Running with a Mask? The Effect of Air Pollution on Marathon Runners' Performance

Shihe Fu and Mengmeng Guo

Southwestern University of Finance and Economics

31 May 2017

Running with a Mask? The Effect of Air Pollution on Marathon Runners' Performance

Shihe Fu
fush@swufe.edu.cn

Mengmeng Guo
gmm@swufe.edu.cn

Research Institute of Economics and Management
Southwestern University of Finance and Economics
Chengdu, China

May 30, 2017

Abstract

Using a sample of over 0.3 million marathon runners in 37 cities and 55 races in China in 2014 and 2015, we estimate the air pollution elasticity of finish time to be 0.041. Our causal identification comes from the exogeneity of air pollution on the race day because runners are required to register a race a few months in advance and we control for city fixed effects, seasonal effects, and weather condition on the race day. Including individual fixed effects also provides consistent evidence. Our study contributes to the emerging literature on the effect of air pollution on short-run productivity, particularly on the performance of athletes engaging outdoor sports and other workers whose jobs require intensive physical activities.

Keywords: Air pollution; marathon; outdoor behavior; mega events; short-run productivity
JEL Code: I18, Q53, R11, Z20

Acknowledgement: We thank Xiaojia Bao, Elena Irwin, Xiaoyan Lei, Carl Lin, Christopher Magee, Shunfeng Song, Todd Sorensen, Junjie Zhang, Xi Zhu, Dilek Uz, seminar and conference participants at Bucknell University, Dongbei University of Finance and Economics, Shanghai University of Finance and Economics, Kunshan Duke University, Hunan University, Ohio State University, Peking University, Xiamen University, Renmin University, Tsinghua University, University of Nevada-Reno, the 2016 China Economists Society Conference, the 2016 North American Regional Science Congress for very helpful comments and Zexin Ye for excellent research assistance.

1. Introduction

An emerging literature finds a sizable, negative effect of air pollution on short-run labor productivity (Zivin and Neidell, 2012; Adhvaryuy *et al*., 2014; Lichter *et al*., 2015; Chang *et al*., 2016a, 2016b; Fu *et al*., 2017). This study contributes to this literature by estimating the causal effect of air pollution on marathon runners' performance (finish time) using a sample of over 0.3 million runners in 37 cities and 55 races in China in 2014 and 2015. Our causal identification relies mainly on the exogeneity of air quality on the race day because runners are required to register a race a few months in advance and air quality on the race day can be considered random. We estimate the air pollution elasticity of finish time to be 0.0408. This effect is economically significant because of large variations in air quality across Chinese cities. For example, an average full-marathon runner will need 20.7 more minutes to cross the finish line if he or she were to run the Beijing Marathon in 2014 when the air is severely polluted, compared with running on a day with average air quality.

The related literature can be grouped into two strands.[1] The first is a large literature documenting a harmful effect of air pollution on human health. Common air pollutants include particulate matter 2.5 micrometers or less in diameter ($PM_{2.5}$), particulate matter 10 micrometers or less in diameter (PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), and ozone (O_3). Long-run exposure to these pollutants can lead to cardiopulmonary diseases, respiratory infections, lung cancer, infant morbidity, asthma, and reduced life expectancy (EPA, 2004; Chay and Greenstone, 2003; Neidell, 2004; Chen *et al*., 2013). More relevant in our setting are the effects of short-run exposure to ambient air pollution. These include decreased lung function, irregular heartbeat, increased respiratory problems, nonfatal heart attacks, and angina.[2] Air pollution can also lower cognitive ability, increase anxiety, and have other negative psychological effects (Lavy *et al*, 2014; Pun *et al*., 2017). In addition, the sports health literature also provides evidence for a negative effect of air pollution on athletes' health and performance (Chimenti *et al*., 2009; Rundell, 2012).

The second strand of literature focuses on the effect of air pollution on short-run labor productivity. Zivin and Neidell (2012) find that ozone reduces productivity of outdoor fruit pickers in California. Chang *et al*. (2016a) find that $PM_{2.5}$ reduces productivity of indoor pear packers in California. Adhvaryu *et al*. (2014) identify that $PM_{2.5}$ reduces hourly productivity of workers in a garment factory in India. He *et al*. (2016) find that $PM_{2.5}$ and SO_2 reduce output of textile workers at two firms in Henan and Jiangsu Provinces, China. Chang *et al*. (2016b) identify the negative effects of air pollution on productivity of workers at two call centers in Shanghai and Nantong, China. Archsmith *et al*. (2016) find that CO and $PM_{2.5}$ negatively affects the productivity of professional baseball umpires in the U.S. Fu *et al*. (2017) provides more comprehensive evidence that air pollution

[1] The third strand of literature is on the negative shocks on athlete human capital accumulation, see Gong *et al*. (2017). Unfortunately, at this stage, we are unable to quantify the long-run effect of air pollution on runners due to data availability constraint.

[2] For more details, please refer to the EPA websites. For example: https://www.epa.gov/pm-pollution; https://www.epa.gov/so2-pollution; https://www.epa.gov/co-pollution.

decreases labor productivity of manufacturing firms using a nationwide longitudinal firm survey sample capturing 90% of manufacturing output in China.

The most closely related paper is by Lichter *et al*. (2015). They find that a 1% increase in the concentration of PM_{10} leads to a 0.02% decrease in professional soccer players' performance (measured by the number of passes in a match) in Germany, an elasticity twice smaller than ours but still comparable. Their causal identification takes advantage of the exogeneity of match scheduling which is controlled by the German Football League and beyond the control of individual teams and players. Our study complements theirs by identifying a similar, robust, negative effect of air pollution on marathon runners' performance.

