.578**
2004	-0.827	-1.981	0.328	**-1.658**	**-0.907**
2005	-0.677	-1.831	0.478	**-1.508**	**-0.757**
2006	-0.337	-1.491	0.817	**-1.168**	**-0.417**
2007	-0.037	-1.191	1.117	**-0.869**	**-0.117**
2008	0.06	-1.094	1.214	**-0.771**	**-0.02**
2009	-0.664	-1.818	0.491	**-1.495**	**-0.744**
2010	-0.604	-1.758	0.55	**-1.435**	**-0.684**
2011	-0.704	-1.859	0.45	**-1.536**	**-0.785**
2012	-0.88	-2.035	0.274	**-1.712**	**-0.961**

Notes: Bounds in bold identify the sign of the policy effect to be negative, and those in bold and italics identify the sign of the policy effect to be positive. Bounds in italics are infeasible. DID_Strong refers to the point estimates of the policy effect under the traditional DID invariance assumption ($\delta = 0$). LB_DID_Weak and UB_DID_Weak represent the lower and upper bounds of the policy effect under the bounded DID variation assumption (δ = DID for Definition III (0.5th quantile) in Table 3). LB_DID_Mid and UB_DID_Mid represent the lower and upper bounds of the policy effect under the middle-ground assumptions including the bounded DID variation assumption (δ = DID_0.75 for Definition III (0.5th quantile) in Table 3) as well as bounded time and intergroup variation assumptions suited for this application.

Table A7 Bounds on the Policy Effect of Higher Education Expansion by Year under DifferentMaintained Assumptions (Definition III and 0.25th & 0.75th Quantiles).

Year	DID_Strong	LB_DID_Weak	UB_DID_Weak	LB_DID_Mid	UB_DID_Mid
	(1)	(2)	(3)	(4)	(5)
1999	-0.199	-1.266	0.867	*-0.885*	*-2.01*
2000	-0.71	-1.776	0.357	*-1.395*	*-1.794*
2001	-0.993	-2.059	0.074	**-1.679**	**-1.025**
2002	-0.855	-1.922	0.212	**-1.541**	**-1.413**
2003	-0.72	-1.786	0.347	*-1.406*	*-1.618*
2004	-0.866	-1.933	0.2	**-1.552**	**-1.456**
2005	-0.688	-1.754	0.379	**-1.374**	**-1**
2006	-0.219	-1.286	0.848	**-0.905**	**-0.521**
2007	-0.168	-1.235	0.899	**-0.854**	**-0.231**
2008	0.076	-0.991	1.143	**-0.61**	**-0.025**
2009	-0.55	-1.617	0.517	**-1.236**	**-0.451**
2010	-0.394	-1.46	0.673	**-1.079**	**-0.727**
2011	-0.457	-1.524	0.61	**-1.143**	**-0.817**
2012	-0.372	-1.438	0.695	**-1.058**	**-0.679**

Notes: Bounds in bold identify the sign of the policy effect to be negative, and those in bold and italics identify the sign of the policy effect to be positive. Bounds in italics are infeasible. DID_Strong refers to the point estimates of the policy effect under the traditional DID invariance assumption ($\delta = 0$). LB_DID_Weak and UB_DID_Weak represent the lower and upper bounds of the policy effect under the bounded DID variation assumption (δ = DID for Definition III (0.25th & 0.75th quantiles) in Table 3). LB_DID_Mid and UB_DID_Mid represent the lower and upper bounds of the policy effect under the middle-ground assumptions including the bounded DID variation assumption (δ = DID_0.75 for Definition III (0.25th & 0.75th quantiles) in Table 3) as well as bounded time and intergroup variation assumptions suited for this application.

Table A8 Measures of Big Five Personality and Corresponding Questions.

Big Five	Questions
Conscientiousness	Feeling successful is important to you.
	In today's society, hard work is rewarded.
	Neatness/cleanliness of respondent's clothing
	Respondent's suspicion of the interview
Agreeableness	"Not being disliked by others" is important to you.
	It is easy for you to get on well with others.
	Respondent's level of cooperation during the interview
Extroversion	Respondent's courteousness
	"Not lonely" is important to you.
	Having fun in life is important to you.
Openness	Respondent's interest in the interview
	Having children to carry on the family name is important.
Neuroticism	How would you rate your inter-personal relationship with others?
	Feel depressed and cannot cheer up in the past month.
	Feel nervous in the past month.
	Feel agitated or upset and cannot remain calm in the past month.
	Feel hopeless about the future in the past month.
	Feel that everything is difficult in the past month.

Source: CFPS (2014).

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