Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Effects of large gatherings on the COVID-19 epidemic: Evidence from professional and college sports

Patrick R. Carlin, Paul Minard, Daniel H. Simon, Coady Wing

O’Neill School, Indiana University, 1315 E 10th St, Bloomington, IN 47405, USA
Cégep Heritage College, Gatineau, QC, Canada

ARTICLE INFO
JEL classification: I10 I18 H0 H12
Keywords: Population health Health economics Quasi-experiments Pandemics

ABSTRACT
We compare COVID-19 case loads and mortality across counties that hosted more versus fewer NHL hockey games, NBA basketball games, and NCAA basketball games during the early months of 2020, before any large outbreaks were identified. We find that hosting one additional NHL/NBA game in March 2020 leads to an additional 7520 cases and 658 deaths. Similarly, we find that hosting an additional NCAA Division 1 men’s basketball game in March 2020 results in an additional 34 deaths. Back-of-the-envelope calculations suggest that the per-game fatality costs were 200–300 times greater than per-game spending.

1. Introduction

In an effort to reduce the transmission of SARS-COV-2 and contain the COVID-19 epidemic, state and local governments have implemented a range of policies designed to limit physical interaction, including school and business closures, stay-at-home orders, and bans on social gatherings (Gupta et al., 2020). Over the course of the epidemic, states have reopened to varying degrees, and people have resumed some activities that involve physical interaction (Nguyen et al., 2020). However, the severity of the epidemic and the appearance of new outbreaks has varied quite widely across locations, and this heterogeneity is not very well understood. An ongoing concern is that large gatherings may stimulate new outbreaks. Several contact-tracing studies provide suggestive evidence that large gatherings were responsible for some infection clusters early in the epidemic. But few, if any, studies examine quasi-experimental variation in the frequency of large events. A key issue is that once the epidemic was underway, the occurrence of most large events may have been partly determined by the state of the local epidemic. This type of endogenous event planning makes it hard to identify the causal effects of large gatherings on downstream cases and deaths.

In this paper, we study the effects of large gatherings on the severity of the first wave of the COVID-19 epidemic by exploiting plausibly exogenous variation in the number of professional and college sports games played in different metropolitan statistical areas (MSAs) during the period leading up to the epidemic. The key identifying assumption in our work is that places that hosted more games in early March 2020 were not systematically more likely to experience a more severe epidemic in the absence of those games. This assumption has substantial credibility because the locations of professional and college sports teams, and professional and college sports schedules were determined prior to the arrival of the virus. Moreover, we bolster this assumption by controlling for population, population density, demographic characteristics, and the total number of professional or college teams in the same MSA.

Exploiting this exogenous scheduling, we compare the cumulative number of COVID-19 cases and deaths through May 2020 across local areas that hosted more vs fewer NHL hockey games, NBA basketball games, and NCAA basketball games between March 1 and March 11, 2020.

After adjusting for baseline covariates, we find that hosting one additional NBA or NHL game during early March 2020 resulted in an additional 7520 COVID-19 cases and 658 COVID-19 deaths in the MSA where the game was played, by the end of May. In contrast, we find that a men’s college basketball game only resulted in an additional 34 deaths per MSA. Using an age-adjusted VSL of $2 million, back-of-the-envelope
calculations suggest that the fatality costs of professional and college sports events in March 2020 were 200–300 times greater than spending at these games.

These estimated effects represent some of the first quasi-experimental evidence on the casual effects of large group events on the spread of COVID-19 cases and deaths. The results speak to an important question about the role that large gatherings played in the early spread of the epidemic in the United States. They also provide some insight into the possible risks associated with the return of large events in the near future. Understanding the transmission effects of large gatherings is critically important as college and professional sports leagues must determine conditions under which allowing games is safe and worthwhile. Our results help inform these decisions. However, our estimates are based on games that were held during a period where people were not trying to mitigate transmission by wearing masks or sitting in more widely-spaced arrangements. It is possible that games would be safer with mitigation techniques in place. Likewise, our results do not speak to the social benefits and costs of holding major sporting events that are televised but do not allow a live audience.

More broadly, state and local governments, event planners, and conference organizers must decide how much gathering is safe enough to justify, given the epidemiological circumstances. Our results could help to guide policymakers who must decide how to regulate gatherings ranging from more private events such as weddings and funerals, to more public events including trade and academic conferences, political conventions, music concerts, and theatrical performances. Understanding the transmission risks associated with mass gatherings takes on increased importance as most states have loosened restrictions on social gatherings, with many experiencing a resurgence of cases and deaths.

2. Related research

In this paper we estimate the effects of major professional and college level indoor sporting events on downstream COVID-19 cases and deaths. Our empirical work contributes to research on the social determinants of the transmission of SARS-CoV-2 and the way that organizational practices, public policies, and individual behaviors have shaped the epidemic.

There is mounting evidence that crowded “super-spreader” events, characterized by close proximity and prolonged contact, have played an outsized role in contributing to the spread of COVID-19 (Qian et al., 2020; Nishiura et al., 2020). To take one prominent example, Dave et al. (2020a) study the impact of the Sturgis Motorcycle Rally in South Dakota, which attracted 500,000 attendees to both outdoor and indoor locales in August 2020. Their synthetic control approach suggests that the rally led to an increase of 6–7 cases per 1000 relative to the synthetic county three weeks after the event. In bringing thousands of people indoors for a period of hours, NHL games, NBA games and NCAA Division I men’s basketball games are also a plausible site of increased infection risk. Attendance at any single game in our sample does not approach the scale of the Sturgis event. However, hockey and basketball games are significant events. For example, in the games we examine, average attendance was about 17,500 persons per game and some MSAs hosted as many as 15 games from March 1 to March 11.

In response to concerns about the risks of large gatherings, governments, businesses, and individual people took steps to reduce physical interactions in a variety of mandated and voluntary ways. Several recent papers investigate the extent to which public policies that prohibit large gatherings and impose more general stay-at-home orders are effective in reducing the scale of an outbreak. Dave et al. (2020c) show that these orders, particularly if enacted in the early stages of an outbreak, reduce downstream COVID-19 case counts and deaths. California was the earliest adopter of a statewide stay-at-home order, and Friedson et al. (2020) estimate via a synthetic control approach that this policy reduced COVID-19 cases by approximately 20–45 fewer cases per 100,000 two to three weeks after adoption. Instrumenting for social distancing using county-level rainfall data, Kapoor et al. (2020) show that increased social distancing in the final weekend before imposition of statewide lockdowns, as measured by smartphone location data, reduced downstream cases and deaths. More recent work by Berry et al. (2021) suggests that stay-at-home policies had little effect on cases and deaths and that earlier results are sensitive to small changes in model specification.