Our findings have a few important implications for professional athletes who engage outdoor sports, for city governments organizing outdoor mega events, and for the growing running industry. Our estimates show that the negative effect of air pollution on top runners is also sizable: a top-twenty full-marathon runner will need 10.2 more minutes to finish the race if she or he were to run the 2014 Beijing Marathon compared with running on a day with average air quality in China. This suggests that professional athletes who participate outdoor sports games to compete for award (such as participating the Olympic Games) should consider the negative impact of air pollution on their performance (Lippi *et al*., 2008; Florida-James *et al*., 2011).

Many city governments organize various mega events, such as the Olympic Games, world or nationwide exhibitions, sports games, or music concerts, to promote media exposure and urban development (Andranovich *et al*., 2001). Since air pollution has significant, negative effects on short-run health and productivity of people, city governments need to consider the costs and benefits of hosting outdoor mega events on polluting days. A lesson can be learned from the 34th Beijing International Marathon hold on October 19, 2014. The average air pollution index is 289 on the race day and 320 during the race hours, which is considered heavily polluted and healthy people should avoid outdoor activities. [3] However, the organizer did not reschedule the race. Many runners quitted and many of the remaining thirty thousand runners ran the race donning all kinds of facemasks.[4] Our empirical evidence reminds hosting cities as well as participants of outdoor mega events that air quality needs to be taken into account.

Our findings are also informative to the growing running industry. The number of runners in China is estimated to be about 10 million, including runners running outdoors and in gym.[5] More and more cities rush to organize running races including marathon races. The running industry, including producers and retailers of running gears, running clubs, and race organizations, is growing rapidly.[6] Our study suggests that the industry stakeholders

[3] Table A1 in the online appendix summarizes the health implications of air quality index.
[4] Many news media reported the event, see for example, http://www.foxnews.com/world/2014/10/19/beijing-marathon-runners-wear-masks-to-combat-smog-from-pollution.html.
[5] http://sports.sina.com.cn/run/2016-06-08/doc-ifxsvenx3635108.shtml (in Chinese).
[6] http://www.nielsen.com/cn/en/insights/news/2016/business-opportunity-looms-as-marathon-mania-sweeps-across-china.html.

need to consider the negative effect of air pollution on runners and the ripple effects on event management and sales of running products.

The rest of the paper is organized as follows: Section 2 describes the data; Section 3 specifies the econometric model and discusses the causal identification issues; Section 4 reports the results and Section 5 concludes.

2. Data

Our data for marathon runners and races are downloaded from www.runchina.org.cn, which is maintained by the Chinese Athletic Association (CAA). This website publishes finish time data for each runner for all the full-marathon and half-marathon races hosted in China since 2014. The running routes of these races are certified by the CAA. We have collected the 2014 and 2015 data. The individual level data includes runner name, gender, age group, the name of the race, and the net time (the difference between the time of crossing the finish line and the time of reaching the start line). There are 37 cities and 55 races. Each city hosts only one race event each year during the sample period. In our sample, 19 cities hosted one race and 18 cities hosted two races. Figure 1 maps all the cities in our sample.

(Insert Figure 1 here)

The daily air quality index (AQI) data at the city level is downloaded from the website of the Ministry of Environmental Protection of China (http://datacenter.mep.gov.cn/). The daily AQI for a city is the maximum of the six pollutant indexes based on hourly data from multiple monitoring stations in that city. These six pollutants are $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3. We have also obtained the hourly data for the concentrations of each of these six pollutants for 44 races from the same website.

The AQI ranges between 0 and 500 and a larger value means worse air quality. A day with AQI below 100 is considered a "blue sky day" and has no health implications. The AQI above 100 has progressively negative effects on health (See Table A1 in the online appendix).

The daily weather condition data are drawn from the Global Weather Database provided by Bloomberg. We select four variables that most likely affect a runner's performance on the race day: precipitation (centimeter), average temperature (in Celsius), average wind speed (kilometer per hour), and relative humidity (in percentage). These daily weather variables are also likely to be correlated with the daily air quality. For example, strong wind may blow pollutants way from a city.

Our final sample includes 314,341 domestic runners. Table 1 reports the summary statistics for the key variables. For full-marathon runners, the variations in finish time are large, ranging between 8,301 seconds (2 hours 18 minutes and 21 second, 2:18:21 for short) and 24,337 seconds (6:45:37) with a mean of 16581 seconds (4:36:21) and a standard deviation of 2,701 seconds (0:45:01). This is consistent with the distribution of world marathon races documented in Allen *et al*. (2016) with a mean of 4:26:33 and a standard deviation of 0:59:11 based on a sample of about 10 million runners. A similar pattern holds for half-marathon runners' finish time. About 19% of runners are females and 50% of runners are young people (aged between 18 and 34).

The air quality index also shows a large variation across cities and days, ranging between 28 and 289 with a standard deviation of 59. The average AQI during race hours has an even larger variation, ranging between 15 and 320 with a standard deviation of 67. These large variations in air quality across races help estimate the pollution effect precisely.

Some medical studies fail to find a correlation between pollutants and marathon runners' performance in the U.S. and some European countries because the concentrations of pollutants on race days rarely exceed the health limits set by the U.S. Environmental Protection Agency or the World Health Organization (WHO) (Marr and Ely, 2010; Helou *et al*., 2012). However, Panel 3 of Table 1 shows that the pollutant concentrations in Chinese cities in general far exceed the health limits. For example, the standard set by the WHO for $PM_{2.5}$, PM_{10}, and SO_2 concentrations is 25, 50, and 20 ug/m^3 for the 24 hour mean; however, their means during the race hours in our sample are about 74, 105, and 22 ug/m^3, respectively, suggesting harmful effects on runners.[7]

(Insert Table 1 here)

3. Model specification and causal identification

To estimate the effect of air quality on marathon runners' performance, we specify the following baseline cross-sectional model:

$$\ln(Finishtime)_{ijt} = \alpha_j + \beta_1 \ln(AQI)_{jt} + \beta_2 W_{jt} + \beta_3 X_i + \varepsilon_{ijt}, \quad (1)$$

where the dependent variable is the logarithmic of $Finishtime_{ijt}$ referring to the net finish time (in second) of runner *i* who ran a race in city *j* on day *t*. α_j denotes city fixed effect. AQI_{jt} is the air quality index on the race day in a city hosting the race. W_{jt} is a vector of weather condition variables including temperature, wind speed, relative humidity, and precipitation. X_i is a vector of runner's demographic variables including a dummy variable indicating female and five dummy variables for five age group categories: aged 35-39, 40-44, 45-59, 50-54, and 55 or above; the default age group is 18-34. β_1, β_2, and β_3 are coefficient vectors to be estimated and ε_{ijt} is the error term.

