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Competing with Clean Air: Pollution Disclosure and College Desirability

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Abstract

Starting in 2013, China's pollution information disclosure program raised public awareness of air quality. This study seeks to analyze quantitatively the impact of information disclosure on college desirability. To that end, I assemble a comprehensive dataset on admission scores for all colleges in China for eight years. In an event study setting, I find that pollution information drives down cutoff scores for colleges in dirty cities by 0.3% for the arts track and 0.6% for the science track of first- and second-tier colleges and no impacts for third-tier colleges. The effect is mainly driven by the increased competition for clean colleges, and is stronger for journalism, economics and environment-related majors. The findings confirm the importance of environmental information and are consistent with people's avoidance behavior against pollution.

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1 Introduction

Every year, around 10 million students take the college entrance exam (CEE) in China, competing to get in to about 2600 universities of different tiers. The CEE score determines students' final admission results, with preference submitted by students themselves and priority given to high scores. To perhaps a surprising degree, preferences of students and their families play an important role in college selecting despite reliance on the standardized CEE. When choosing their colleges, parents and students take multiple factors into account including teaching and research quality, alumni network, and opportunities and amenities in that city. Whether air quality has an amenity value that can affect college desirability remains largely unanswered[1].

China has been experiencing high concentrations of air pollutants. In 2013, the annual average exposure to fine particulate matter in China was more than five times higher than that of the US (Brauer et al., 2016). To try to address severe pollution, the Chinese government declared a "war against pollution" at the beginning of 2014 at the National People's Congress (Greenstone and Schwarz, 2018). Complementary with the war, China launched a nationwide, real-time air quality monitoring and disclosure program in 2013. Since then, regular air quality monitoring has been carried out and hourly data are released on government's open platform. The emergence of disclosure program provides information shock and largely rises public awareness on air pollution.

This paper provides the first quantification of the impact of an amenity information shock on college desirability. The analysis presented herein leverages a comprehensive dataset on cutoff scores of China's college entrance exam, containing the number of admitted students, cutoff scores that vary at college, year, province and major for all colleges in China for eight years. This dataset is augmented with satellite products on air quality measured in each city where the college is located, as well as the timing of pollution information rollout from

[1]Students with respiratory diseases are reported to only apply for universities in clean cities: news.sinovision.net/society/201701/00396862.htm

China's government. Using these datasets, this paper takes advantage of pollution disclosure by city as a natural experiment and conducts an event study to quantify the impact of this information shock on college desirability as captured by cutoff scores. Lower cutoff scores in dirty colleges mean less severe competition and lower demand for the college. Apart from comparing dirty and clean colleges, I also show the difference is attributed to the increased competition for clean colleges. Heterogeneous impacts over tiers, tracks, and majors are also discussed.

This study makes three contributions to the existing literature. First, this study provides evidence on people's avoidance behavior and location choice against pollution in developing countries. Choosing where to spend their four-year undergraduate program serves as a medium-term location choice decision. Compared with migration, which is largely affected by job opportunities and has much higher costs, college choice is a necessary decision on location faced by all high school graduates, and could overcome the censored results estimated from migration. While billions of residents of developing countries are faced with high air pollution which endangers their physical and economic health, a few existing studies find people's avoidance behavior or willingness to pay for improvements is low in developing countries (Yusuf and Resosudarmo, 2009; Kremer et al., 2011; Zhang and Mu, 2018; Ito and Zhang, forthcoming). This study provides new empirical evidence of avoidance behavior by investigating students' and parents' demand for colleges with different air quality.

Second, this study provides evidence of the impact of pollution information disclosure programs which has proven important for emission control and public awareness. Most existing studies focus on the polluter side, and conclude that Toxic Release Inventory (TRI) in US (Cohen, 1997; Graham, 2000; Konar and Cohan, 2001; Stephan, 2002; Hamilton, 2005; Sanders, 2012; Mastromonaco, 2015), Program for Pollution Control, Evaluation and Rating in Indonesia (Afsah, Blackman and Ratunanda, 2000; Garcia, Sterner and Afsah, 2007; Blackman, 2010), National Pollutant Release Inventory in Canada (Antweiler and Harrison, 2003), and Green Rating Project in India (Blackman, 2010) are tied to the decline in pollution emissions and stock returns. On the public behavior side, Sanders (2012); Mastromonaco (2015) finds stricter TRI reporting has a negative impact on the housing market near toxic emitters. Huet-Vaughn, Muller and Hsu (2018) finds more phone call complaints when real-time visual emission camera at Shenango coke plants is on. Most related to this study, Barwick et al. (2019) finds China's air quality disclosure shock in 2013 induces more online searches, fewer outdoor purchase trips, and lower housing demand. Unlike Barwick et al. (2019), this study focuses on the impact on college desirability, an important content of education system and job market in China.

Third, this study contributes to the links between environmental conditions and education outcomes. In addition to substantial findings of the biological impact of air pollution on academic performance, including pre-college performance (Currie et al., 2009; Ham, Zweig and Avol, 2014), CEE scores (Ebenstein, Lavy and Roth, 2016; Amanzadeh, Vesal and Fatemi, 2019), and final exams in colleges (Roth, 2016), this study contributes to the literature by showing that air quality is an influential factor for the final results of college entrance exams. Thus, family preferences - not just standardized scores - are both malleable and consequential for educational outcomes in China.

The remainder of this paper is organized as follows. Section 2 provides background on China's air quality disclosure program, and introduces college entrance exam including the exam policy and admission process. Section 3 describes the data for empirical analysis. Section 4 discusses my empirical setting. Section 5 and 6 reports the empirical results and robustness tests. Section 8 concludes.

2 Background

2.1 Pollution disclosure program in China

The conversation on China's pollution has shifted dramatically in recent years. Before 2013, citizens had limited access to environmental information, such as data on air, water or soil quality. National media used to report “fog” for poor visibility and deny that smog was caused by emissions[2]. Although the Ministry of Environmental Protection (MEP) started to report an air pollution index (API) in 2000, API only covered 86 major cities, one-fourth of the total, and was not widely published in broadcasts and media. Besides, API only incorporated PM10, SO_2, NO_2, and failed to capture the level of PM2.5, a major pollutant and threat to human health. Focussing on the threshold value for “clean” and “polluted” days, Chen et al. (2012) and Ghanem and Zhang (2014) found evidence of manipulation of API reports, which clearly compromises the information transparency of China’s air quality.

Public debate and pressure for air pollution disclosure were triggered by the US Embassy’s release of hourly PM2.5 data for its neighborhood in Beijing. Starting in 2013, regular air quality monitoring has been carried out and hourly data are released on the Chinese government’s open platform. This disclosure campaign was a component of China’s pollution reduction plan, with the aim of providing a scientific system of air quality monitoring and enhancing public awareness. The new air quality index (AQI) incorporates six major pollutants, PM2.5, PM10, O_3, CO, SO_2, NO_2. The number of monitors increased gradually. Figure 1 provides the timing of monitors rollout and their locations. Only 496 monitors started to report at the beginning of 2013, and the number was 1605 in 2018. The county-coverage rate increased from 0.16 to 0.54. This discrete, localized timeline allows an observational study on the causal effects of pollution disclosure.

After monitors started to report, hourly data is not only posted on the government website, but also widely broadcast by local media and newspaper. There are also some mobile applications scraping these reports and widely used by citizens. While this pollution disclosure does not imply a shift from no to complete information, it triggers a surge in public awareness on air pollution problems.

[2] www.newyorker.com/news/news-desk/china-tries-new-tactic-combat-pollution-transparency for example

2.2 Colleges and college entrance exam in China

In China, a total of 2,631 colleges were registered in 2017 and classified in four tiers by the Ministry of Education[3]. First-tier colleges are mainly national key universities under the control of central government, concentrated with the highest ability students, teachers and resources. Second-tier colleges are less selective universities mostly under the control of provincial governments. Third-tier colleges are mainly private universities or independent schools jointly run by higher education institutions and social forces that are able to offer a bachelor's degree. Most of them are similar to for-profit colleges or community colleges with bachelor degree in the US. Fourth-tier colleges are 3-year vocational colleges that do not offer a bachelor degree, and are designed for practical skills like nursing and machinist rather than abstract subjects.

All the colleges offering bachelor degrees recruit students via the college entrance exam. Every year, high school graduates take the CEE from June 7th to 9th for math, Chinese, English and the other three subjects depending on arts or science track[4]. Although the exams take place in the same period across the country, five provinces[5] design their own exams independently, and the rest take three different exams[6] based on provincial policies. Therefore, scores are only comparable within province-year-track. Student's overall score is the sum of these six subjects and is the determinant of their final admission result. First-tier colleges are usually considered elite universities (Jia and Li, 2016), while those admitted to third-tier colleges are very likely to go to colleges in home provinces[7]. Unlike the top three tiers, CEE score is not necessary for admission to fourth-tier colleges.

[3]www.moe.gov.cn/srcsite/A03/moe_634/. College list is updated by the Ministry of Education every year.

[4]Arts: geography, history, politics; Science: physics, chemistry, biology

[5]Beijing, Shanghai, Tianjin, Jiangsu, Zhejiang

[6]In 2018, provinces using National I exam: Chongqing, Shaanxi, Gansu, Ningxia, Qianghai, Xinjiang, Heilongjiang, Jilin, Liaoning, Inner Mongolia, Hainan; National II: Shanxi, Hebei, Henan, Anhui, Hubei, Hunan, Jiangxi, Fujian, Guangdong, Shandong; National III: Yunnan, Guizhou, Sichuan, Tibet, Guangxi

[7]For example, in Jiangxi province, the number of admits for first- and second-tier colleges are almost the same for colleges in Jiangxi and outside Jiangxi, about 30 thousand per year. For third-tier colleges, the number of admits for colleges in Jiangxi is 17201, 33247, 16457 in 2010, 2012, 2014, while the number of admits outside Jiangxi is 5828, 12297, 7152.

Apart from differing test contents, there are three different application systems. For most provinces, students take the exam first, and the exam is graded independently by their home provinces. Based on the score distribution, the provincial government announces cutoff scores for the three tiers for arts and science. After knowing their real scores and the three cutoffs, students fill applications for individual universities. For Beijing and Shanghai, students apply for individual universities before taking the exam. For Xinjiang, Shanxi and Heilongjiang, students apply before knowing their real scores, but estimate it based on the announced solutions and their recalled answers. In all cases, the cutoff of each individual university is unknown ex ante. Thus, the cutoff score could reflect the competition and demand for each university.