Efforts to measure the effects of group events on subsequent levels of COVID-19 cases and deaths must reckon with the endogeneity of individuals’ behavior. That is, irrespective of the timing of policy decisions which prohibit large events, individuals may adjust their own propensity to voluntarily attend such events based on their perception of the severity of the local outbreak. Gupta and Wing (2020) examine the role of mandated vs voluntary behaviors in explaining changes in physical mobility patterns during the epidemic. Their analysis suggests that private/voluntary responses to prevailing health risks were a major component of overall changes observed physical mobility patterns and that government mandates played a smaller role. Dave et al. (2020b) use a synthetic control design to estimate the impacts of the Wisconsin Supreme Court’s abolishing of the state’s stay at home order, finding no impact on social distancing as proxied by smartphone location data, and no impact on COVID-19 cases or mortality. Nguyen et al. (2020) also examine the timing and nature of state reopening policies on social distancing using smartphone location data. They find that when measures of mobility increase by 6–8% in the days following reopening, much of this rise happens independently of state policies, suggesting that individual choices about how to respond to the epidemic are important in shaping policy impact and are partly endogenous to individuals’ perception of the severity of the local epidemic.

There is also a substantial pre-COVID literature on the role of mass events in spreading other infectious diseases. Evidence from this literature is mixed. The epidemiological literature reports occasional influenza outbreaks at religious, music and sporting events; see Gautret and Stefen (2016) for a review. A systematic review by Zielinski (2009) concludes that most international sporting events have not led to increased influenza outbreaks. On the other hand, Gitter (2017) finds that existing influenza outbreaks seem to reduce sporting event attendance, suggesting again that the impact of large gatherings on the course of an epidemic is endogenous to public perceptions of the epidemic’s severity.

Interestingly, two studies taking advantage of quasi-experimental variation suggest professional sporting events increase influenza transmission in the U.S. Exploiting plausibly exogenous variation in whether a local team qualifies for the Super Bowl, Stoecker et al. (2016) finds that cities whose teams qualify for the championship game experience 18% more influenza deaths than do comparable cities. Cardazzi et al. (2020) estimate the effect of professional sports on influenza mortality from 1962 to 2016, deriving estimates from discontinuous changes in the presence of local teams, owing to league expansion or team relocation. They too find that professional sports events are associated with increased influenza mortality. These studies suggest that large events probably do increase influenza transmission, perhaps having the largest effect when the prevalence of the disease is low enough that people are not making major behavioral changes (mask wearing, spaced seating, etc.) to reduce the risk of the event.

In addition to our study, there is one other study that examines the effects of large sporting events on the course of local COVID-19 outbreaks. Ahammer et al. (2020) was developed independently but almost simultaneously with our paper and it also examines the association between sporting events and the influenza season. The two studies have a few key differences. First, our analysis controls for population and the number of teams in each county or MSA, which enables greater confidence that our results derive from mainly from variation in scheduled games, not other local characteristics that may be correlated with the number of games and also with the potential for SARS-CoV-2 transmission. We also use cell phone mobility data from SafeGraph to demonstrate that game days do in fact generate physical congregations of people at sporting venues that is far in excess of the
level of activity around the venues on days with no scheduled games. This helps establish the games actually do generate the kind of mixing activity that could help spread the virus, and helps rule out the possibility that the gathering effects of home game days is matched by the gathering effects of concerts and other epidemiologically relevant events on non-game days.

Second, while Ahammer et al. (2020) estimate the effects of NBA and NHL games only, we also estimate the effect of NCAA men’s college basketball games. This increases the total number of games we observe from 801 to 3164, and increases the geographic scope of our analysis considerably. 41 counties in 36 MSAs hosted at least one NBA or NHL game during March 2020, whereas 258 counties in 172 MSAs hosted an NCAA game. All together, these 172 MSAs in which an NCAA game was played in March 2020 comprise 747 counties. Including NCAA games in our analysis may be important from an epidemiological point of view, as recent research indicates university students interact with higher numbers of other individuals on a daily basis than the general population (Weeden and Cornwell, 2020).

Third, we have obtained data on attendance for NBA and NHL games, enabling us to assess whether transmission effects increase with the number of attendees at a game. For NCAA games we are unable to obtain attendance data, but we do observe the capacity of NCAA venues. Again, this allows us to examine whether effect size increases with potential attendance.

Fourth, our observations of both games and COVID-19 outcomes extends over a longer period. Although, like Ahammer et al. (2020), we focus on games in March 2020, we extend our analysis to include games from January 1. This allows us to assess any differential effects of games held at different stages of the initial outbreak. Whereas Ahammer et al. (2020) measure cases and deaths through April 30, we extend our analysis of cases and deaths to May 31. This allows us to obtain a more complete estimate of the impact of the games that we observe.

3. Conceptual framework

The central idea in our study is that – in early 2020 – large sporting events were played during an epidemiologically sensitive period, when the virus was circulating in many cities but people were not yet taking steps to mitigate the risk of infection. Under these conditions, large sporting events may have generated a substantial number of downstream cases. However, the actual public health effects depends greatly on how many people attending the game were actually infected.

The empirical strategy we use in the paper is quite simple. We compare the severity of the COVID-19 epidemic during the first wave of the pandemic across counties and MSAs that hosted more vs fewer large sporting events during March 2020. We use OLS regressions to adjust for covariates. But the basic assumption is that the schedule of home games during the first two weeks of March 2020 is not systematically related to other factors that might explain the spread of the virus.

Although our approach is not complicated, we think it does provide some leverage to identify the causal effects of large sporting events held during the early stages of the epidemic, even when the underlying epidemiological process that generates the data is more complicated than a simple regression model implies. To help make this point, we lay out a conceptual model of the way that a large social event might affect the spread of the virus. The model itself is quite stylized and is not meant to be a realistic description of the epidemiological processes that govern the spread of COVID-19. Instead, it helps clarify the sense in which our empirical strategy is compatible with a more complicated model of epidemiological dynamics.

To start, we use \( c = 1, \ldots, C \) to index a set of communities, and we let \( v_c \) represent the degree to which the virus has started to circulate in community \( c \) during the pre-epidemic period. For simplicity, assume that \( v_c \) is normalized to have mean 0 in the average community in the population. We adopt a potential outcomes notation to define the effect of an additional large group event held in community \( c \) during the pre-epidemic period. Specifically, let \( H_c(0) = \alpha_0 + \alpha_1 v_c \) represent the severity of the epidemic in community \( c \) if the community does not hold an additional event. Similarly, let \( H_c(1) = \beta_0 + \beta_1 v_c \) represent the severity of the epidemic in community \( c \) if it does hold an additional large group event during the pre-epidemic period. Let \( D_c \) be a dummy variable indicating whether the community actually holds the additional large group event. Then the realized downstream severity of the epidemic is:

\[
H_c = H_c(0) + D_c [H_c(1) - H_c(0)]
\]

In this simple formulation, the eventual severity of the epidemic depends on both the baseline level of viral circulation in the community \( v_c \) and also on whether the community held an extra large group event during the pre-epidemic period. Specifically, \( \alpha_0 \) represents the downstream severity of the epidemic in the average community in the absence of an additional large group event. \( \beta_0 = \beta_1 = 0 \) is the average treatment effect of an extra large group event across the communities, and \( \delta_1 = \beta_1 - \alpha_1 \) captures a deviation in the average treatment effect associated with an incremental increase in the degree of pre-epidemic viral circulation in the community. Finally, \( \epsilon_c = \alpha_1 v_c + \delta_1 D_c v_c \) represents the idiosyncratic variation in the severity of the epidemic which comes from both the initial conditions and the effect of the large group event. In principle, the causal effect of the group event will be larger in communities that had higher levels of viral spread during the pre-epidemic period.