Since we have two years data, we also include a dummy variable indicating year 2015. Ideally we would also like to control for seasonal effects by including eleven monthly dummies, but there is no race in February and only one race in July; therefore, we include

[7] The mean concentration of ozone is below the WHO limit of 100 ug/m^3 for the 8 hour mean. The WHO air quality guidelines for different types of pollutants are online at http://www.who.int/phe/health_topics/outdoorair/outdoorair_aqg/en.

five bimonthly dummies.[8] We also include a dummy indicating whether a runner finished a full marathon or a half marathon. To match with the available daily weather data, we use daily AQI in our baseline models and also use average AQI during race hours as robustness checks.

To identify the causal effect of air quality on a marathon runner's finish time, we rely mainly on the exogeneity of air quality on the race day. In general, runners are required to register a race a few months in advance. For example, Beijing Marathon requires registration two months in advance; Wuhan Marathon, three months. While a runner can anticipate the average air quality of a city in a particular season or month, it is unlikely to predict precisely the air quality on the race day. This implies that air quality on the race day can be treated as random and exogenous to runners. Note that predictable average air quality of a city in a particular season is controlled for by city fixed effects and bimonthly dummies. Therefore, the coefficient β_1 can be interpreted as the causal effect of air pollution on runners' finish time.

This causal identification strategy has been used in the environmental economics literature. For example, Lichter *et al*. (2015) estimate the effect of PM_{10} concentration on professional soccer players' performance in Germany using the exogeneity of match scheduling as the identification—the scheduling is controlled by the German Football League and beyond the control of teams and players implying that air quality on the match day is exogenous to players. Lavy *et al*. (2014) estimate the negative effect of air pollution during exam period on Israeli students' test scores. Park (2016) estimates the negative effect of high temperature during exam periods on New York students' test scores. Our research design complements these studies.

There are a few other identification issues worth discussion.

First, each certified marathon route is different in terms of geographic features such as altitude, surface, profile of flatness, curvature, and landscape along the course. Since these characteristics hardly change over time, they are subsumed into city fixed effects.

Second, some runners may choose a particular city or a particular season to run a race based on their preferences or other unobserved characteristics. This concern is also taken care of by the inclusion of city fixed effects and bimonthly dummies.

Third, it is possible that there are other unobserved personal characteristics which correlate with air quality on the race day, biasing our estimate of the key coefficient $\beta_{1.}$ For example, some runners may have spent more time training themselves which helps them better adapt to air pollution; some runners may simply have different genes that affect their performance on a polluting day; some runners may have different reference points in finish time which may provide different psychological incentives (Allen *et al*., 2016). This issue can be addressed by constructing an individual panel data and including runner fixed effects in the model. Specifically, we drop runners with the same name, gender, and age group showing up in the same race because these must be different persons. Then we treat

[8] Using quarterly dummy variables generates very similar results.

runners with the same name, gender, and age group as the same person. This generates a runner panel dataset and we re-estimate model (1) by replacing city fixed effects with runner fixed effect and cluster the standard errors at the runner level.

Fourth, runners in the same race may be affected by event-specific factors. For example, some races are better organized or invite top runners generating stronger peer effects (Aral and Nicolaides, 2017). This implies that finish time of runners in the same race may be correlated. We cluster the standard errors at the race level.

There is, however, one issue we cannot deal with. Some runners may quit the race (or quit during the race) when they know the air quality on the race day is bad. This "avoidance behavior" creates a sample selection problem. Unfortunately, we cannot access the registration data; therefore, we cannot gauge the sample selection bias using methods such as Heckman's two-step consistent estimator. The quitters are likely to be a mixture of both fast and slow runners, so the sample selection bias is very likely to be small. However, our individual runner panel data model does not suffer sample selection bias since we compare the effects for the same runner across races.

Runners may exert more or less effort deliberately during a race when they know that the air quality is bad. These endogenous behavioral adjustment will bias our estimates either downward or upward (Zivin and Neidell, 2013). We argue that either case is unlikely for marathon running. If runners try to slow down hoping to breathe in less pollutants, they will take a longer time to finish and will be exposed to pollution longer; in addition, a longer time will lower their rank and lose financial awards or pride. If runners try to speed up to finish the race earlier, they will inhale more pollutants due to intense lung functioning and most probably will not be able to sustain the speedup—after all, the full marathon has 42.195 kilometers! To be more important, if they could have run faster, why didn't they do so?

4. Results

4.1 Cross-sectional results

Table 2 presents the results of estimating model (1) using the full sample. All columns include city fixed effects and bimonthly dummies and the standard errors are clustered at the race level. Column 1 excludes weather condition and demographic variables and the estimated pollution effect on finish time is significantly positive with an elasticity of 0.0273. Column 2 adds weather variables and the coefficient of ln(Air quality index) becomes slightly larger, 0.0408, and more significant. The coefficients of weather variables seem to be reasonable: high temperature and raining slows down the speed of running, while moderate wind speed and humidity helps speed up (Chimenti *et al.*, 2009; Helou *et al.*, 2012).

(Insert Table 2 here)

Column 3 further adds gender and age group dummies and the estimated pollution effect is identical to Column 2. This suggests that air pollution on the race day is orthogonal to observed individual characteristics, implying that the correlation between air pollution and unobserved individual characteristics is likely to be very small too (Oster, 2016). This is our preferred specification since we have included all the possible control variables in our data.