Receiving students' applications, final admission decisions are made by provincial governments using two mechanisms: sequential and parallel mechanism. In sequential mechanism, priority is given to students' first choice in their application form. That is, in the first round, only the first choices of students are considered. Students left unassigned would have their second choices considered in the second round. In contrast, in parallel mechanism, priority is given to test scores. Students submit several *parallel* desirable choices within three tiers. If the first choice of high score student could not be satisfied, his second paralleled choice will be considered immediately. Previously, all the provinces used sequential mechanism for CEE admission, which is shown less likely to reveal students' true preference (Chen and Kesten, 2017). Since 2001, provinces rolled out parallel mechanism in different formats. By 2012, 28 out of 31 provinces adopted parallel mechanism, and the number remains the same in 2017.

3 Data

3.1 Test scores

The primary data I use is scraped from *Sina Gaokao* which collects individual cutoff scores from colleges' official websites. The dataset includes the min, max and mean score for all the admitted students, and the number of admitted students at the college-year-province-track and college-year-province-major level. The data is publicly available and serves as important guidance for college applications in the next few years. I merge this dataset with the colleges' tier and locations.

3.2 Pollution from monitors and satellite

Data on city-level monitor rollout is from MEP's official reports. The start date of report is considered the timing of information disclosure. If multiple monitors exist in the same city, I use the first report of the first monitor as the exposure time to air quality information. Since CEE takes place in June every year, I consider relative year rather than calendar year as the disclosure timing for further analysis.

Pollution data is also from MEP's official reports, including hourly data for six major pollutants and AQI. To fill the data gap before monitor reports, I use PM2.5 reanalysis product provided by van Donkelaar et al. (2015). This dataset is recovered by combining inputs from aerosol optical depth (AOD) from NASA's MODIS installed on satellite Terra's platform, ground-level monitoring stations in China, US and Canada, and atmospheric chemistry models. The product has 0.05 by 0.05 degree resolution at the monthly frequency. I process it at the city-year level to show the annual air quality near each college.

4 Empirical Framework

4.1 Identification strategy

To estimate the effect of pollution disclosure on cutoff scores, I restrict the sample to colleges located in clean and dirty cities, each taking account of one-forth of all the colleges in China. My identification strategy compares scores before and after the disclosure with an event study approach:

$$S_{ijt} = \alpha Dirty_i + \gamma Dirty_i \times D_{it} + \eta_{ij} + \lambda_{jt} + \varepsilon_{ijt} \tag{1}$$

where S_{ijt} denotes the college desirability, as captured by the mean score for college i's admits in province j year t. $Dirty_i$ denotes college i is located in a polluted city. The variable of interest, D_{it}, is equal to 1 if disclosure happened before June in year t and 0 otherwise. Province by year effects λ_{jt} could absorb the exam difficulty and competition, and college by province effects η_{ij} could capture *natural* preference or the distance between college and home province.

I conduct a pooled analysis first with all the three tiers and two tracks. Since colleges of three tiers are quite different in their resources, teachers and student ability, and cutoff scores for three tiers are announced earlier than applications for most provinces, I also separately estimate the equation for three tiers to quantify effects in different subgroups. Finally, heterogenous responses are separated for two tracks and multiple majors.

Apart from comparing dirty and clean colleges, I also conduct an event study using the whole sample. If the difference between clean and dirty colleges exists, I try to attribute the difference to either increased competition for clean colleges or the decreased desirability of dirty colleges, or both effects. The econometric specification is:

$$S_{ijt} = \alpha_1 Dirty_i + \alpha_2 Clean_i + \gamma_1 Dirty_i \times D_{it} + \gamma_2 Clean_i \times D_{it} + \eta_{ij} + \lambda_{jt} + \varepsilon_{ijt} \qquad (2)$$

where $Clean_i$ refers to college i is located in a clean city.

4.2 Sample and balance tests

I use AQI to classify dirty and clean college groups for two reasons. First, from the public perspective, AQI is the most used indicator by government agencies, apps, newspapers, and media, not individual pollutants. People are provided the AQI value at the hourly and daily level, as well as corresponding classification and recommended precautions like avoiding outdoor exercises. This is the most common information people could get about air quality, especially for those with limited knowledge on the meaning of individual pollutants. Second, from the science perspective, all the six major pollutants could affect human health, and major pollutants driving down air quality could be different every day. AQI, as an aggregated score, represents the worst quality or highest dose among those components, and in turn indicates whether the city or college is clean or dirty better than individual pollutants.

AQI=100 is the threshold for good and polluted days used by Chinese government, and polluted months are those with average monthly AQI higher than 100. I define low pollution cities whose average number of polluted month is smaller than two, and high pollution cities are those with high pollution for more than seven month. This classifies about 200 colleges into each group.

Table 1 reports summary statistics of the study sample. Clean cities have yearly average PM2.5 lower than $30\mu g/m^3$, corresponding to “Good” air quality by China’s classification. This means air quality in clean cities is considered satisfactory and air pollution poses little risk. In contrast, dirty cities have yearly average PM10 and PM2.5 higher than thresholds of “Unhealthy for Sensitive Groups”. In dirty cities, adverse health effects are likely to take place especially for people with respiratory diseases, older adults and children. PM10, PM2.5 and AQI in the dirty group are more than twice the value of those in clean group. Sharp difference exists in pollution between clean and dirty group, while conveniently for my purposes there is less difference in test scores. The balanced panel shows the low possibility of omitted variable bias.

5 The Effects of Pollution Disclosure on College Desirability

5.1 Effects on cutoff scores

I first conduct pooled analysis using all three tiers and two tracks. If a city started to disclose air quality between July 2014 to June 2015, year 2015 is considered year 1 for all colleges in that city. Figure 2 shows raw cutoff scores and score residuals after controlling multiple fixed effects step by step with a balanced panel from year -2 to year 3. From the raw data, average cutoff score is higher by 4 points for dirty colleges before the treatment, and starts to converge to 1 point afterwards. With province by year fixed effects, the relatively flat trend of cutoff scores prior to the information disclosure confirms the *stable* ranking and preference of universities over years. The jump of blue lines and the drop of red lines suggests that the effect took place since the year of pollution disclosure. It is more difficult to get into clean colleges after exposed to air quality information.

Table 2 reports the estimated effects of the air quality disclosure on college desirability. Panel A compares dirty and clean colleges, and cutoff scores went down by 2 points due to the information shock. Disentangling the difference between clean and dirty colleges, the effect is attributed to the increased competition for clean colleges by 1.5 points, as is shown in Panel B. The results are quite robust with different fixed effects specification.

5.2 Tier and track difference

Given the difference of resources and quality among colleges, I separately estimate the effects for three tiers. In the whole sample, the number of colleges is 202, 353, and 255 in first-, second-, and third-tier respectively; restricting sample within clean and dirty colleges, the number of colleges is 103, 187 and 115. Figure 3 shows raw cutoff scores and score residuals for first-tier colleges. The trend is similar to pooled result, but the score difference between dirty and clean colleges is larger: before the treatment, average cutoff score is higher by 8 points for dirty colleges, and converges to 5 points afterwards. For second-tier colleges, the score difference is negligible between dirty and clean group before, but starts to expand by 3 points after the disclosure, as is shown in Figure 4. Statistical results are reported in Table 3.

In contrast, Figure 5 and Table 3 report no significant impact on third-tier colleges. Given the admission quota, most third-tier admits go to colleges in home province and the decision is hardly affected by air quality. The information shock only affects application choices for top two tiers given the large number of colleges and quota outside their home provinces.

Heterogenous responses for science and arts track are also separately estimated, as is shown in Figure 6, 7, and Table 4. Finally, results for six specifications and magnitude relative to the mean are reported in Figure 8 and Table 5. Compared with the arts track, science track has a larger response by 1 points, equivalent to a 0.3% larger response relative to the mean. One possibility is that the number of colleges for science track is more than that for arts track, and the sorting effect is larger due to more cities of option. Another potential reason is that students and parents get more understanding of air pollution and its adverse impact from science training, and thus care more about the environmental conditions in general. The third reason lies in the future job market. When recruiting employees, science-related jobs depend on technical skills and job entrance exams, so the signal of educational background is not as pivotal as that for arts-related jobs.

5.3 Major difference

When applying for colleges, students submit their ideal college list and preferred majors for each college in order, and check "yes" or "no" for further adjustment within that college. On the college side, colleges set fixed quotas for each major for each province when deciding the total quota in that province. The admission process for majors is the same as college admission, with priority given to higher scores. Those above the cutoff score for that university but ranked in lower places may be less likely to get into popular majors. If all the submitted preferred majors have no position left, the student will be adjusted into other majors with vacancy if free adjustment is allowed. Thus, cutoff scores at the major level could also show the demand and competition for different majors.

To show heterogeneous responses to pollution disclosure across majors, I conduct similar event studies for ten majors for first-tier colleges. Among them, five majors I'm interested in include: 1) environment, students care more about air quality and environment in general; 2) health, students care more about health conditions for themselves and for others; 3) engineering, future polluters contribute to air pollution; 4) economics, students make rational choice with pollution affecting their utility; 5) journalism and communication, students read more news and adjust to information quickly. I also use other five *popular* majors: 6) computer science; 7) law; 8) political science and international relation; 9) math, physics, chemistry and biology; 10) architecture and design. Given the various major names called by different colleges, I use all majors filtered by relevant keywords to assign these ten majors of interest.

Results in Table 6 shows the parameter of interest and magnitude relative to mean scores. Large impacts are found in journalism, economics, computer science, and environment-related majors, around 0.5% of the mean. Scores for engineering majors go down by 0.2%. In contrast, almost no impact is found in health-related majors. This shows majors with more theory work or lab experiments seem to be affected less by pollution information disclosure.

6 Robustness

6.1 Pollution before and after disclosure

If pollution itself changes due to pollution disclosure, I could not separate the effect of information shock and pollution shock. If the increasing air pollution and the start of monitors took place hand in hand, the event study will overestimates the treatment effect. In contrast, if industries were worried about their exposed environmental performance after monitors went on, or if governments strategically located monitors in cities with decreasing pollution trends, or if governments strategically relocated polluting sources to cities without monitors, the treatment effect will be underestimated.

To investigate this, I use satellite PM2.5 product provided by van Donkelaar et al. (2015) as the dependent variable to test the treatment effect of information disclosure on pollution. Figure 9 shows the yearly average PM2.5 before and after disclosure in clean and dirty groups. Annual average PM2.5 remains around $63.5\mu g/m^3$ for dirty colleges and $34.5\mu g/m^3$ for clean colleges, with a difference smaller than $1\mu g/m^3$ before and after the treatment. The number of polluted months is also constant before and after the treatment - colleges in dirty group experience 11.3 months with high PM2.5 in a year while colleges in clean group have 6 months fewer. I also estimate using the event study setting and find no significant results. This confirms that the effect on cutoff scores results from an information shock rather than a pollution shock.