Although it is quite simple, this “random coefficients” model of the effect of large group events helps clarify three specific points. First, it provides an explanation of why large group events are safe in “normal times” and hazardous in an epidemiologically sensitive period. The treatment effect of a large event will be negligible if the virus is not circulating during the pre-epidemic period, but it may be large if the virus has started to spread. Second, the model allows for the possibility that the severity of the epidemic may vary substantially across communities due to both differences in initial conditions and differences in risky events and behaviors that occur early in the epidemic. Third, the model provides some insights into the challenges involved in identifying the causal effects of large group events during an epidemic.

In practice, the pre-epidemic spread of the virus in a community is typically unmeasured. A basic question is whether we can learn much about the average causal effect of a large group event from a regression model like:

\[
H_c = \alpha_0 + \delta_1 D_c + \epsilon_c
\]

The key assumption in a model like this is that \( E[\epsilon_c | D_c = 1] = E[\epsilon_c | D_c = 0] = 0 \). Substituting the structure of the unobserved component of the model clarifies what this means. Start with the sub-group of communities that host an extra large group event:

\[
E[\epsilon_c | D_c = 1] = E[\epsilon_c | v_c, D_c = 1] = (\alpha_1 + \delta_1) E[v_c | D_c = 1]
\]

Repeat the exercise for the sub-group of communities that do not hold a large group event:

\[
E[\epsilon_c | D_c = 0] = E[\epsilon_c | v_c, D_c = 0] = \alpha_1 E[v_c | D_c = 0]
\]

The result implies that a regression of the severity of the epidemic on pre-epidemic large events identifies the average causal effect of the large event as long as \( (\alpha_1 + \delta_1) E[v_c | D_c = 1] = \alpha_1 E[v_c | D_c = 0] = 0 \). In essence, the requirement is that the average pre-epidemic level of viral spread must be the same in communities that do and do not hold an extra event.
In particular, we argue that the timing and number of large group events during a pre-epidemic period would identify the epidemiologically sensitive periods are difficult to arrange. However, in this paper, we argue that NHL, NBA, and NCAA games held in different cities is plausibly exogenous of local variation.

4.2. Analytic samples

Most of our analysis is organized around two separate analytic samples. The first analytic sample consists of 296 counties located in the 36 MSAs that are home to an NHL or NBA team. The second sample consists of the 402 counties located in the 129 MSAs that are home to an NCAA Division 1 men’s basketball team, but do not have any professional sports teams.

The NHL/NBA and NCAA analytic samples consist of distinct (non-overlapping) sets of MSAs. Table 1 reports summary statistics for the two samples. A key difference between the two samples is that the NHL/NBA sample is made up of larger urban areas than the NCAA sample, which consists of smaller cities that are home to colleges with NCAA teams but do not host any major professional sports franchises. The average county in the NHL/NBA sample has a population of about 496,000 and was located in an MSA that held about 25 NHL/NBA games in early March 2020. In contrast, the average county in the NCAA analytic sample has a population of about 169,000 people and was located in an MSA that held about 13 NCAA Men’s Basketball games during early March 2020.

5. Econometric methods

Our analysis is organized around regression models that link games in the early spring with the downstream severity of the epidemic. We examine the effects of additional games in the county where the game was held as well as spillover effects to other counties. And we study the relationship between the epidemic and games in two non-overlapping samples to look at both college basketball games played in smaller urban areas and professional basketball and hockey games played in larger cities. Because they are based on different geographical areas and different city sizes, the two sets of results are complementary. In particular, some important threats to validity – such as the sources of cross-city variation in games, possible confounding from unmeasured city level risk factors, and out-migration of college student populations – tend to be more plausible in one of the sample and less plausible in the others.

To fix ideas, let \( y_m \) be a measure of the severity of the epidemic in county \( j \) from MSA \( m \). We focus on two outcome measures: (i) the cumulative number of confirmed COVID-19 cases per 1000 people by May 31, 2020, and (ii) the cumulative number of COVID-19 deaths per 1000 people by May 31, 2020. \( G_m \) represents the number of games played in MSA \( m \) between March 1 and March 11, 2020. Since the cumulative number of cases and deaths per 1000 people in a county are both non-

### Table 1

Summary statistics.

| Variable                      | Pro sample means | Pro sample standard deviations | NCAA sample means | NCAA sample standard deviations |
|-------------------------------|------------------|-------------------------------|------------------|-------------------------------|
| **County-level variables**    |                  |                               |                  |                               |
| Cases per 1000                | 5.678            | 9.471                         | 3.580            | 5.286                         |
| Deaths per 1000               | 0.295            | 0.425                         | 0.171            | 0.275                         |
| County population (1000s)     | 496.475          | 989.525                       | 169.406          | 254.602                       |
| County population density     | 942.658          | 1882.178                      | 248.431          | 222.857                       |
| Percent male                  | 0.493            | 0.012                         | 0.495            | 0.019                         |
| Percent Black                 | 0.129            | 0.143                         | 0.129            | 0.154                         |
| Percent Hispanic              | 0.122            | 0.120                         | 0.087            | 0.124                         |
| Percent 65+                   | 0.158            | 0.033                         | 0.171            | 0.036                         |
| **MSA-level variables**       |                  |                               |                  |                               |
| NHL/NBA March games in MSA    | 3.750            | 3.202                         | 0.992            | 1.064                         |
| NHL/NBA teams in MSA          | 2.833            | 1.797                         | 1.326            | 0.651                         |
| MSA population density        | 1.361            | 1.073                         | 527.917          | 513.261                       |
| MSA population (1000s)        | 4082.130         | 3692.281                      | 248.431          | 222.857                       |
| N                             | 296              | 402                           |                  |                               |

An experiment that randomly assigned some communities to hold a large group event during a pre-epidemic period would identify the average effect even though the effect in any given community would depend on the unmeasured level of viral spread at baseline.

In practice, randomized experiments of large group events during epidemiologically sensitive periods are difficult to arrange. However, in this paper, we argue that NHL, NBA, and NCAA games held in different cities during March 2020 are a close approximation to the ideal randomized experiment. In particular, we argue that the timing and number of games held in different cities is plausibly exogenous of local variation in the initial severity of the epidemic and of other risk factors that may have affected the early spread of the virus.

4. Data

4.1. Data sources

We use county-level data on confirmed cases of COVID-19 and COVID-19 deaths through May 31, 2020 from the database maintained by The New York Times (2020). We choose this date as this roughly corresponds to the end of the first wave of the pandemic in the US. In a few cases the New York Times data use non-standard geography, combining cases and deaths from certain counties. Most importantly, the five counties in New York City (New York, Kings, Queens, Bronx and Richmond counties) are combined into a single geographical unit.

We collected data on 2019–2020 National Hockey League (NHL) hockey games from The Hockey Reference website (Hockey Reference, 2020). Data on National Basketball Association (NBA) games came from the Basketball Reference website (Basketball Reference, 2020). For each team, we counted the number of home games played from March 1 through March 11 (for some robustness checks we use games played from January 1 to March 11), when both leagues canceled the remainder of the 2019/2020 season. We excluded games played outside the US because our COVID-19 case data is only for the US. We also collected data on NCAA men’s college basketball games during the same time period, for all 353 Division 1 teams, using ESPN’s website (ESPN, 2020). We included regular-season games and any home conference-tournament games played. Finally, we collected data on the number of professional basketball, hockey, baseball, and football franchises operating in each county and MSA.