Female runners on average take 9.2% more time to finish a marathon race. Compared with young runners aged between 18 and 34, older runners run faster. This is somewhat surprising and we do not have a good explanation for this. One possible interpretation could be that older runners on average are richer, spend more time on training, and have gained more running experience.

Column 3 also shows that a 10% increase in air quality index causes a 0.408% increase in finish time of a marathon runner. Put in a different way, doubling air quality index increases finish time by 4.08%. Evaluating at the mean air quality index of 102 and mean finish time of 16581 seconds (4:36:21) for a full marathon, a 10% increase in air quality index will increase finish time by about 1.1 minutes. This effect seems small but actually not. Suppose a runner takes 16581 seconds to finish a full marathon on a day with average air quality (AQI is 102), this runner will needs 20.7 more minutes to finish the 2014 Beijing Marathon during which the AQI is 289. For the best full-marathon runner (a young male runner) in our sample, the finish time is 8301 seconds (2:18:21) and the AQI on the race day (March 15, 2015) in that city (Wuxi) is 105. If he were to run the Beijing Marathon in 2014, a back-of-the-envelope calculation suggests that he would need 9.9 more minutes to cross the finish line.

Column 4 replicates the model in Column 3 but assumes a linear relationship between AQI level and finish time. A one unit increase in AQI increases finish time by about 2.7 seconds; a one standard deviation increase in air pollution (59) slows down a runner's finish time by 2.7 minutes. A runner who can finish a full marathon on a day with average AQI of 102 will need about 8.5 more minutes to finish the Beijing Marathon in 2014, which is in the ballpark compared with the log-log models.

4.2 Results for full-marathon and half-marathon samples

We also estimate model (1) for the full-marathon and half-marathon subsamples. Table 3 reports the results based on the full-marathon runner sample. Column 1 uses the full sample of full-marathon runners and the estimated pollution elasticity of finish time is 0.0274, one third smaller than the baseline estimate of 0.0408 but still sizable. This elasticity is slightly larger for male runners (0.0290) and young runners (0.0352) and moderately smaller for female runners (0.0163) and old runners (0.0214). We do not have a clear answer yet why the pollution elasticity varies across demographic traits.[9] However,

[9] For example, male and young runners may run more aggressively. Lichter *et al*. (2015) find that PM_{10} has a larger effect on soccer players who are midfielders and defenders because those positions require more active physical activities than strikers.

the positive, significant estimates of the pollution elasticity of finish time confirm that overall, air pollution negatively affects runners' performance.

(Insert Table 3 here)

Top runners are generally professional athletes competing for cash awards. Column (6) shows that for top ten runners in each race, the pollution elasticity is slightly smaller (0.0228) but still statistically significant at the 10% level even with a much smaller sample. Column (7) includes top twenty runners in each race and the estimated pollution elasticity is 0.0286 and significant at the 1% level, confirming that even for well-trained professional athletes, air pollution also exerts a negative effect on their performance. For this small sample, the mean finish time is 11686 seconds (3:14:46). If a top twenty runner were to run the Beijing Marathon in 2014, he or she would need 10.2 more minutes to finish the race. Column 8 includes the top thirty runners and the effect is almost identical.

Table 4 reports the estimate results for half-marathon runners, parallel to the columns in Table 3. The overall pattern is very similar except that the pollution elasticity is uniformly larger (even for top runners), ranging between 0.0263 and 0.0519, possibly because half-marathon runners run more aggressively and are affected more by air pollution.

(Insert Table 4 here)

4.3 Nonlinear effect

Different degree of air pollution severity may have different impacts on runners' performance. This nonlinear effect is identified in Table 5. Column 1 replicates the baseline results (same as Column 3 of Table 2). Column 2 replaces ln(air quality index) by a dummy variable indicating whether AQI is above 100 or not. Compared with a blue sky day (AQI<=100), a non-blue-sky day increases a runner's finish time by 3.67%. Column 3 uses two dummy variables: AQI between 100 and 200 (slightly and moderately polluted) and AQI above 200 (severely or heavily polluted). Compared with a blue sky day, running on a slightly or moderately polluted day increases finish time by 2.90%; running on a severely or heavily polluted day increases finish time further by three times—a 7.65% increase. This shows that worse air quality imposes a progressively negative impact on runners, consistent with the finding in Lichter *et al*. (2015) that a higher concentration of PM_{10} exceeding the EU limit has a stronger effect on soccer players' performance.[10]

(Insert Table 5 here)

The nonlinear effect is also confirmed in Column 4 where four dummy variables are used. Compared with excellent air quality (AQI below 50, the default category), even good air quality (AQI between 50 and 100) has a significantly negative effect on runners (4.37%); slight pollution (AQI between 100 and 150) increases finish time by 6.17%; moderate pollution (AQI between 150 and 200) increases finish time by 5.69% and severe or worse pollution (AQI above 200) increases finish time by 9.72%. Column 5 estimates a level

[10] Lavy *et al*. (2014) also find a nonlinear effect of air pollution on students' test scores.

model including both the linear and quadratic term of AQI level. The results also show a nonlinear (concave) pattern: the implied largest pollution effect occurs when AQI is 215.[11]

The nonlinear pollution effect, in terms of demographic heterogeneity, can also be found across runners. Table 6 presents quantile regression results for full- and half-marathon runners.[12] Note that "q10" in Column 1 denotes the runners whose finish time is below the bottom 10 percentile meaning that they are the top 10% fast runners. For full-marathon runners, air pollution has a three times larger effect on top 10% (fast) runners than on bottom 10% (slow) runners, regardless of gender. It is interesting to see that in Panel 2 for half-marathon runners the pattern is reversed: air pollution has a larger effect on bottom 10% (slow) runners.