6.2 Parallel pre-trend

To make sure dirty and clean colleges have parallel trend before the disclosure event, I estimate a dynamic specification as follows:

$$\begin{aligned} S_{ijt} = Dirty_i + \beta_{-2} \times 1(k=-2) \times Dirty_i + \beta_{-1} \times 1(k=-1) \times Dirty_i \\ +\beta_1 \times 1(k=1) \times Dirty_i + \beta_2 \times 1(k=2) \times Dirty_i + \beta_3 \times 1(k=3) \times Dirty_i \\ +\eta_{ij} + \lambda_{jt} + \varepsilon_{ijt} \end{aligned} \tag{3}$$

where β_{-2} is the difference of dirty and clean college in their cutoff scores two years before the disclosure year, comparing with the disclosure year normalized to zero. With parallel pre-trend, β_{-2} and β_{-1} should be small and insignificant. β_1, β_2, β_3 are the treatment effect in each year after the disclosure event.

Table 7 reports the estimated βs for pooled analysis, three tiers, and two tracks. None of the pre-period has significant parameters, which confirms the validity of parallel trends assumption. The post-period parameters show the impact becomes larger with time especially for the second-tier colleges and science track, indicating that students and parents learn and adjust to the information as time goes on.

Besides, the results are also robust with time trends added using the following specifications:

$$S_{ijt} = \alpha Dirty_i + \gamma Dirty_i \times D_{it} + \lambda Clean_i \times Trend_t + \eta_{ij} + \varepsilon_{ijt} \tag{4}$$

$$S_{ijt} = \alpha Dirty_i + \gamma Dirty_i \times D_{it} + Trend_{it} + \eta_{ij} + \varepsilon_{ijt} \tag{5}$$

where $Clean_i \times Trend_t$ denotes linear time trend for the whole clean group. $Trend_{it}$ is city-specific linear time trend. Results in Table 8 show the robustness of specifications. The effect of disclosure on cutoff scores remains -2 points for dirty colleges with and without linear time trends controlled.

6.3 Alternative classification

To check the sensitivity of my results, another classification is used to construct dirty and clean college groups. I define the clean group as colleges with yearly average AQI below 80, and dirty group as colleges with yearly average AQI above 120, given AQI=100 as the threshold for good and polluted days. This also classifies about 200 colleges into each group, about one forth of all China's colleges.

Figure 10 and Table 9 report the estimated effects for three tiers two tracks. The magnitude of the effects is quite similar as that in Figure 8 and Table 5. The disclosure drives cutoff scores down by 2.5 and 2 points for science and arts track respectively.

6.4 Placebo analysis

Instead of using actual disclosure years, I conduct placebo tests using cutoff scores in 2008-2012 before the study period and 2010 as fake event year. This test examines the comparability of dirty and clean colleges before the study period.

Results shown in Figure 11 and Table 10 indicate that the placebo disclosure year does not generate any impact on the cutoff scores. In general, admission to a dirty college is more difficult than clean college and the difference is the same over five years. With the same specification, the estimated parameter is small and insignificant for first- and second-tier colleges.

6.5 Pollution spikes

Apart from discretely comparing dirty and clean colleges, I conceptualize cutoff scores this year as a function of pollution spikes last year, and examine how such relationship changes as pollution disclosure takes place in the city. The estimation equation is as follows:

$$S_{ijt} = \gamma D_{it} + \beta P_{it-1} \times D_{it} + \eta_{ij} + \lambda_{jt} + \varepsilon_{ijt} \tag{6}$$

where P_{it-1} denotes yearly pollution one year before in college city i. Due to data limitation for other pollutants before monitors started, I use satellite PM2.5 product to construct this variable. Here, three specifications are used: 1) logged yearly average PM2.5; 2) the number of high PM2.5 months last year, namely the number of months with monthly average PM2.5 over $35\mu g/m^3$, threshold value given by China's AQI standard; 3) the number of very high PM2.5 months last year, monthly average PM2.5 over $75\mu g/m^3$. The key parameter of interest is β, which represents average changes in cutoff scores with the increase in PM2.5 in pollution-disclosing cities.

Table 11 reports estimation of β coefficients. When yearly average PM2.5 increases by 1%, cutoff scores for first- and second-tier colleges go down and the magnitude is larger for science track, consistent with my main findings. Compared with *high months* specification, the number of *very high months* is a more powerful factor affecting cutoff scores. 35 and $75\mu g/m^3$ are thresholds for excellent-good-polluted air quality. This shows students and parents care more about the number of polluted months than not so clean months when making college choice decisions. Again, pollution disclosure has no significant impact on third-tier colleges, whichever tracks or pollution specifications.

6.6 Effects on min & max scores

To test the robustness of my results, I use min and max scores at college-year-province level instead of mean scores. Though min scores are usually the thresholds for admission, in reality, it is possible that some students with scores below the cutoff get accepted due to extra scores from other characteristics such as being an ethnic minority, being a child of a military martyr, or having talents in sports, music and math, etc (Jia and Li, 2016). Max scores are also not an *ideal* indicator for college desirability because it could be driven by outliers or some bad application strategies for students with higher scores.

Table 12 reports the parameters of interest for three tiers, two tracks. The results are quite similar with those using mean scores. In general, pollution disclosure drives down the desirability of first- and second-tier colleges, and small and insignificant impacts are found in third-tier colleges.

7 Conclusion

In this paper, I provide empirical evidence that information disclosure can lead to higher competition for colleges with better air quality. Examining the nationwide monitor roll-out starting from 2013 and analyzing comprehensive cutoff data for all China's colleges in 2008-2016, I find that first- and second-tier colleges in clean cities receive more severe competition captured by higher cutoff scores. This effect is higher for science track and for journalism, economics, and environment-related majors. My findings are consistent with the avoidance behaviors against adverse environmental conditions and highlight the importance of environmental information transparency.

From the public perspective, good colleges are less attractive with dirty environment conditions, which broadens the externality of pollution. Given the cutoff scores of individual colleges, the decreased cutoff by 3 points for science track and 2 points for arts track is equivalent to a lowered ranking by 10 schools measured by CEE scores, namely 5% of all colleges in each tier. For local governments, clearing the air is an effective way to attract talents and even more beneficial when considering human capital accumulation, as college graduates tend to work close to their universities especially in large cities[8].

In terms of student numbers, the magnitude of this effect is about 0.3% for the arts track and 0.6% for the science track. Given the distribution of test scores, this effect is equivalent to about 20 and 30 thousand students in China. Namely, every year, 20 thousand students that would have applied to other colleges instead sort to clean colleges after exposed to environmental information.

If assuming the quality of colleges remains stable before and after the information shock, this effect refers to a tradeoff between college quality and clean air faced by students and their parents. From the graduate wage survey in 2018, average monthly wage is 300, 400, 700 RMB lower for 1-, 3-, 5-year graduates, comparing No. 110 college with No. 100 college. Namely, students gives up $4K income over the first five years after graduation. Assuming a steady wage growth in the first ten years and same wage later, over a forty-year lifetime working period, the forgiven income is $85K over the whole life cycle, as a tradeoff of better air quality during undergraduate study.

From the research perspective, my result confirms that pollution could serve as an exogenous variation on school choices. When estimating the payoff of schooling, education studies try to address the problem that different types of students go to different schools by

[8]In 2017, 60, 70, 45% of college graduates in Beijing, Shanghai, Guangzhou chose to work in the city they graduated from. The number is 20-45% for other large cities: www.jiemodui.com/N/85364.html

using the distance to schools as an instrument or exploring the discontinuity around cutoff scores. My findings exploit another variation for future studies especially for areas with poor environmental conditions.

My findings have some policy implications for countries with pollution challenges. First, it confirms that providing pollution information will work. It is costly to build monitors and to collect and deliver their reports, but it is worthwhile if the public raises awareness and conduct further avoidance behaviors. Consistent with Barwick et al. (2019), this study adds another aspect of the value of information. Second, this paper supports the benefit of environmental regulations. Beyond the existing literature on the value of air quality focussing on health and productivity, this result suggests air pollution also affects school choices, and improving air quality could attract high ability students and enhance human capital accumulation. Third, my work shows students and parents do care about environmental conditions of schools. Given the concentrated population on campus and the importance of college learning over the life cycle, this study may call for further emphasis on both indoor and outdoor air quality improvement at schools.