We incorporate covariates into some regression models and we also gathered additional covariate data to help shed light on several potential threats to the internal validity of our study. Specifically, we use U.S. Census Bureau data to measure county and MSA population and population density, and the fractions of each county’s population that is male, Black, Hispanic, and over age 65. We obtained data on the number of influenza deaths in each county in 2019 from the CDC Wonder database. We use Department of Transportation data to measure the on the total number of airplane passengers who flew into the MSA from Italy in the first quarter of 2020. We used data from National Oceanic and Atmospheric Administration to estimate the average daily air temperature between January 1, 2020 and March 31, 2020 for each county. Finally, we use data from the Covid Tracking Project to measure the number of COVID-19 tests conducted in each county.

### 4.2. Analytic samples

Most of our analysis is organized around two separate analytic samples. The first analytic sample consists of 296 counties located in the 36 MSAs that are home to an NHL or NBA team. The second sample consists of the 402 counties located in the 129 MSAs that are home to an NCAA Division 1 men’s basketball team, but do not have any professional sports teams.

The NHL/NBA and NCAA analytic samples consist of distinct (non-overlapping) sets of MSAs. Table 1 reports summary statistics for the two samples. A key difference between the two samples is that the NHL/NBA sample is made up of larger urban areas than the NCAA sample, which consists of smaller cities that are home to colleges with NCAA teams but do not host any major professional sports franchises. The average county in the NHL/NBA sample has a population of about 496,000 and was located in an MSA that held about 25 NHL/NBA games in early March 2020. In contrast, the average county in the NCAA analytic sample has a population of about 169,000 people and was located in an MSA that held about 13 NCAA Men’s Basketball games during early March 2020.

### 5. Econometric methods

Our analysis is organized around regression models that link games in the early spring with the downstream severity of the epidemic. We examine the effects of additional games in the county where the game was held as well as spillover effects to other counties. And we study the relationship between the epidemic and games in two non-overlapping samples to look at both college basketball games played in smaller urban areas and professional basketball and hockey games played in larger cities. Because they are based on different geographical areas and different city sizes, the two sets of results are complementary. In particular, some important threats to validity – such as the sources of cross-city variation in games, possible confounding from unmeasured city level risk factors, and out-migration of college student populations – tend to be more plausible in one of the sample and less plausible in the others.

To fix ideas, let \( y_m \) be a measure of the severity of the epidemic in county \( j \) from MSA \( m \). We focus on two outcome measures: (i) the cumulative number of confirmed COVID-19 cases per 1000 people by May 31, 2020, and (ii) the cumulative number of COVID-19 deaths per 1000 people by May 31, 2020. \( G_m \) represents the number of games played in MSA \( m \) between March 1 and March 11, 2020. Since the cumulative number of cases and deaths per 1000 people in a county are both non-
negative and skewed, we specify an exponential conditional mean function linking the severity of the epidemic by the end of May with games played in March:

\[ Y_{jm} = \exp(x_{jm} \beta + G_{jm}) + \epsilon_{jm} \]

In the model, \( x_{jm} \) represents a vector of pre-epidemic county covariates and includes a constant. \( \beta \) is the associated vector of coefficients. \( \epsilon_{jm} = Y_{jm} - E[Y_{jm} | x_{jm}, G_{jm}] \) is the conditional expectation function (CEF) residual. \( \Delta = 100 \times [\exp(\delta) - 1] \) represents the percent increase in cases per 1000 people (or deaths per 1000 people) generated by a one additional game played in the county. We estimate the coefficients using a Poisson regression and use a cluster robust variance matrix to compute standard errors that allow for dependence across observations from the same MSA and to accommodate heteroskedasticity.\(^1\)

5.1. Threats to validity

This model identifies the effect of an additional game on the downstream severity of the epidemic under the assumption that after adjusting for the covariates in \( x_{jm} \), counties with more home games in the pre-epidemic period did not have any systematic differences in unmeasured characteristics that would have led them to have more severe epidemics by May 31, 2020 in the absence of a difference in games. The assumption seems credible given that the schedule of home games was determined long before the start of the COVID-19 epidemic.

Viewed at the level of individual teams, the case for the study design is quite strong. Over the course of the entire season, each team plays the same number of home games and away games. But the distribution of home games and away games is not balanced across teams over shorter segments of the season. And during the epidemiologically sensitive period running from March 1 to the end of the season on March 11, some cities were scheduled for more home games than others. However, the unit of analysis in the study is not a sports franchise, it is the population of people living in the county or MSA where the games take place. In practice, some counties and MSAs are home to more than one professional or college sports team. This means that there are really two sources of variation in the number of March games across cities: variation due to scheduling, and variation due to the total number of teams playing in the county or MSA. Although the number of teams in a county or MSA is also pre-determined relative to the epidemic, the number of teams is not randomly assigned across cities.

The main threat to validity in the model stems from the possibility that some of the variation in the number of home games in a county arises because larger counties or MSAs are more likely to host multiple professional teams. Locations with more teams will have more games, but they may also have larger populations, higher population density, more domestic and international travel, more frequently-used public transportation systems, and more events and activity of other kinds, as well. If SARS-CoV-2 spreads more easily or is more deadly because of a collection of factors that may be associated with the number of teams in the city, then our analysis might suffer from omitted variable bias that would make the effect of a game look worse than it really is in practice. Our regression models adjust for the number of teams in an MSA, county population, county population density, and the demographics of each county. These factors may account for most of the important sources of heterogeneity across cities when it comes to viral transmission. But we cannot fully rule out the possibility cities with more teams are different in other ways that are harder to measure but may also be associated with the spread of the epidemic.

We pursue a number of robustness checks and sensitivity analysis to help assess concerns about confounding from unmeasured factors. We obtained data on four possible confounders that may played a role in the early transmission of the virus or that may serve as reasonable proxy measures of such confounders (temperature, 2019 flu deaths, Italian airplane passengers, and the number of COVID-19 tests conducted by May 31, 2020). We treat these as “extra covariates” and assess their balance across levels of the March Games variable. In addition, we study the extent to which the relationship between the severity of the epidemic and sporting events is driven by games in March rather than games over a longer time horizon. The variation in games played between January and March comes mainly from the number of teams in a city and many of the games likely occur before the virus had begun to circulate. In contrast, quasi-random scheduling variation plays a bigger role cross-city variation in games played in the first 11 days of March and the games are played during an epidemiologically sensitive period in which the virus was circulating but was still quite rare and badly understood by the population. A strong association in March that decays when games from earlier in the season are included would supports a causal interpretation of our main analysis.