(Insert Table 6 here)

4.4 Runner fixed effect model results

Since unobserved individual runners' characteristics may bias our estimated pollution elasticity, we estimate panel data models with runner fixed effects and report the results in Table 7. Column 1 uses a sample of runners who have run just two full-marathon races or two half-marathon races; in this case the dummy variable indicating full marathon is subsumed into the runner fixed effect. For these runners, the pollution elasticity of finish time is 0.0071, much smaller than the baseline results possibly because these runners have better training or better experience. We consider this estimate the low bound of pollution effect on runners' performance. This effect is still economically sizable. For example, evaluating at the mean finish time of 16774 seconds (4:39:34) for full-marathon runners and mean AQI of 104 in this sample, if a runner were to run the Beijing Marathon in 2014, he or she will need 3.5 more minutes to cross the finish line. For top runners, 3.5 minutes may lower his or her rank by a few or significantly decrease the probability of breaking the world record. The economic cost of 3.5 minutes is also huge for top runners. The Beijing Marathon offers the top eight runners cash awards. The best male runner whose finish time is also less than 2 hour 9 minutes would be awarded USD40,000; the second best, USD20,000 if his finish time is less than 2 hour 10 minutes.[13] For top runners, the opportunity cost of one minute is USD20,000!

(Insert Table 7 here)

Column (2) of Table 7 uses a sample of runners who have run two or three full-marathon or half-marathon races. The estimated pollution elasticity is 0.0054 and significant at the 1% level. Column (3) expands the sample to include runners who have also finished four

[11] In our sample only two races have AQI above 200: 2014 Hefei Marathon with AQI 215 and 2014 Beijing Marathon with AQI 289.
[12] Our quantile regressions estimate the top and bottom 10 percentile of finish time conditional on the same set of independent variables as in Column 3 of Table 2.
[13] See Table A2 in the online appendix for the award scheme for the 2014 Beijing Marathon. Other races in China follow this scheme very closely.

races, and the estimates are very close. Columns 4-7 show that the negative impact is mainly on male runners and young runners, consistent with Tables 3 and 4.

4.5 Robustness checks

The above analysis uses daily air quality index to match the available daily weather condition variables. Since runners are exposed to the outdoor pollution mainly during the race hours, it is important to check whether average air pollution during the race hours causes similar negative effects on runners. In our sample, all races are scheduled on a weekend day and start as early as 7 am and close as late as 2:30 pm. Therefore, we use the average of hourly AQI from 6 am to 3 pm to replace the daily AQI and re-estimate all models.[14] It turns out that the negative effects of air pollution during the race hours are very similar to the estimates using the daily AQI albeit slightly smaller. The main reason is that the correlation between the average AQI on the race day and the average AQI during the race hours are very high: the correlation coefficient is 0.974 and statistically significant at the 1% level. As a demonstration, we present the full sample results in Table 8 which is parallel to Table 2.

(Insert Table 8 here)

Taking our preferred specification as the example, Column 3 shows an elasticity of 0.0262 using the average AQI during the race hours. This is smaller than 0.0408 using the average AQI of the race day but estimated more precisely with a smaller standard error. When the finish time is used as dependent variable, the coefficient of average AQI during the race hours is 2.0223, close to 2.731 estimated using the average AQI of a race day. It is worth noting that the coefficients of demographic variables and full marathon dummy are almost identical to those in Table 2 but are estimated more precisely. This further suggests that air pollution on the race day is orthogonal to observed individual characteristics and choice and is also unlikely to be correlated with unobserved individual characteristics.

Many medical studies find a correlation between different types of pollutants and athletes' health and sport performance using laboratory or field survey data (Carlisle and Sharp, 2001; Chimenti *et al*. 2009). To identify the effects of different types of pollutants, we re-estimate Column 3 model in Table 8 by replacing average AQI during the race hours with the average concentration of one of the six pollutants during the race hours: $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3.[15] The results are presented in Table 9. Except O_3, the negative effect of each pollutant concentration is similar in magnitude: the elasticity ranges between 0.0265 and 0.0501, comparable to the elasticity of 0.0262 using the AQI.[16] Because of high correlations between these pollutant concentrations, it is difficult to isolate the contribution of each pollutant concentration. Regardless, a horse race model including all types of pollutant concentrations shows that either $PM_{2.5}$ or PM_{10} concentration is still statistically

[14] Hourly AQI data for the morning period are missing for six races so we use their daily AQI as the proxy.
[15] Pollutant concentrations during morning hours are missing for eleven races so the sample size becomes smaller.
[16] The correlation coefficients between O_3 and PM $_{2.5}$, PM_{10}, NO_2, CO are negative and statistically significant at the 1% level.

significant with a larger magnitude, suggesting that particulate matter is more harmful to runners.

(Insert Table 9 here)

5 Conclusion

Using a sample of more than 0.3 million marathon runners of 55 races hosted by Chinese cities in 2014 and 2015, we estimate the air pollution elasticity of finish time to be 0.0408. This shows that air pollution has a significant, negative effect on runners' performance. Our causal identification uses the exogeneity of air quality on the race day because runners are required to register a race a few months in advance and the air quality on the race day can be considered random. Based on a panel dataset of runners who ran more than one race, our estimates with runner fixed effects confirm the negative impact of air pollution on runner performance albeit in a smaller magnitude.

Our study contributes to the emerging literature on the effects of air pollution on short-run productivity. Our findings remind city governments that the negative effect of air pollution on health and performance of participants should be taken into account when organizing mega outdoor events. Our findings are also informative for professional athletes who compete for awards in outdoor sports games such as football, running, and biking and for workers whose jobs require intensive physical activities and long exposure to ambient air pollution.

.

References:

Adhvaryu, A., N. Kala, A. Nyshadham, 2014, Management and shocks to worker productivity: evidence from air pollution exposure in an Indian Garment, Working Paper, University of Michigan.

Allen, E., P. Dechow, D. Pope, G. Wu, 2016, Reference-dependent preferences: evidence from marathon runners, *Management Science*, forthcoming.