Figure 1: Monitors Distribution and County Coverage Rate, 2013-2018

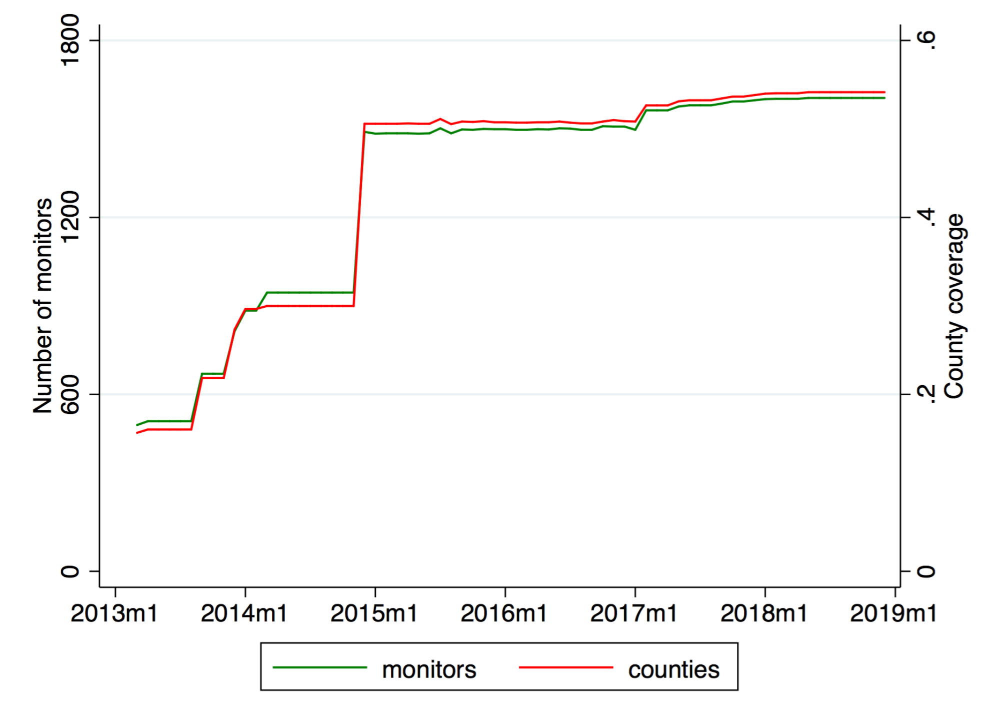
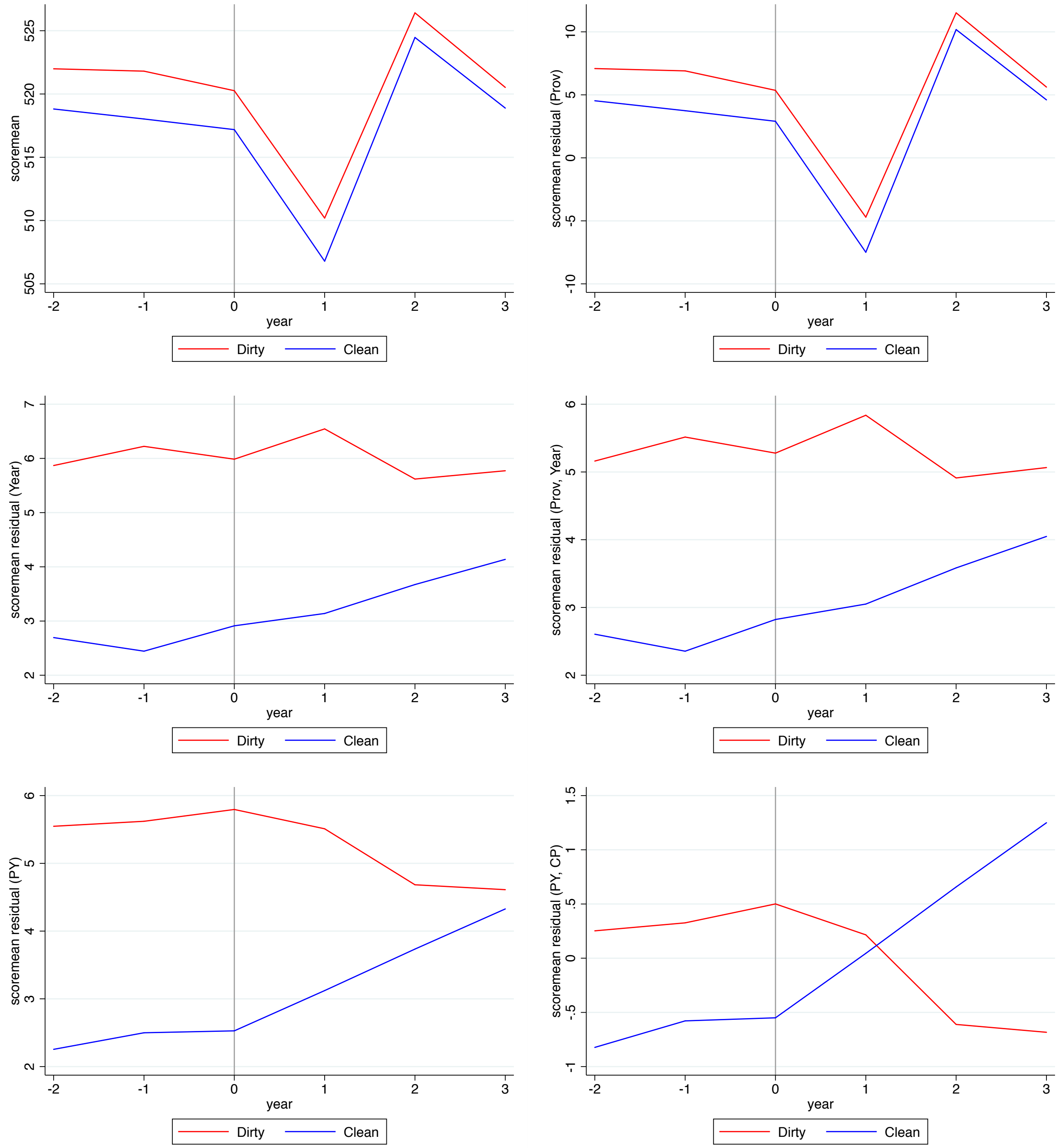


Table 1: Summary Statistics

	Whole sample	High	Low	Difference
College	848	214	191	
Yearly PM10	113.50	167.50	75.01	92.49
	(39.06)	(27.94)	(16.32)	[5.41]
Yearly PM2.5	46.61	72.54	29.63	42.92
	(17.81)	(11.54)	(9.10)	[2.53]
Yearly AQI	98.87	138.23	69.14	69.09
	(28.88)	(18.91)	(11.73)	[3.74]
Mean score for admits	573.02	582.63	576.55	6.08
arts, first-tier	(43.28)	(46.03)	(47.51)	[0.84]
	18864	7178	5372	
Mean score for admits	570.89	582.74	575.92	6.81
science, first-tier	(50.59)	(54.63)	(54.57)	[0.83]
	29200	10348	7519	
Mean score for admits	515.03	516.75	518.69	-1.94
arts, second-tier	(41.48)	(40.65)	(42.59)	[0.62]
	36296	10447	7823	
Mean score for admits	494.21	496.75	497.03	-0.27
science, second-tier	(49.67)	(49.22)	(50.25)	[0.64]
	50736	13433	11147	
Mean score for admits	456.46	453.23	452.63	0.60
arts, third-tier	(37.82)	(39.06)	(37.14)	[1.02]
	10592	3137	2526	
Mean score for admits	430.63	428.98	423.89	5.09
science, third-tier	(45.65)	(46.92)	(46.55)	[1.18]
	12216	3818	2693	

Notes: Standard deviations are reported in parentheses. Standard errors are reported in brackets.

Figure 2: Cutoff scores and score residuals, pooled analysis



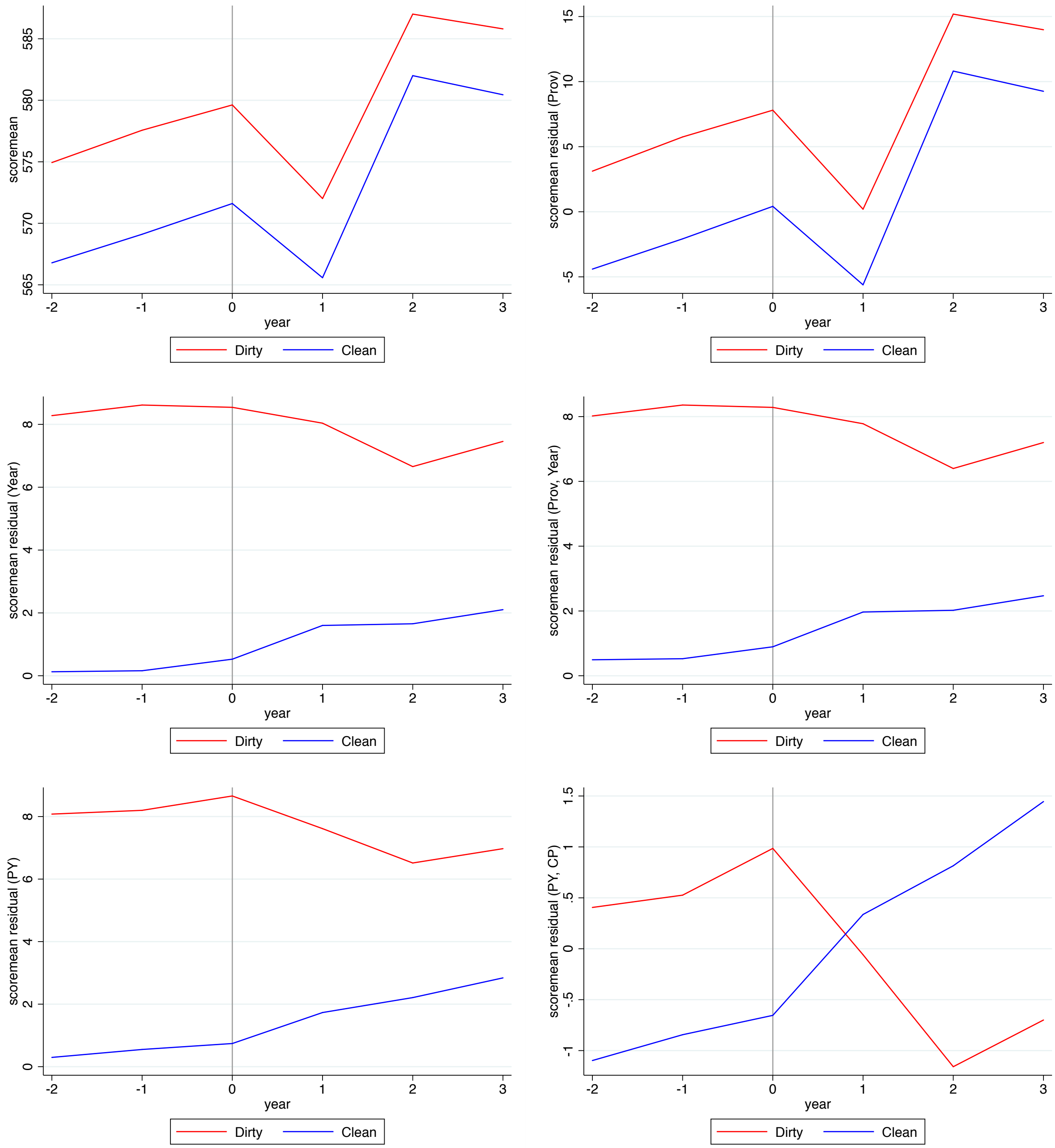
Notes: Panel A includes no control; Panel B includes province fixed effects; Panel C includes year fixed effects; Panel D includes province fixed effects and year fixed effects; Panel E includes province by year fixed effects; Panel F includes province by year and city by province fixed effects.