To help mitigate concerns that stem from variation in the number of teams in an MSA, we include controls for the number of teams operating in the MSA in our regression models. Our main specifications include a dummy variable set to 1 if the MSA is home to multiple professional sports teams. In principle, controlling for the number of teams means that the coefficient on the number of games in March is identified mainly by scheduling variation that is independent of the number of teams. However, there are limits to this strategy of controlling for both March games and number of teams because the two variables are highly correlated. Fig. 5 shows the connection between March games and number of teams because the two variables are highly correlated. Fig. 5 shows the connection between March games and number of teams in the MSA on the vertical axis and the number of teams in the MSA on the horizontal axis. Each point in the graph is a county and we jittered the number of teams in the county to make the graph more readable. There is a strong relationship between March games and number of teams in the professional sample. In contrast, the connection between number of teams and March games is much weaker in the NCAA sample, which consists of counties located in an MSA that has at least one Division I NCAA Men’s Basketball team but is not home to any professional sports franchises.

Although our main specifications adjust for the presence of 2 or more teams in the MSA, later in the paper, we report sensitivity analysis in which we adjust for the number of teams in an MSA more flexibly to try to isolate “pure” scheduling variation and to attempt to account for possible confounding that might occur if the number of teams in city is indeed associated with other unmeasured factors that affect the early severity of the epidemic. We also examine models in which we use the number of MLB and NFL teams as an alternative measure of a multi-team city that is less collinear with the number of NHL/NBA games played in March. Finally, analysis of the NCAA sample itself may be the best check against concern that the number of teams in the city is associated with other sources of confounding.

\(^1\) In this case, the exponential model is roughly equivalent to fitting OLS regressions of log cases per 1000 and log deaths per 1000 on covariates and games. However, some counties have zero cases or deaths and so the log is not defined. The Poisson estimator offers a similar functional form but accommodates cases where the outcome is equal to zero in some cases. Gourieroux et al. (1984) show that the Poisson quasi-MLE is a consistent estimator of the parameters of the conditional expectation function under the assumption that \( E[Y_{jm} | x_{jm}, G_{jm}] = \exp(x_{jm} \beta + G_{jm}) \) only and that a full specification of the Poisson density function is not required. The conventional Poisson estimator of the variance matrix is restrictive and requires that the conditional variance function is equal to the conditional mean function, an assumption that is often violated due to overdispersion or heteroskedasticity. Accordingly, we estimate standard errors using a cluster robust variance matrix that allows for heteroskedasticity, overdispersion, and dependence among observations from the same MSA. See also Wooldridge (2010) for more discussion of the use of the Poisson estimator to fit models with exponential conditional mean functions but which are robust to deviations from the Poisson density function.
5.2. Geographic spillovers and attendance effects

It is likely that people commute across counties to attend games, and that fans who attend games interact with people from other counties within the MSA. This suggests that games held in one county may affect the downstream severity of the epidemic in other counties in the same MSA. At the same time, the own-county effect of a game may be larger than the spillover effect to other counties.

To explore this possibility, let $G_{jm}$ be the number of March games played in county $j$ from MSA $m$. And let $\Omega_m$ represent the set of counties contained in MSA $m$. Then $G_m = \sum_{h \in \Omega_m} G_{jm}$ is the total number of March games held in the MSA. Let $H_{jm} = G_m - G_{jm}$ be the number of games played outside of county $j$ but still inside $j$’s MSA.

To estimate the own-county and spillover effects of large sporting events on the severity of the epidemic, we fit regressions with the following form:

$$Y_{jm} = \exp[x_{jm} \beta + G_{jm} \delta_1 + H_{jm} \delta_2] + \epsilon_{jm}$$

In this model, $\delta_1$ represents the effect of a game on the county where the game was played, and $\delta_2$ represents the effect of a game played in the MSA but outside the county itself. We compute the percentage change in cases and deaths from an additional own-county game and additional out-of-county games using $\Delta_k = 100 \times \exp[\delta_k] - 1$ for $k = [1, 2]$.

Our main analysis is focused on the effect of games on the later severity of the epidemic. But it is possible that the epidemiological effect of a large group event depends on the size of the event itself. Attendance at the game may matter because larger events provide more opportunities to spread the virus than smaller events. Data on actual attendance on professional and college sporting events is not readily available. For NHL and NBA games, attendance data is based on ticket sales which could be misleading if some people bought tickets but chose not to attend in early March. For NCAA basketball games, attendance data is even more scarce and the closest proxy is the seating capacity of the stadium. Although both of these measures are problematic, we explored the possibility of a dose-response relationship between the severity of the epidemic by the end of May 2020 and attendance/capacity measures associated with March games using models with the following structure:

$$Y_{jm} = \exp[x_{jm} \beta + A_m \delta] + \epsilon_{jm}$$

In these models, $A_m$ represents the total number of tickets sold, which may differ from actual attendance. We view these variables as measures
of “potential” game attendance in early March.

6. Results

We present the results of our analysis in four parts. First, we present simple visual evidence of the basic associations that underlie our analysis. Then we examine regression based evidence (and related sensitivity analysis) for professional sports sample. In the third set of results, we examine regression based estimates for the college sample. Finally, we present some additional analysis of spillover effects and attendance effects in both samples.

6.1. Visual evidence on sporting events and downstream cases and deaths

The mechanism underlying our analysis is that large sporting events increase social interaction, thereby increasing the transmission of the Coronavirus. In order to validate this mechanism, we gathered cellphone data from SafeGraph. Fig. 1 compares the average number of cellphone visits around each stadium in our professional sports sample on game days versus non-game days for each day from January 1, 2020 to March 11, 2020. The horizontal axis reports the combined number of NHL and NBA games played in the MSA where the county is located between March 1, 2020 and March 12, 2020. The vertical axis in the left panel measures the cumulative number of confirmed cases of COVID-19 per 1000 people in the county as of May 31, 2020. In the right panel, the vertical axis measures the cumulative number of COVID-19 deaths per 1000 people in the county as of May 31, 2020. The slope of the fitted line is .95 in the left panel and .071 in the right panel.
Although it is likely that stadiums sometimes host large non-sports events (such as concerts) on days when the stadium is not scheduled to host a sports event, the figure makes it clear that there are many more visits to the areas surrounding the stadiums on game days compared to off days during the pre-epidemic period in our study. This provides evidence that although other events may substitute for large, professional sporting events, they are a far from perfect substitute. Thus, the cellphone mobility data validate our central assumption, that large sporting events do increase the level of physical interaction between people. These data also show a small decline in cellphone mobility around the stadium at the end of February and early March, suggesting that attendance did decline slightly.

Fig. 3 shows the association between the number of home games in a county and the severity of the epidemic for the 296 counties in MSAs with an NBA or NHL team. In both panels, the horizontal axis measures the number of home games that occurred between March 1 and March 11, 2020. In the left panel, the vertical axis measures the cumulative number of COVID-19 cases per 1000 people as of May 31, 2020. The right panel shows the COVID-19 deaths per 1000, also as of May 31, 2020. Each point in the scatter plot is one of the 296 counties in MSAs that are home to at least one NHL or NBA team. Both cases and deaths are higher in counties that had more home games between March 1 and March 11. The slope of the simple regression line suggests that one additional NBA or NHL game during the early epidemic period is associated with a 0.95-unit (17%) increase in the number of cases and a 0.07-unit (24%) increase in the number of deaths per 1000 people in a county by May 31.