Andranovich, G., M. Burbank, C. Heying, 2001, Olympic cities: lessons learned from mega-event politics, *Journal of Urban Affairs* 23, 113–131.

Aral, S., C. Nicolaides, 2017, Exercise contagion in a global social network, *Nature Communications* 8:14753, DOI: 10.1038/ncomms14753.

Archsmith, James, A. Heyes, and S. Saberian, 2016, Air quality and error quantity: pollution and performance in a high-skilled, quality focused occupation, Working Paper, available at http://dx.doi.org/10.2139/ssrn.2683656.

Carlisle, A.J., N.C. Sharp, 2001, Exercise and outdoor ambient air pollution, *British Journal of Sports Medicine* 35, 214–222.

Chang, T., J. G. Zivin, T. Gross and M. Neidell, 2016a, Particulate pollution and the productivity of pear packers, *American Economic Journal: Economic Policy* 8, 141 – 169.

Chang, T., J. G. Zivin, T. Gross and M. Neidell, 2016b, The effect of pollution on worker productivity: evidence from call-center workers in China, NBER Working Paper 22328.

Chay, K. Y., M. Greenstone, 2003, The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession, *Quarterly Journal of Economics* 118, 1121-1167.

Chen, Y., A. Ebenstein, M. Greenstone, H. Lie, 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy, *Proceedings of the National Academy of Sciences of the United States of America* 110, 12936-12941.

Chimenti, L., G. Morici, A. Paterno, A. Bonannò, M. Vultaggio, V. Bellia, M. Bonsignore, 2009, Environmental conditions, air pollutants, and airway cells in runners: A longitudinal field study, *Journal of Sports Sciences* 27(9): 925–935.

EPA (U.S. Environmental Protection Agency), 2004, Air quality criteria for particulate matter.

Florida-James, G., K. Donaldson, V. Stone, 2011, Athens 2004: the pollution climate and athletic performance, *Journal of Sports Sciences* 22, 967–980.

Fu, S., V. B. Viard, P. Zhang, 2017, Air quality and manufacturing firm productivity: comprehensive evidence from China, Working Paper, available at http://dx.doi.org/10.2139/ssrn.2956505.

Gong, J., A. Sun, Z. Wei, 2017, Choosing the pond: on-the-job experience and long-run career outcomes, *Management Science,* forthcoming.

Graff Zivin, J., M. Neidell, 2012, The impact of pollution on worker productivity, *American Economic Review* 102, 3652-3673.

Graff Zivin, J., M. Neidell, 2013, Environment, health, and human capital, *Journal of Economic Literature* 51, 689-730.

He, J., H. Liu, A. Salvo., 2016, Severe air pollution and labor productivity: evidence from industrial towns in China, IZA Working Paper 8916.

Helou, N., M. Tafflet, G. Berthelot, J. Tolaini, A. Marc, M. Guillaume, C. Hausswirth, J.F. Toussaint, 2012, Impact of environmental parameters on marathon running performance, *PLoS ONE* 7(5): e37407.

Lavy, V., A. Ebenstein, S. Roth, 2014, The impact of short term exposure to ambient air pollution on cognitive performance and human capital formation. NBER Working Paper No. 20648.

Lichter, A., N. Pestel, E. Sommer, 2015, Productivity effects of air pollution: Evidence from professional soccer, IZA Discussion Paper No. 8964.

Lippi, G., G. C. Guidi, N. Maffulli, 2008, Air pollution and sports performance in Beijing, *International Journal of Sports Medicine* 29, 696–698.

Marr, L., M. Ely, 2010, Effect of air pollution on marathon running performance, *Medicine & Science in Sports & Exercis*e 42(3), 585-591.

Neidell, M. J., 2004, Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma, *Journal of Health Economics* 23, 1209 – 1236.

Oster, E., 2016, Unobservable selection and coefficient stability: theory and evidence, *Journal of Business & Economic Statistics*, forthcoming.

Park, J., 2016, Temperature, test scores, and educational attainment, Working Paper, Department of Economics, Harvard University.

Pun, V. C., J. Manjouride, H. Suh, 2017, Association of ambient air pollution with depressive and anxiety symptoms in older adults: results from the NSHAP study, *Environmental Health Perspectives* 125, 342-348.

Rundell, K. W., 2012, Effect of air pollution on athlete health and performance, *British Journal of Sports Medicine* 46, 407-412.

Zivin, J. G., M. Neidell., 2012, The impact of pollution on worker productivity, *American Economic Review* 102, 3652 – 3673.

Table 1: Summary Statistics

Variable	Mean	Standard deviation	Minimum	Maximum	Sample size
Panel 1: Runner characteristics					
Finish time (in seconds)	12775	4732	3941	24337	314,341
Finish time for full-marathon runners (seconds)	16581	2701	8301	24337	172,523
Finish time for half-marathon runners (seconds)	8147	1311	3941	20712	141,818
Full-marathon runner (dummy)	0.55	0.50	0	1	314,341
Female (dummy)	0.19	0.39	0	1	314,341
Age 18-34 (dummy)	0.50	0.50	0	1	314,341
Age 35-39 (dummy)	0.15	0.36	0	1	314,341
Age 40-44 (dummy)	0.15	0.36	0	1	314,341
Age 45-49 (dummy)	0.10	0.30	0	1	314,341
Age 50-54 (dummy)	0.05	0.22	0	1	314,341
Age 55 or above (dummy)	0.05	0.23	0	1	314,341
Panel 2: Air quality and weather condition on the race day					
Air quality index	102.19	58.86	28.00	289.00	314,341
Precipitation (cm)	0.148	0.33	0	2.2	314,341
Temperature (Celsius)	16.53	4.05	6	25	314,341
Wind speed (kilometer per hour)	11.36	8.73	3.52	68.04	314,341
Relative humidity (percent)	70.53	18.29	5.56	97.47	314,341
Panel 3: Average air quality and pollutant concentration (ug/m^3) during race hours					
Air quality index	101.05	66.59	15.22	319.57	314,341
$PM_{2.5}$	73.89	60.89	5.89	268.57	271,296
PM_{10}	104.79	77.98	12.78	347.29	271,296
SO_2	21.83	15.57	6.10	94.89	271,296
NO_2	45.34	24.70	10.33	116.44	271,296
O_3	54.42	31.75	10.40	200.00	271,296
CO	1.20	0.61	0.36	2.67	271,296