Table 2: Effects of pollution disclosure on cutoff scores, pooled analysis

	Panel A: only dirty and clean colleges				
Dirty	3.990	3.345	2.698**	3.222***	
	(2.636)	(2.417)	(1.167)	(0.756)	
Dirty×Post	-2.308	-2.308	-1.014	-2.062***	-2.062***
	(3.971)	(3.972)	(1.245)	(0.424)	(0.445)
R^2	0.0006	0.3245	0.3299	0.3751	0.9298
Observations	61434	61434	61434	61434	61434
	Panel B: all colleges				
Dirty	11.93***	10.80***	9.480***	9.939***	
	(1.999)	(2.127)	(0.918)	(0.693)	
Dirty×Post	-2.308	-2.308	0.340	-0.578	-0.578
	(3.971)	(3.972)	(0.977)	(0.451)	(0.474)
Clean	8.586***	8.052***	6.728***	6.678***	
	(2.224)	(1.955)	(1.048)	(0.976)	
Clean×Post	-1.295	-1.295	1.354**	1.454***	1.454***
	(3.885)	(3.886)	(0.556)	(0.304)	(0.319)
R^2	0.0054	0.3522	0.3580	0.4046	0.9263
Observations	123024	123024	123024	123024	123024
province FE		Y	Y		
year FE			Y		
prov-year FE				Y	Y
college-prov FE					Y

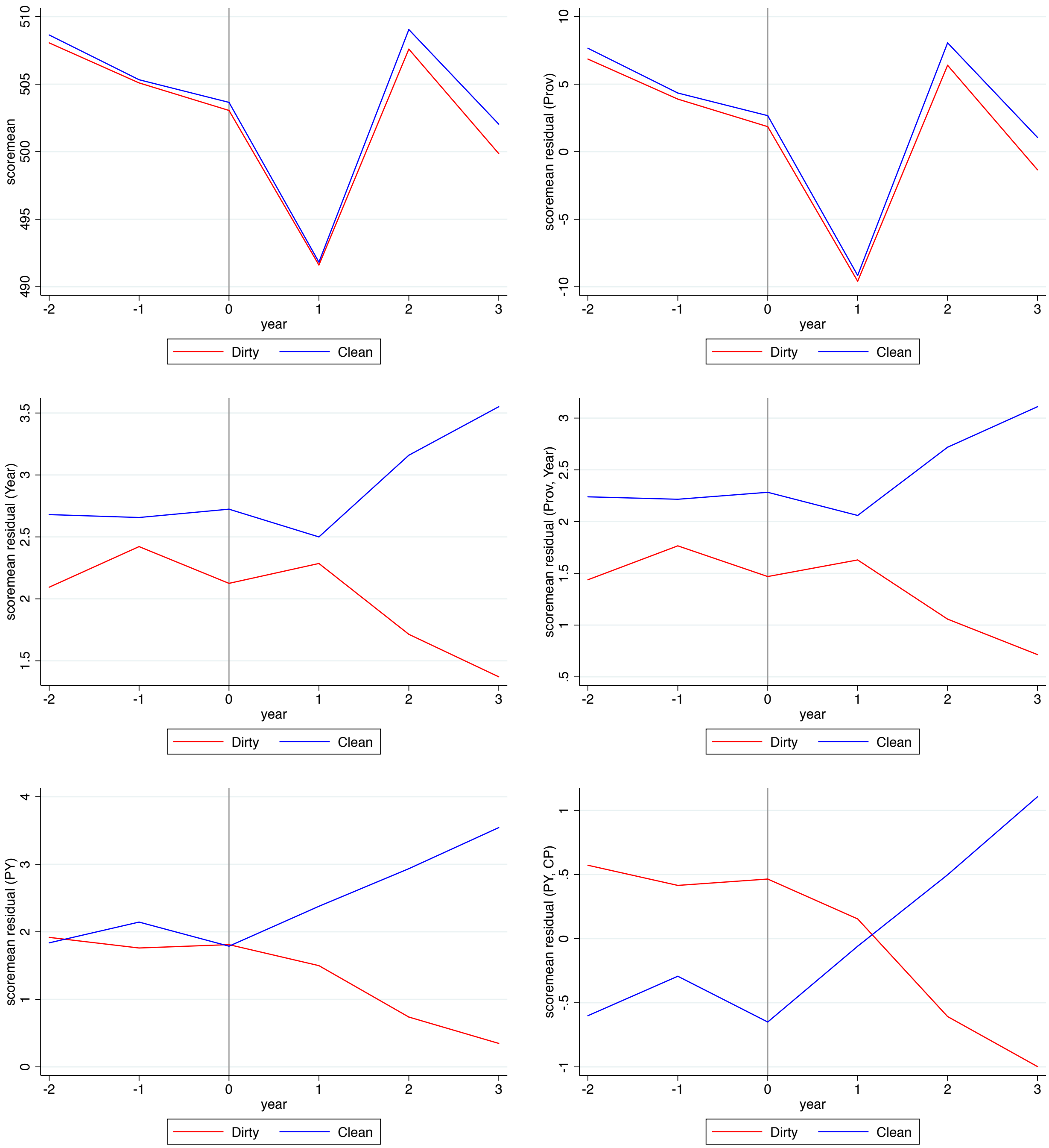
Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Figure 3: Cutoff scores and score residuals, first-tier colleges



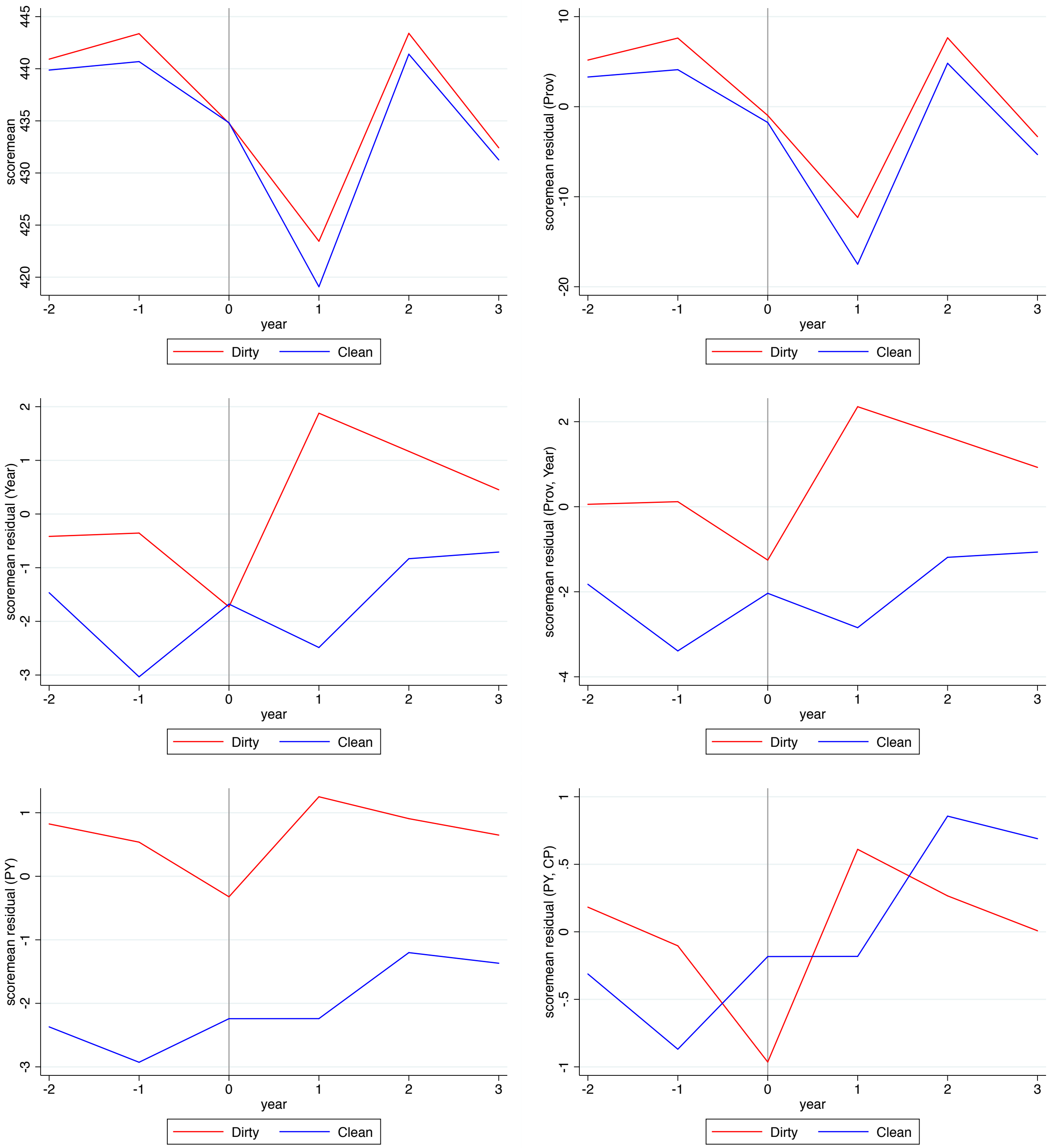
Notes: Panel A includes no control; Panel B includes province fixed effects; Panel C includes year fixed effects; Panel D includes province fixed effects and year fixed effects; Panel E includes province by year fixed effects; Panel F includes province by year and city by province fixed effects.

Figure 4: Cutoff scores and score residuals, second-tier colleges



Notes: Panel A includes no control; Panel B includes province fixed effects; Panel C includes year fixed effects; Panel D includes province fixed effects and year fixed effects; Panel E includes province by year fixed effects; Panel F includes province by year and city by province fixed effects.

Figure 5: Cutoff scores and score residuals, third-tier colleges



Notes: Panel A includes no control; Panel B includes province fixed effects; Panel C includes year fixed effects; Panel D includes province fixed effects and year fixed effects; Panel E includes province by year fixed effects; Panel F includes province by year and city by province fixed effects.

Table 3: Effects of pollution disclosure on cutoff scores, three tiers

	First	Second	Third
Dirty×Post	-2.974***	-2.083***	-0.431
	(0.424)	(0.451)	(1.303)
R^2	0.7833	0.5151	0.3564
Observations	21522	31014	8898
Dirty×Post	-1.295***	-1.070**	1.221
	(0.416)	(0.373)	(1.501)
Clean×Post	1.727***	0.944**	1.536*
	(0.404)	(0.365)	(0.679)
R^2	0.7889	0.4775	0.3459
Observations	41100	62658	19266
prov-year FE	Y	Y	Y
college-prov FE	Y	Y	Y