Fig. 4 shows the association between NCAA games and downstream cases and deaths for the 402 counties in MSAs that are home to at least one Division I NCAA men’s basketball team but are not home to any professional sports teams. Both cases and deaths are higher in counties in MSAs that had more home games between January and early March. The slope of the simple regression line suggests that one additional NCAA men’s basketball game during the early epidemic period is associated with a 0.88-unit (24%) increase in the number of cases and a 0.07-unit (41%) increase in the number of deaths per 1000 people in a county by May 31.

Table 2  
Effect of NHL/NBA March 2020 games.

| Panel A: Cases per 1000 | (1) | (2) | (3) | (4) |
|------------------------|-----|-----|-----|-----|
| Games in MSA | 0.114*** | 0.104*** | 0.153*** | 0.159*** |
| (0.022) | (0.026) | (0.052) | (0.048) |
| 2+ teams in MSA | 0.518 | 0.642 | 0.475 |
| (0.379) | (0.419) | (0.345) |
| Logged population in MSA | – 0.512* | – 0.719** |
| (0.278) | (0.293) |
| Logged population density in MSA | 0.232 | 0.762* |
| (0.411) | (0.415) |
| Constant | 1.160*** | 0.756** | 6.708* | 8.715* |
| (0.218) | (0.320) | (4.077) | (4.768) |
| Demographic controls | X |
| N | 296 | 296 | 296 | 296 |

| Panel B: Deaths per 1000 | (1) | (2) | (3) | (4) |
|-------------------------|-----|-----|-----|-----|
| Games in MSA | 0.147*** | 0.134*** | 0.181** | 0.203*** |
| (0.021) | (0.026) | (0.086) | (0.061) |
| 2+ teams in MSA | 0.951*** | 1.071** | 1.104** |
| (0.339) | (0.430) | (0.452) |
| Logged population in MSA | 0.733** | 0.926*** |
| (0.344) | (0.347) |
| Logged population density in MSA | 0.533 | 0.780 |
| (0.673) | (0.550) |
| Constant | 2.023*** | 2.805*** |
| (0.253) | (0.244) |
| Demographic controls | X |
| N | 296 | 296 | 296 | 296 |

Sample is all counties in MSAs with NHL/NBA teams. Standard errors are clustered by MSA. *Statistical significance at the 10% level; **significance at the 5% level; ***significance at the 1% level. Dependent variables are cases/deaths per 1000 people. Cases and deaths are measured through May 31st.
Table 2 reports estimated coefficients from Poisson regressions based on the sample of 296 counties in MSAs that have an NHL or NBA team. Column (1) is a basic model with no covariates. Column (2) controls for whether a county has more than one team major professional sports team. Column (3) adds a control for the log of the county population and the log of the county population density. Column (4) adds controls for county level demographics (percent male, percent Black, percent Hispanic, percent over age 65). Panel A reports results from models where the outcome is the number of COVID-19 cases per 1000 population as of May 31, 2020. Panel B shows results from models of the number of COVID-19 deaths per 1000 as of May 31, 2020. Throughout, we compute the percent change in cases and deaths per 1000 people in a county as $\%\Delta = 100 \times [\exp(\delta) - 1]$, where $\delta$ is the coefficient on the number of games played in the surrounding MSA.

The results of the full model in Panel A reveal that an additional NHL/NBA game in an MSA increases downstream cases per 1000 people in a county within the MSA by about 17.2%. Similarly, the results of Panel B reveal that an additional game increases downstream deaths per 1000 people in the county by 22.5%. Both of these effects are statistically significant at the .01 level, based on standard errors that are clustered at the MSA level. To put these results in perspective, we used the estimated coefficients from the full model to estimate the number of additional cases and deaths that would have occurred in an MSA, if each MSA had held one more game than it actually did. Specifically, we let $Y_{jm}^{real}$ be the predicted number of cases per 1000 people in county $j$ from MSA $m$ based on the realized values of the county’s covariates and games variable. And we let $Y_{jm}^{extra}$ be the predicted number of cases per 1000 people if the MSA had held one additional game. The implied number of induced cases in the county is $NC_{jm} = (Y_{jm}^{extra} - Y_{jm}^{real}) \times \frac{Pop_{jm}}{1000}$.

We sum these estimates of the number of new cases across all of the counties in each MSA to obtain estimates of the number of new cases in each MSA in our sample. We use the same method to estimate the number of additional deaths expected from hosting one additional game in March. In the average MSA, hosting one additional game would have led to 7520 additional cases and 658 additional COVID-19 deaths. Across the 36 MSAs in our professional sports sample, an additional game in each MSA would generate over 270,000 additional cases of COVID-19 and more than 23,000 additional COVID-19 deaths.

One challenge in identifying the effect of games on cases and deaths is that while some of the variation in the number of home games is a function of team schedules, which are plausibly exogenous, Fig. 5 above clearly shows that the number of home games in an MSA also depends heavily on the number of NBA/NHL teams located in that MSA. This relationship poses a threat to validity because the number of teams in an MSA may be correlated with unobserved local factors, including other large events (concerts, plays, conventions, etc.), as well as number of visitors, mass transit usage, etc.
To assess the extent to which our main results are identified based on exogenous scheduling variation, we examine how our results change as we consider the effect of games played in successively shorter periods of time. We first look at the effect of all games played during 2020. During the long time period, most of the variation in the number of games played in an MSA comes from the number of teams hosted by the MSA. Then, we exclude games played during the first half of January 2020 from our sample. Then we exclude all of January 2020, then all of February, recreating our primary analysis, which is based on games played only during March 2020. The idea is that as we increase the fraction of the season that we include in our analysis, the amount of variation in number of games that is explained by exogenous scheduling differences declines. At the extreme, if we include the entire season of games, then the only variation in games comes from the number of teams.

The results reveal that as the period of included games gets shorter, the effect of games increases, with the largest effect when we limit our sample to March 2020. These results provide strong evidence that our results are being driven by the scheduling variation in games rather than unobserved cross-sectional variation correlated with variation in the number of teams across MSAs. In addition, the stronger effects that we observe in March are consistent with the fact that by that point, there were many more infected (and still unaware) people to transmit the disease. In contrast, the games played in January would be expected to have less effect because there were many fewer infected people then.

As noted above, if the number of teams in an MSA is correlated with other factors that increase the spread of the virus (e.g., mass transit usage, more international travelers, more concerts, plays, conventions, etc.), then it is important to include the number of teams in our regression model. However, the relationship between games and teams is so mechanically strong, that including both variables incorporates high levels of multicollinearity into the regression.

In our main specifications we attempt to balance these conflicting concerns by including a dummy variable for MSAs with at least two professional sports teams. In this way, we attempt to control for the unobservable characteristics correlated with number of teams, but use a dummy variable to reduce the collinearity between number of games and teams.

To further investigate how the number of teams influences our results, in Table 4 we report estimates from models that adjust for the number of teams in an MSA in several different ways. Column 1 repeats our main specification from Table 2, which adjusts for a dummy variable indicating that the MSA is home to 2 or more teams. Column 2 includes a
count of the total number of professional sports teams (NBA, NHL, MLB, and NFL) in the MSA. In this specification, the coefficient on games becomes negative, and the standard error is inflated by more than 50%.