Table 2: Full sample results

Variable	1	2	3	4
ln (Air quality index)	0.0273**	0.0408***	0.0408***	
	(0.0114)	(0.0030)	(0.0026)	
Air quality index				2.7311***
				(0.4434)
Full marathon dummy	0.6731***	0.6731***	0.6944***	8216.7570***
	(0.0057)	(0.0056)	(0.0052)	(88.7156)
Year 2015 dummy	0.0098*	0.0202***	0.0171***	247.6191***
	(0.0051)	(0.0026)	(0.0023)	(49.4088)
Precipitation		0.0282***	0.0280**	134.2860
		(0.0085)	(0.0076)	(99.1048)
Temperature		0.0049***	0.0047***	85.9956***
		(0.0006)	(0.0006)	(9.9105)
Wind speed		-0.0007***	-0.0007***	-3.5602
		(0.0002)	(0.0002)	(4.0870)
Relative humidity		-0.0008***	-0.0008***	-2.6216
		(0.0002)	(0.0002)	(3.4924)
Female			0.0919***	988.7489***
			(0.0030)	(35.8090)
Age 35-39			-0.0257***	-383.6603***
			(0.0034)	(57.8405)
Age 40-44			-0.0453***	-663.6623***
			(0.0041)	(76.2775)
Age 45-49			-0.0516***	-758.7814***
			(0.0049)	(90.5476)
Age 50-54			-0.0489***	-727.1522***
			(0.0054)	(95.9789)
Age 55 or above			-0.0309***	-473.3934***
			(0.0050)	(82.2323)
Adjusted R^2	0.8299	0.8306	0.8417	0.8107

Note: The dependent variable for Columns (1)-(3) is ln (Finish time). The dependent variable for Column 4 is finish time. All models also include city fixed effects and bimonthly dummies. Standard errors are clustered at the race level (55 races) and reported in the parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels, respectively. Sample size: 314,341.

Table 3: Full-marathon runners

	1	2	3	4	5	6	7	8
	Full sample	Male	Female	Young	Old	Top 10	Top 20	Top 30
ln (Air quality index)	0.0274***	0.0290***	0.0163***	0.0352***	0.0214***	0.0228*	0.0286***	0.0289***
	(0.0035)	(0.0033)	(0.0053)	(0.0055)	(0.0038)	(0.0122)	(0.0103)	(0.0083)
Female dummy	Y	N	N	Y	Y	Y	Y	Y
Age categories	Y	Y	Y	N	N	Y	Y	Y
Adjusted R^2	0.1188	0.1000	0.0985	0.1042	0.0748	0.7961	0.7830	0.7819
Sample size	172,523	149,630	22,893	75,538	96,985	837	1,670	2,497

Note: The dependent variable is ln (Finish time). All models also include weather condition variables on the race day, year 2015 dummy, bimonthly dummies, and city fixed effects. Standard errors are clustered at the race level and reported in the parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Half-marathon runners

	1 Full sample	2 Male	3 Female	4 Young	5 Old	6 Top 10	7 Top 20	8 Top 30
ln (Air quality index)	0.0494***	0.0518***	0.0422***	0.0519***	0.0455***	0.0263**	0.0289***	0.0385***
	(0.0105)	(0.0099)	(0.0114)	(0.0111)	(0.0116)	(0.0110)	(0.0112)	(0.0116)
Female dummy	Y	N	N	Y	Y	Y	Y	Y
Age categories	Y	Y	Y	N	N	Y	Y	Y
Adjusted R^2	0.1453	0.0693	0.0738	0.1396	0.1402	0.7379	0.7168	0.7060
Sample size	141,818	105,362	36,456	79,975	61,843	940	1,880	2,820

Note: The dependent variable is ln (Finish time). All models also include weather condition variables on the race day, year 2015 dummy, bimonthly dummies, and city fixed effects. Standard errors are clustered at the race level and reported in the parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Nonlinear effect

	1	2	3	4	5
ln(Air quality index)	0.0408***				
	(0.0026)				
Air quality index>100 (dummy)		0.0367***			
		(0.0087)			
100<Air quality index<=200 (dummy)			0.0290***		
			(0.0066)		
50<Air quality index<=100 (dummy)				0.0437*	
				(0.0261)	
100<Air quality index<=150 (dummy)				0.0617***	
				(0.0174)	
150<Air quality index<=200 (dummy)				0.0569***	
				(0.0173)	
Air quality index>200 (dummy)			0.0765***	0.0972***	
			(0.0098)	(0.0149)	
Air quality index					10.8739***
					(1.9357)
Air quality index squared					-0.0253***
					(0.0061)
Adjusted R^2	0.8417	0.8415	0.8416	0.8416	0.8108

Note: The dependent variable is ln (Finish time) in Columns 1-4 and finish time in Column 5. All models also include weather condition variables on the race day, female dummy, age category dummies, year 2015 dummy, bimonthly dummies, and city fixed effects. Standard errors are clustered at the race level and reported in the parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels, respectively. Sample size: 314,341.