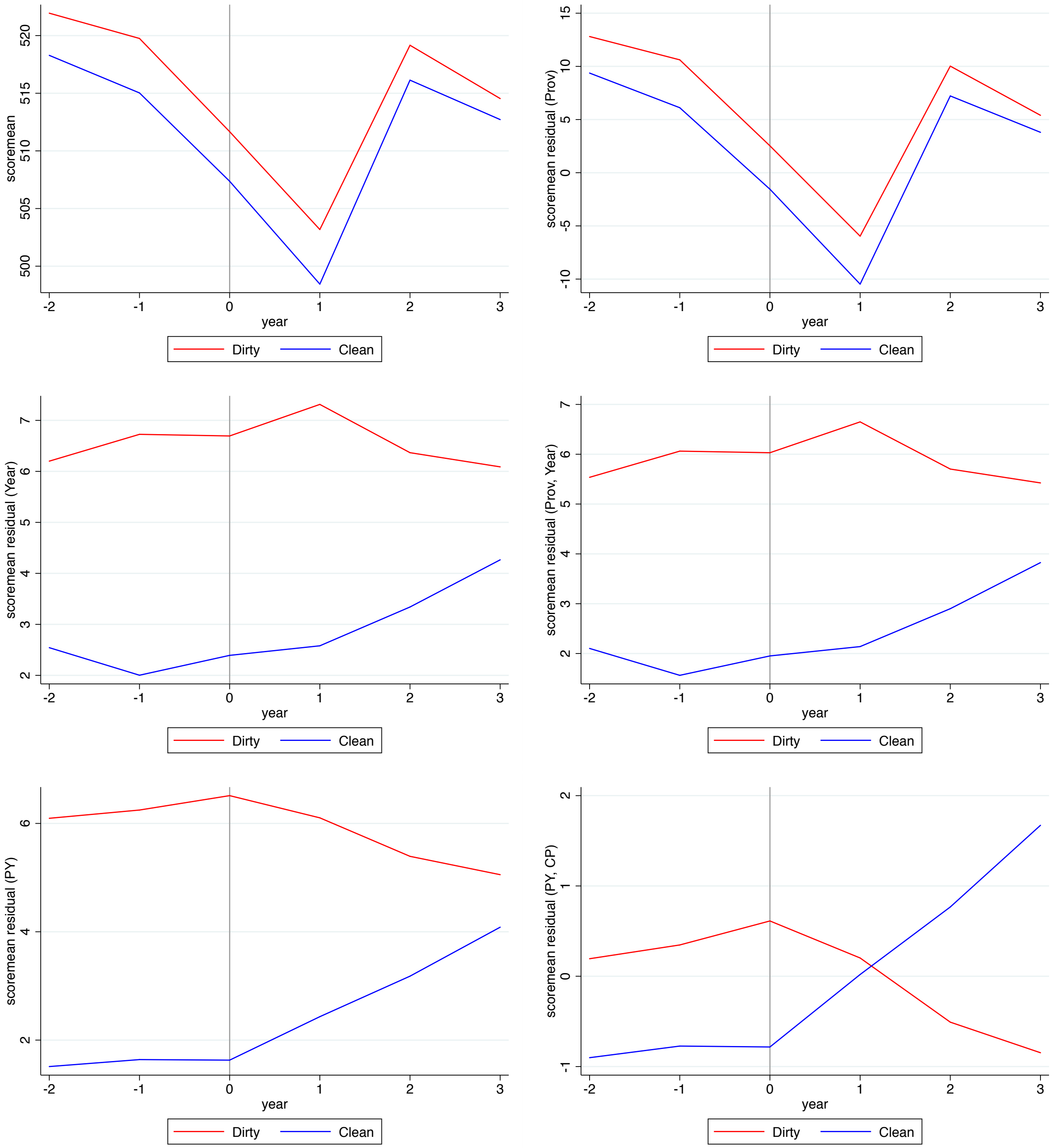
Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Table 4: Effects of pollution disclosure on cutoff scores, science and arts

	Science	Arts
Dirty×Post	-2.441***	-1.393**
	(0.433)	(0.519)
R^2	0.9778	0.9786
Observations	35346	26088
Dirty×Post	-0.502	-0.491
	(0.460)	(0.540)
Clean×Post	1.916***	0.869**
	(0.367)	(0.325)
R^2	0.9768	0.9781
Observations	70674	52350
prov-year FE	Y	Y
college-prov FE	Y	Y

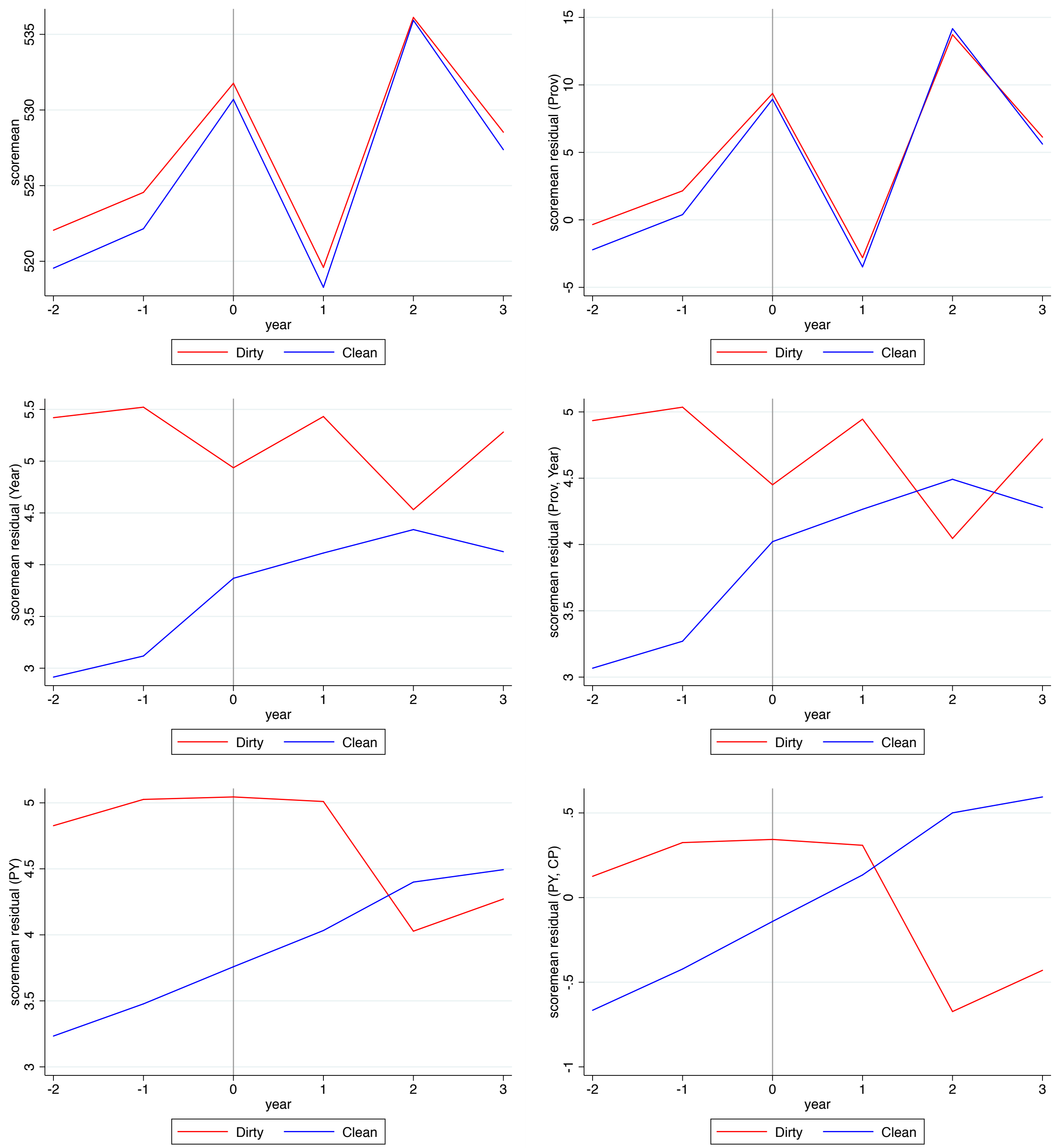
Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Figure 6: Cutoff scores and score residuals, science track



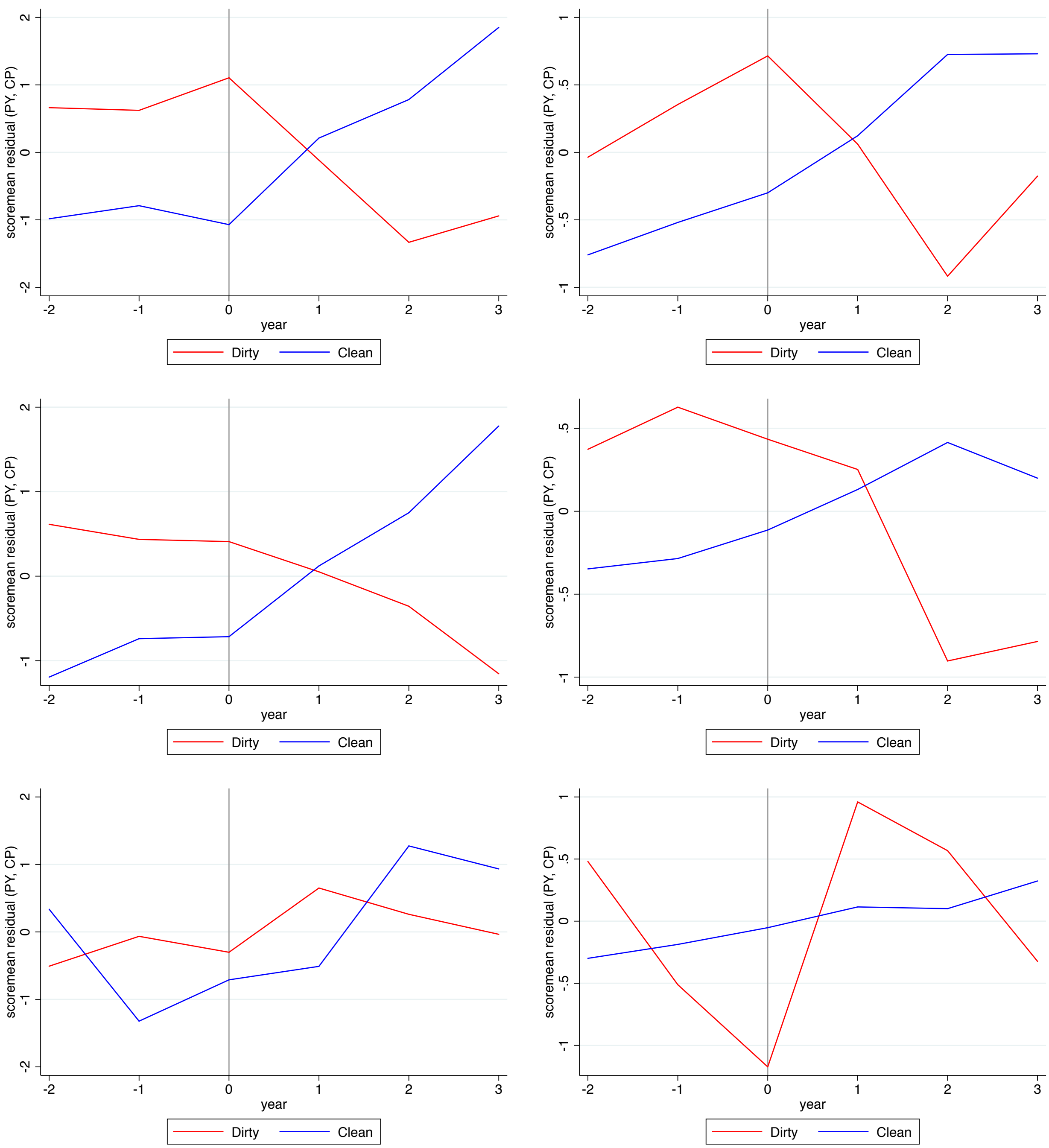
Notes: Panel A includes no control; Panel B includes province fixed effects; Panel C includes year fixed effects; Panel D includes province fixed effects and year fixed effects; Panel E includes province by year fixed effects; Panel F includes province by year and city by province fixed effects.