In an effort to better control for unobserved city characteristics correlated with the number of professional teams, while avoiding the instability associated with the multicollinearity between games and teams, we break the number of professional sports teams in an MSA into two components: NBA/NHL teams and MLB/NFL teams. NBA/NHL teams can serve as a proxy for unobservable local characteristics related to the spread of the virus and are also highly correlated with the number of home games in March. In contrast, the number of MLB/NFL teams in an MSA is not very correlated with the number of March NBA/NHL home games.

In column 4, we control for the count of MLB/NFL teams only. When we do so, the coefficient on games remains positive and statistically significant. Similarly, in column 5 we control for both the count of MLB/NFL teams, and a dummy variable indicating MSAs with at least two NBA/NHL teams. In this way, we try to further control for any additional correlation between teams and unobserved local factors, while still limiting the multicollinearity between NBA/NHL teams and games. Again, the coefficient on games is little changed, revealing a large positive and statistically significant effect. These results suggest that multicollinearity between NBA/NHL teams and makes our results unstable when we try to adjust too finely for the number of NHL/NBA teams. At the same time, the analysis based on MLB/NFL teams provide some support that the number of home games does causally affect cases and deaths, even after adjusting for unobservable local characteristics that might be correlated with the presence of professional sports teams.

To further explore whether our results are biased by local characteristics, we run a series of balancing regressions, where we examine the regression adjusted association between March 2020 games and various local characteristics that might also be correlated with the spread of the virus. In particular, we focus on four factors that are not included in our main analysis but which may proxy for some of the kinds of factors that

Table 5: Effect of NHL/NBA March 2020 games – additional local variables.

|                  | (1)         | (2)         | (3)         | (4)         | (5)         | (6)         |
|------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| **Panel A: Cases per 1000** |             |             |             |             |             |             |
| Games in MSA     | 0.1595***   | 0.1445**    | 0.1441***   | 0.0513      | 0.0424      | 0.0276      |
| (0.0482)         | (0.0626)    | (0.0502)    | (0.0549)    | (0.0287)    | (0.0607)    |
| Average air temperature | – 0.1999   |             |             |             |             |             |
| (0.0243)         |             |             |             |             |             |             |
| 2019 state flu death rate | 80.8399*** |             |             |             |             |             |
| (26.1931)        |             |             |             |             |             |             |
| Passengers from Italy Q1 2020 | 0.0001**   |             |             |             |             |             |
| (0.0000)         |             |             |             |             |             |             |
| Testing per state population |             |             |             |             |             |             |
| 2+ teams         | 0.4749      | 0.4454      | 0.6897      | 0.7611**    | 0.3651      | 0.7340**    |
| (0.3451)         | (0.3742)    | (0.4300)    | (0.3224)    | (0.3523)    | (0.3246)    |
| Logged population in MSA | – 0.7194** | – 0.6381**  | – 0.5698**  | – 0.9132*** | – 0.3306    | – 0.7312**  |
| (0.2934)         | (0.2986)    | (0.2795)    | (0.3432)    | (0.2289)    | (0.3134)    |
| Logged population density in MSA | 0.7616*     | 0.6958*     | 0.6901      | 0.7628**    | 0.5739**    | 0.7870*     |
| (0.4154)         | (0.4026)    | (0.4226)    | (0.3888)    | (0.2398)    | (0.4080)    |
| Constant         | – 8.7148*   | – 9.6521*   | – 9.8007**  | – 5.6454    | – 13.5235***| – 7.5791    |
| (4.7680)         | (5.6973)    | (4.7503)    | (4.9832)    | (3.1540)    | (4.8510)    |
| Demographic controls | X           | X           | X           | X           | X           | X           |
| N                | 296         | 296         | 295         | 294         | 296         | 277         |
| **Panel B: Deaths per 1000** |             |             |             |             |             |             |
| Games in MSA     | 0.2035***   | 0.1857**    | 0.1973***   | 0.0920      | 0.0929**    | 0.0680      |
| (0.0615)         | (0.0790)    | (0.0638)    | (0.0775)    | (0.0406)    | (0.0835)    |
| Average air temperature | – 0.0288   |             |             |             |             |             |
| (0.0292)         |             |             |             |             |             |             |
| 2019 state flu death rate | 31.6207    |             |             |             |             |             |
| (30.1743)        |             |             |             |             |             |             |
| Passengers from Italy Q1 2020 | 0.0000*    |             |             |             |             |             |
| (0.0000)         |             |             |             |             |             |             |
| Testing per state population |             |             |             |             |             |             |
| 2+ teams         | 1.1036***   | 1.0571**    | 1.2042**    | 1.3540***   | 0.9837***   | 1.3250***   |
| (0.4516)         | (0.5131)    | (0.4901)    | (0.4117)    | (0.3924)    | (0.4325)    |
| Logged population in MSA | – 0.9362***| – 0.7946**  | – 0.8852*** | – 1.1509*** | – 0.5645*   | – 0.9613*** |
| (0.3469)         | (0.3410)    | (0.3403)    | (0.3919)    | (0.3111)    | (0.3640)    |
| Logged population density in MSA | 0.7796      | 0.6176      | 0.7354      | 0.8626      | 0.6407*     | 0.8852      |
| (0.5503)         | (0.5031)    | (0.5525)    | (0.5464)    | (0.3838)    | (0.5678)    |
| Constant         | 7.5641      | 7.2802      | 6.3151      | 7.6431      | 6.4190      | 4.8132      |
| (7.1701)         | (8.0877)    | (6.8522)    | (6.7171)    | (4.7974)    | (4.1596)    |
| Demographic controls | X           | X           | X           | X           | X           | X           |
| N                | 296         | 296         | 295         | 294         | 296         | 277         |

Sample is all counties in MSAs with NHL/NBA teams. Column 1 is the main NBA/NHL regression results; column 2 includes temperature as a covariate; column 3 includes the 2019 flu death rate as a covariate; column 4 includes Italian passengers as a covariate; column 5 includes testing per population as a covariate; column 6 drops observations in the NY MSA. Standard errors are clustered by MSA. *Statistical significance at the 10% level; **significance at the 5% level; ***significance at the 1% level. Dependent variables are cases/deaths per 1000 people. Cases and deaths are measured through May 31st.
might be thought to confound the connection between games and downstream COVID-19 infections and deaths: average temperature in Celsius in March; 2019 state flu deaths per capita; number of passengers per capita arriving in an MSA from Italy during the first quarter of 2020; and the number of COVID-19 tests per capita conducted in the state by the end of May 2020. Cities with warmer temperatures in March may be more likely to have other kinds of activities that increase social interaction and virus transmission. Similarly, cities in states that had higher rates of flu deaths in 2019 may be more susceptible to local outbreaks of transmittable diseases. Cities with more passengers arriving from Italy in the first quarter of 2020 may have been more likely to experience a major outbreak during the first wave of the pandemic, as travelers from Italy appear to have contributed to the spread of the virus in the US (Prince and Simon, 2020). Finally, we would expect reported cases to depend on the testing rate in the state.