Table 6: Quantile regression results

	1	2	3	4	5	6
	Panel 1: Full-marathon runners sample					
	Full sample		Male		Female	
	q10	q90	q10	q90	q10	q90
ln (Air quality index)	0.0341***	0.0114***	0.0340***	0.0121***	0.0373***	0.0028
	(0.0029)	(0.0026)	(0.0036)	(0.0024)	(0.0058)	(0.0049)
Female	Y	Y	N	N	N	N
Sample size	172,523	172,523	149,630	149,630	22,893	22,893
	Panel 2: Half-marathon runners sample					
ln (Air quality index)	0.0302***	0.0555***	0.0312***	0.0615***	0.0325***	0.0335***
	(0.0072)	(0.0057)	(0.0072)	(0.0079)	(0.0120)	(0.0079)
Female	Y	Y	N	N	N	N
Sample size	141,818	141,818	105,362	105,362	36,456	36,456

Note: The dependent variable is ln (Finish time). "q10" and "q90" stand for 10% and 90% quantile regressions, respectively. All models also include weather condition variables on the race day, age category dummies, year 2015 dummy, bimonthly dummies, and city fixed effects. Bootstrapped standard errors are reported in the parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Runner fixed effect model results

	1 2 races	2 2-3 races	3 2-4 races	4 2-3 races male	5 2-3 races female	6 2-3 races young	7 2-3 races old
ln(Air quality index)	0.0071**	0.0054***	0.0051***	0.0058***	0.0039	0.0100***	0.0013
	(0.0033)	(0.0015)	(0.0013)	(0.0017)	(0.0030)	(0.0025)	(0.0017)
Adjusted R^2	0.9383	0.9333	0.9285	0.9314	0.9410	0.9230	0.9430
Sample size	65,700	100,017	121,849	80,987	19,030	45,551	54,466

Note: The dependent variable is ln (Finish time). All models also include weather condition variables on the race day, year 2015 dummy, bimonthly dummies, and individual runner fixed effects. Standard errors are clustered at the individual level and reported in the parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Full sample results using air quality index during a race

Variable	1	2	3	4
ln (Air quality index during a race)	0.0184**	0.0262***	0.0262***	
	(0.0081)	(0.0017)	(0.0014)	
Air quality index during a race				2.0234***
				(0.3495)
Full marathon dummy	0.6734***	0.6731***	0.6944***	8217.2970***
	(0.0057)	(0.0056)	(0.0052)	(88.5594)
Year 2015 dummy	0.0103**	0.0202***	0.0171***	253.2970***
	(0.0047)	(0.0022)	(0.0019)	(49.4013)
Precipitation		0.0247***	0.0244***	115.9485
		(0.0089)	(0.0081)	(103.4104)
Temperature		0.0055***	0.0052***	91.1419***
		(0.0006)	(0.0006)	(10.9733)
Wind speed		-0.0002	-0.0002	-1.1355
		(0.0002)	(0.0002)	(4.0875)
Relative humidity		-0.0004*	-0.0004**	-0.2893
		(0.0002)	(0.0002)	(3.5127)
Female			0.0918***	988.7191***
			(0.0030)	(35.8152)
Age 35-39			-0.0257***	-383.6670***
			(0.0034)	(57.8664)
Age 40-44			-0.0453***	-663.6308***
			(0.0041)	(76.3144)
Age 45-49			-0.0516***	-758.7166***
			(0.0049)	(90.5915)
Age 50-54			-0.0490***	-727.1477***
			(0.0054)	(96.0222)
Age 55 or above			-0.0309***	-473.1737***
			(0.0050)	(82.3586)
Adjusted R^2	0.8299	0.8306	0.8417	0.8107

Note: The dependent variable for Columns (1)-(3) is ln (Finish time). The dependent variable for Column 4 is finish time. All models also include city fixed effects and bimonthly dummies. Standard errors are clustered at the race level and reported in the parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels, respectively. Sample size: 314,341.

Table 9: Effects of pollutants during a race

Variable	1	2	3	4	5	6	7
ln(Air quality index)	0.0262***						
	(0.0014)						
ln($PM_{2.5}$)		0.0270***					
		(0.0016)					
ln(PM_{10})			0.0265***				
			(0.0024)				
ln(SO_2)				0.0459***			
				(0.0045)			
ln(NO_2)					0.0501***		
					(0.0073)		
ln(CO)						0.0410***	
						(0.0057)	
ln(O_3)							-0.0218***
							(0.0057)
Sample size	314,341	271,296	271,296	271,296	271,296	271,296	271,296
Adjusted R^2	0.8417	0.8410	0.8409	0.8410	0.8408	0.8409	0.8406

Note: The dependent variable is ln (Finish time). All models also include weather condition variables on the race day, female dummy, age category dummies, year 2015 dummy, bimonthly dummies, and city fixed effects. All pollutant variables as well as air quality index are defined as the average of hourly data between 6 am and 3 pm on the race day. Standard errors are clustered at the race level and reported in parentheses. "*", "**", and "***" indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 1 Cities that hosted marathon races in 2014 and 2015

Online Appendix:

Table A1: Air quality index and its health implication

Air quality index	Air quality	Health implication for healthy people
0-50	Excellent	No health implication.
51-100	Good	No health implication.
101-150	Slightly polluted	Slight irritation may occur.
151-200	Moderately polluted	Irritation may occur; should reduce outdoor exercises.
201-300	Severely polluted	Noticeably affected; should reduce outdoor activities.
>300	Heavily polluted	Reduced endurance in activities; should avoid outdoor activities.

Table A2: Cash award scheme in the 2014 Beijing Marathon

Male Runner			Female Runner		
Rank	Award(US$)	Time	Rank	Award(US$)	Time
1	40000	<2:09:00	1	40000	<2:27:00
	20000	≥2:09:00		20000	≥2:27:00
2	15000	<2:10:00	2	15000	<2:28:00
	10000	≥2:10:00		10000	≥2:28:00
3	8000	<2:11:00	3	8000	<2:29:00
	6000	≥2:11:00		6000	≥2:29:00
4	5000		4	5000	
5	3000		5	3000	
6	2000		6	2000	
7	1500		7	1500	
8	1000		8	1000	