Figure 7: Cutoff scores and score residuals, arts track



Notes: Panel A includes no control; Panel B includes province fixed effects; Panel C includes year fixed effects; Panel D includes province fixed effects and year fixed effects; Panel E includes province by year fixed effects; Panel F includes province by year and city by province fixed effects.

Figure 8: Cutoff residuals, science and arts, three tiers



Notes: All these six panels include province by year and city by province fixed effects. Panel A shows residuals for science track, first-tier colleges. Panel A, C, E are for science track, Panel B, D, F are for arts track; Panel A, B are for first-tier colleges, Panel C, D are for second-tier colleges, Panel E, F are for third-tier colleges.

Table 5: Effects of pollution disclosure on cutoff scores, two tracks, three tiers

	Sci 1	Sci 2	Sci 3	Arts 1	Arts 2	Arts 3
Dirty×Post	-3.468***	-2.810***	-0.674	-1.691***	-1.517***	0.298
	(0.471)	(0.515)	(1.374)	(0.442)	(0.482)	(1.295)
	-0.61%	-0.57%	-0.20%	-0.29%	-0.29%	0.03%
R^2	0.9514	0.8682	0.7582	0.9255	0.8265	0.7027
Observations	12696	17898	4752	8826	13116	4146
Dirty×Post	-1.742***	-0.723	1.287	-0.631	-1.299***	1.340
	(0.46)	(0.479)	(1.411)	(0.529)	(0.330)	(1.681)
	-0.30%	-0.15%	0.27%	-0.02%	-0.25%	0.25%
Clean×Post	1.757***	2.033***	1.833**	1.129**	0.174	0.878
	(0.409)	(0.436)	(0.775)	(0.428)	(0.351)	(0.738)
	0.31%	0.41%	0.46%	0.19%	0.03%	0.20%
R^2	0.9547	0.8619	0.7298	0.9248	0.7983	0.6703
Observations	24636	35784	10254	16464	26874	9012
prov-year FE	Y	Y	Y	Y	Y	Y
college-prov FE	Y	Y	Y	Y	Y	Y

Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Table 6: Effects of pollution disclosure on cutoff scores by major

	γ	std.err.	% of mean	R^2	Observations
Environment	-2.404**	(1.150)	-0.42%	0.9122	13166
Health	0.117	(0.805)	0.02%	0.8389	14347
Engineering	-1.087**	(0.411)	-0.19%	0.8744	129621
Economics	-2.761***	(0.638)	-0.47%	0.7885	50316
Journalism	-3.097***	(1.011)	-0.53%	0.8107	6821
Computer Science	-2.585***	(0.431)	-0.45%	0.9014	35432
Law	-1.201	(1.61)	-0.21%	0.7808	13265
Political Science	-0.723	(0.894)	-0.12%	0.8543	4109
Basic Science	-0.559	(0.563)	-0.10%	0.9032	44148
Design	0.288	(0.469)	0.05%	0.8950	17164

Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Figure 9: Yearly average PM2.5, number of high PM2.5 months, before and after disclosure

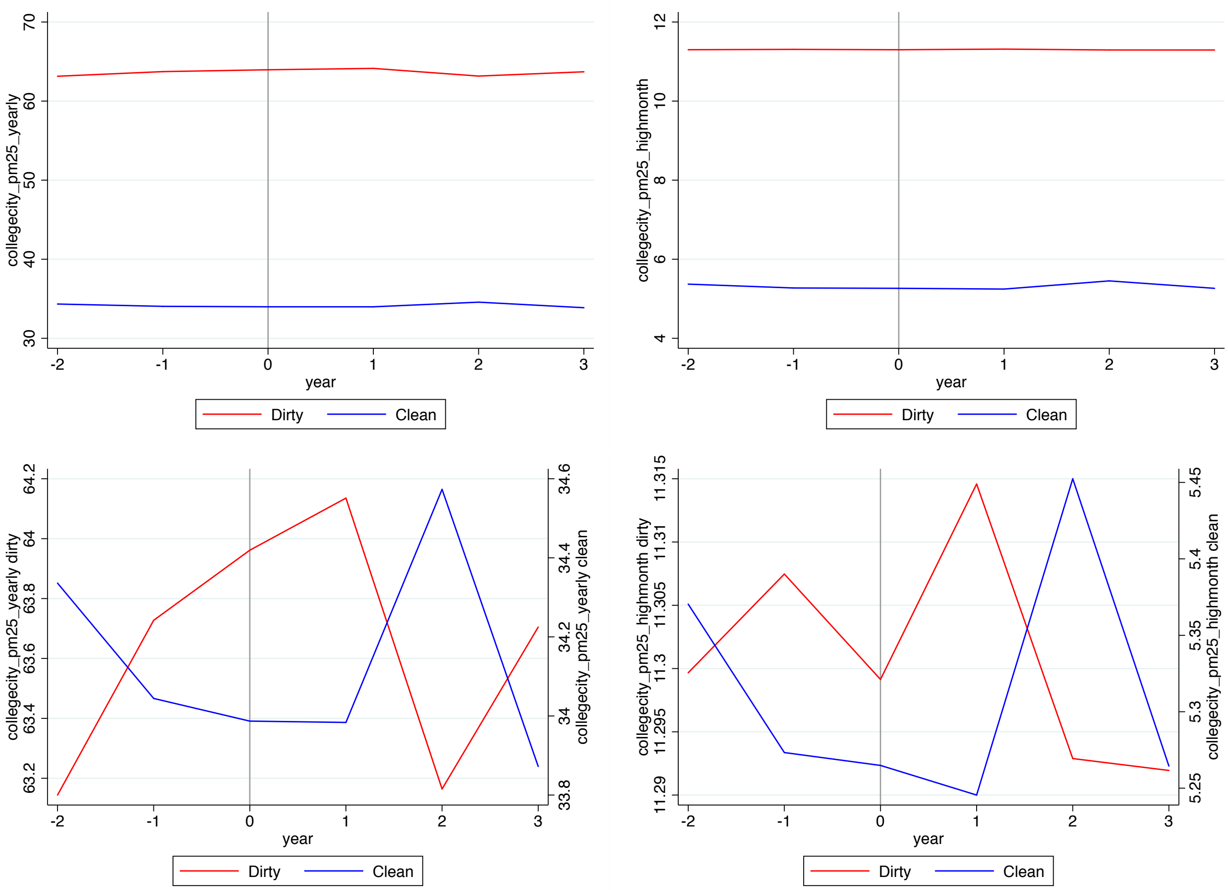


Table 7: Effects of pollution disclosure on cutoff scores, dynamic event time

	Pooled	1st-tier	2nd-tier	3rd-tier	Sci	Arts
β_{-2}	0.0492	-0.108	0.0686	1.379	-0.293	0.354
	(0.346)	(0.467)	(0.488)	(0.825)	(0.300)	(0.354)
β_{-1}	-0.164	-0.246	-0.453	1.540	-0.290	0.244
	(0.269)	(0.267)	(0.397)	(0.971)	(0.249)	(0.383)
β_1	-0.923	-1.958***	-1.005*	1.435	-1.240**	-0.375
	(0.690)	(0.584)	(0.555)	(2.110)	(0.528)	(1.044)
β_2	-2.357***	-3.590***	2.315***	0.175	-2.709***	-1.687***
	(0.332)	(0.458)	(0.430)	(1.226)	(0.392)	(0.454)
β_3	-3.021***	-3.729***	-3.313***	0.0160	-3.957***	-1.52***
	(0.466)	(0.613)	(0.534)	(1.351)	(0.549)	(0.492)
R^2	0.9298	0.9238	0.8733	0.7859	0.9778	0.9786
Observations	61434	21522	31014	8898	35346	26088
prov-year FE	Y	Y	Y	Y	Y	Y
college-prov FE	Y	Y	Y	Y	Y	Y

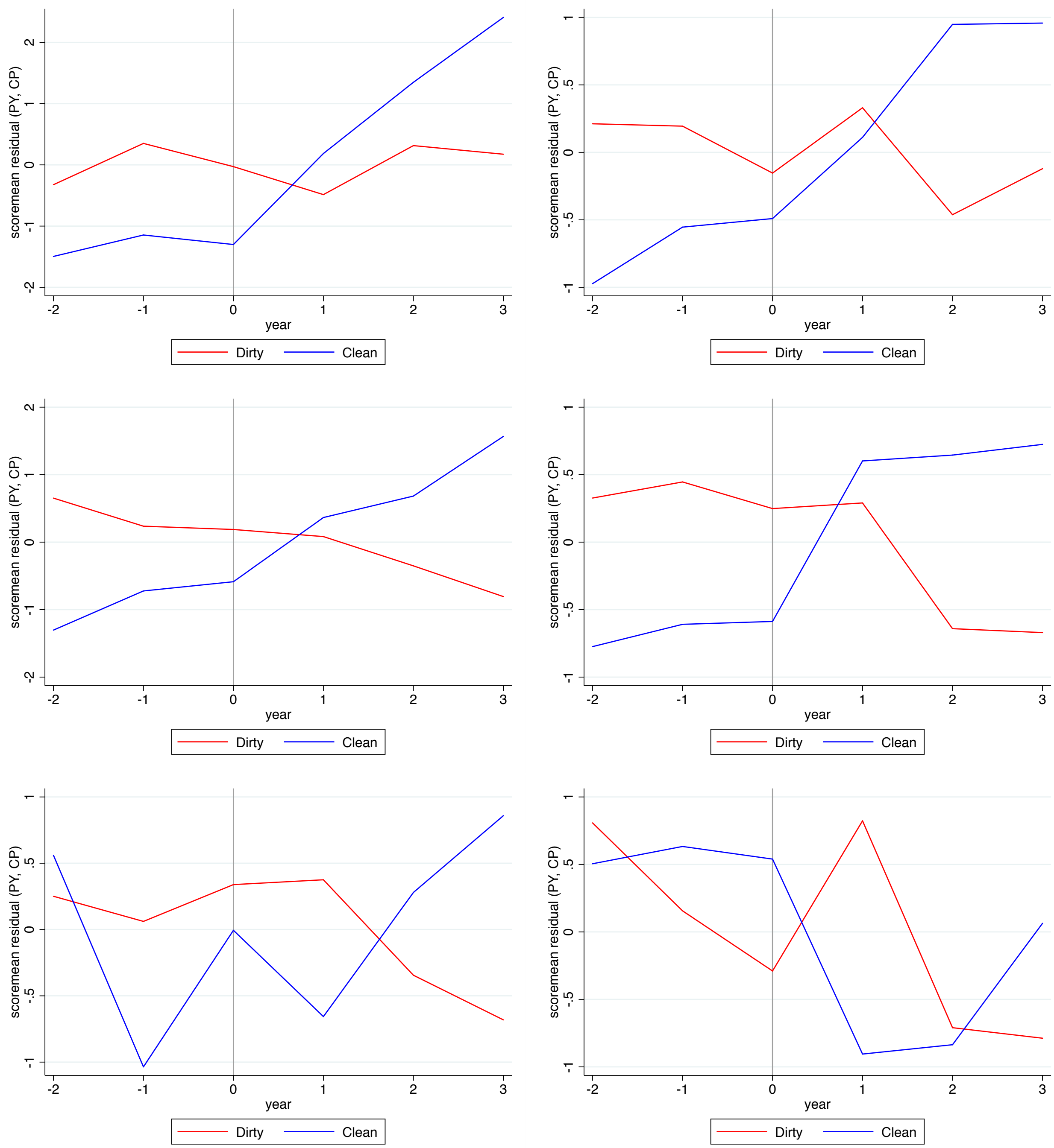
Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Table 8: Effects of pollution disclosure on cutoff scores, with time trends controlled

	Baseline		Clean group trend		City-specific trends	
Dirty	3.222***		4.538***		4.773***	
	(0.756)		(4.27)		(1.190)	
Dirty×Post	-2.062***	-2.062***	-2.308***	-2.308***	-2.308***	-2.308***
	(0.424)	(0.445)	(0.599)	(0.266)	(0.575)	(0.266)
R^2	0.3751	0.9298	0.3245	0.8792	0.3773	0.8798
Observations	61434	61434	61434	61434	61434	61434
prov FE	Y		Y		Y	
college-prov FE		Y		Y		Y

Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Figure 10: Cutoff residuals using different classification



Notes: All these six panels include province by year and city by province fixed effects. Panel A shows residuals for science track, first-tier colleges. Panel A, C, E are for science track, Panel B, D, F are for arts track; Panel A, B are for first-tier colleges, Panel C, D are for second-tier colleges, Panel E, F are for third-tier colleges.

Table 9: Effects of pollution disclosure on cutoff scores using different classification

	Sci 1	Sci 2	Sci 3	Arts 1	Arts 2	Arts 3
Dirty×Post	-2.601***	-2.460***	-0.754	-1.506***	-1.986***	0.744
	(0.485)	(0.500)	(1.406)	(0.423)	(0.427)	(1.582)
R^2	0.9502	0.8659	0.7145	0.9233	0.8143	0.6563
Observations	8676	16872	5016	6252	12906	4494
Dirty×Post	0.805*	-0.307	-0.527	0.284	-0.465	-1.229
	(0.412)	(0.286)	(0.976)	(0.275)	(0.334)	(0.930)
Clean×Post	3.486***	2.169***	0.236	1.818***	1.560***	-1.922*
	(0.405)	(0.443)	(0.711)	(0.326)	(0.348)	(1.048)
R^2	0.9548	0.8618	0.7294	0.9249	0.7985	0.6706
Observations	24636	35784	10254	16464	26874	9012
prov-year FE	Y	Y	Y	Y	Y	Y
college-prov FE	Y	Y	Y	Y	Y	Y

Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Table 10: Effects of pollution disclosure on cutoff scores, placebo analysis

	Sci 1	Sci 2	Sci 3	Arts 1	Arts 2	Arts 3
Dirty×Post	-0.649	0.170	1.894**	-0.343	0.100	1.040
	(0.385)	(0.360)	(0.916)	(0.288)	(0.353)	(0.755)
R^2	0.9869	0.9833	0.9733	0.9891	0.9802	0.9720
Observations	19077	38795	18602	13609	31398	17055
prov-year FE	Y	Y	Y	Y	Y	Y
college-prov FE	Y	Y	Y	Y	Y	Y

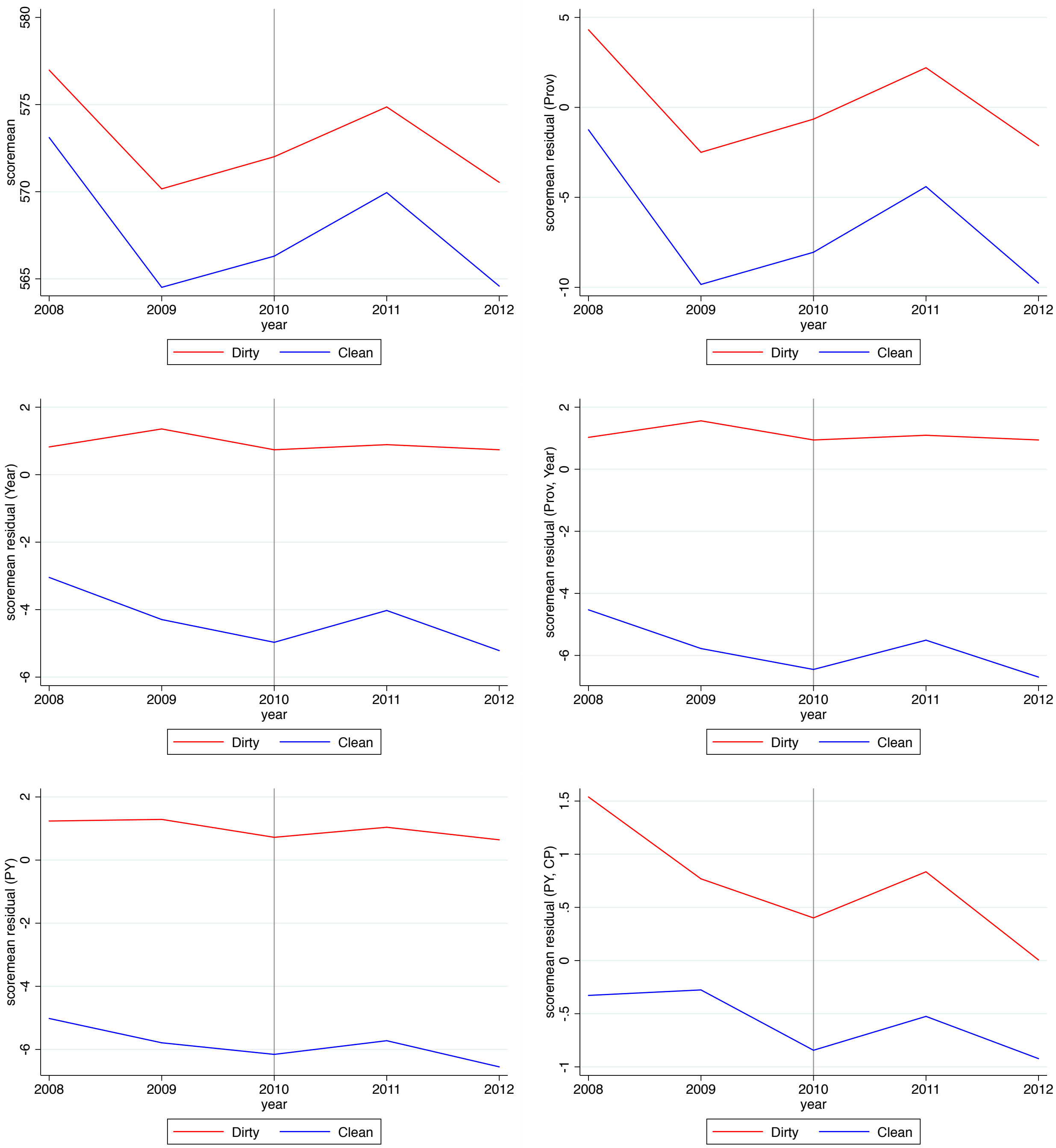
Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Table 11: Effects of pollution disclosure on cutoff scores, pollution gradient

Pollution×1(after)	Sci 1	Sci 2	Sci 3	Arts 1	Arts 2	Arts 3
ln Year mean	-3.185***	-2.025***	-1.656	-1.402**	-1.302***	0.379
	(0.698)	(0.462)	(1.881)	(0.641)	(0.447)	(1.200)
High month	-0.328***	-0.236***	-0.180	-0.139*	-0.153**	0.0903
($>35 \mu g/m^3$)	(0.0883)	(0.0597)	(0.218)	(0.0785)	(0.0589)	(0.134)
Very high month	-0.384**	-0.338***	-0.193	-0.268**	-0.230**	-0.0132
($>75 \mu g/m^3$)	(0.138)	(0.0861)	(0.394)	(0.113)	(0.0893)	(0.328)

Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

Figure 11: Cutoff residuals, placebo analysis



Notes: Panel A includes no control; Panel B includes province fixed effects; Panel C includes year fixed effects; Panel D includes province fixed effects and year fixed effects; Panel E includes province by year fixed effects; Panel F includes province by year and city by province fixed effects.

Table 12: Effects of pollution disclosure on min and max scores

	Min score					
	Sci 1	Sci 2	Sci 3	Arts 1	Arts 2	Arts 3
Dirty×Post	-3.472***	-1.950***	-1.626	-1.618**	-1.875***	-1.321
	(1.091)	(0.406)	(1.325)	(0.724)	(0.500)	(2.305)
R^2	0.7754	0.7395	0.7043	0.7682	0.7433	0.6593
Observations	8980	16652	4152	6176	12956	3736
	Max score					
	Sci 1	Sci 2	Sci 3	Arts 1	Arts 2	Arts 3
Dirty×Post	-1.858***	-2.361**	-0.952	-1.461**	-1.548**	-0.634
	(0.534)	(1.016)	(0.680)	(0.571)	(0.627)	(1.126)
R^2	0.9157	0.8084	0.6492	0.8745	0.7968	0.6148
Observations	14990	28054	10209	10475	22516	9268
prov-year FE	Y	Y	Y	Y	Y	Y
college-prov FE	Y	Y	Y	Y	Y	Y

Notes: * significant at 1 percent level, ** significant at 5 percent level, * significant at 10 percent level. Standard errors are clustered by province.

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