We report these results in Table 4. The results in the first column reveal that, in our sample of MSAs with NBA/NHL teams, all four variables are statistically significantly correlated with the number of games in the MSA, even after adjusting for the covariates included in our main specifications. Counties in MSAs with more games tend to have lower temperature in March, more 2019 flu deaths, more passengers arriving from Italy during Q1 2020, and tend to be located in states that conducted fewer tests per capita. These results reveal a positive effect of March 2020 games on both games and deaths. Although the coefficient on March games is not statistically significant in the full model of cases (Panel A), the results in Panel B indicate that each additional home game in March 2020 increased deaths by about 28%. These results correspond to an additional 34 deaths per MSA. Across the 129 MSAs in our professional sports sample, an additional game in each MSA would generate nearly 4400 additional COVID-19 deaths.

Table 6 shows estimated Poisson regression coefficients for models of cases and deaths using data from the 402 counties located in MSAs with NCAA teams and no professional teams. Panel A shows models of cases per 1000. And Panel B shows models of deaths per 1000. The estimates reveal a positive effect of March 2020 games on both games and deaths. However, our results appear to be sensitive to the inclusion of the NYC area. To further assess whether these local characteristics are influencing our results, we rerun our full model, including each of the four local measures. We report these results in Table 5. Controlling for average March temperature, 2019 flu deaths, and number of COVID-19 tests has very little effect on our results. When we control for number of passengers arriving from Italy, our estimated coefficient on games is smaller, and noisier.

Another concern is that perhaps our results are all being driven by New York City (NYC), which suffered the worst outbreak during first wave of the pandemic. To examine this issue, we re-estimate our full model excluding the 19 counties in the NYC MSA. We report these results in column 5. Consistent with these concerns, we find that the effect of March 2020 games is smaller and noisier when we exclude the NYC MSA. These results are also consistent with the results above showing that the inclusion of passengers arriving from Italy reduces the estimated impact of NBA/NHL games.

Taken together, the above results provide substantial evidence that the number of home NBA/NHL games in an MSA during March 2020 increased COVID-19 cases and deaths. However, our results appear to be sensitive to the inclusion of the NYC area.

6.3. Effects of college sporting events

To better identify the effects of games, we turn to our analysis of NCAA games played in MSAs without any professional sports teams. From a study design point of view, the college sample has several advantages over the professional sample. The MSAs in the college sample have smaller populations and are generally a more homogeneous collection of cities than the MSAs in the professional sample. By focusing on the college sample, we avoid many of the concerns about unobserved and possibly unique local characteristics of the largest urban areas included in the professional sample. Moreover, the college sample excludes NYC, precluding concerns that the results are driven by one large MSA that had a severe early outbreak of Covid-19. Furthermore, as shown in Fig. 5 there is a much weaker relationship between teams and games in the NCAA sample.

Table 6 shows estimated Poisson regression coefficients for models of cases and deaths using data from the 402 counties located in MSAs with NCAA teams and no professional teams. Panel A shows models of cases per 1000. And Panel B shows models of deaths per 1000. The estimates reveal a positive effect of March 2020 games on both games and deaths. Although the coefficient on March games is not statistically significant in the full model of cases (Panel A), the results in Panel B indicate that each additional home game in March 2020 increased deaths by about 28%. These results correspond to an additional 34 deaths per MSA. Across the 129 MSAs in our professional sports sample, an additional game in each MSA would generate nearly 4400 additional COVID-19 deaths.

As we did for the professional sports sample, we again examine how the effect of games increases as we successively restrict attention to games played in a shorter and later time period. We report the results of this analysis in Fig. 7.

Just as we saw in the professional sample, the effect of a home game steadily increases as we restrict the home games to a shorter and later period. The largest effect is for games played in March 2020. Again, this provides support that our results reflect scheduling variation rather than variation from the number of teams in the MSA, which may be correlated with unobserved local factors.

Next, we consider different measures of the number of teams in the MSA, to assess whether we find evidence of multicollinearity or

---

Table 6

|                      | (1)  | (2)  | (3)  | (4)  |
|----------------------|------|------|------|------|
| **Panel A: Cases per 1000** |      |      |      |      |
| Games in MSA         | 0.196*** | 0.199*** | 0.197*** | 0.068  |
|                      | (0.034) | (0.049) | (0.048) | (0.055) |
| 2+ NCAA teams in MSA | 0.014  | 0.277  | 0.192  |      |
|                      | (0.230) | (0.251) | (0.209) |      |
| Logged population in MSA | −0.310* | 0.412*** | (0.181) | (0.148) |
|                      | (0.182) | (0.138) |      |      |
| Logged population density in MSA | 0.004  | 0.290** | (0.118) | (0.126) |
|                      | (2.431) | (1.792) |      |      |
| Demographic controls | X    |      |      |      |
| N                    | 402  | 402  | 402  | 402  |

|                      | (1)  | (2)  | (3)  | (4)  |
| **Panel B: Deaths per 1000** |      |      |      |      |
| Games in MSA         | 0.313*** | 0.284*** | 0.312*** | 0.247*** |
|                      | (0.042) | (0.071) | (0.081) | (0.068) |
| 2+ NCAA teams in MSA | 0.164  | 0.088  | −0.018 |      |
|                      | (0.295) | (0.323) | (0.301) |      |
| Logged population in MSA | 0.306** | 0.485*** | (0.155) | (0.146) |
|                      | (0.186) | (0.170) |      |      |
| Logged population density in MSA | 0.662*** |      |      |      |
| Constant             | 2.229*** | 2.252*** | (1.980) | (2.236) |
|                      | (1.45)  | (1.14)  |      |      |
| Demographic controls | X    |      |      |      |
| N                    | 402  | 402  | 402  | 402  |
Evidence that our estimated effect of games is biased by unobserved local factors correlated with the number of teams in the MSA. We report these results in Table 7. Column 1 repeats our main specification, where we include a dummy for MSAs with two or more NCAA teams. In column 2, we replace the dummy with a count of the number of teams in the MSA. Column 3 includes the log of teams in the MSA. The results are robust across all three specifications, suggesting that the dummy for two or more teams is effectively controlling for any local factors correlated with number of teams. At the same time, consistent with the evidence in Fig. 5, these results provide no evidence that multicollinearity between number of teams and games leads to unstable or noisy estimates of the effects of March games in the college sample.

To further explore whether our results are biased by local characteristics, we examine the four additional variables discussed above: average temperature in March; 2019 state flu deaths per capita; number of passengers per capita arriving in an MSA on flights from Italy during the first quarter of 2020 (Q1 2020); and the number of COVID-19 tests per capita conducted in the state by the end of May 2020 Fig. 8.

The balancing regressions in Table 4 provide no evidence that these local factors are correlated with the number of games in the MSA in the college sample. Table 8 shows estimates from augmented regressions that include these additional variables as covariates in our full model. Consistent with the balancing table results, the coefficient on games is not affected by the inclusion of any of these additional local factors. Taken together, these results provide no evidence that multicollinearity between number of teams and games leads to unstable or noisy estimates of the effects of March games in the college sample.

Although the estimates from the college sample are quite robust, one might be skeptical because nearly all universities shut down in late March 2020, sending students home. This raises the question of whether we should observe an effect of these games in the MSAs where they occurred, if so many students left shortly after the games were played.

We believe there are several reasons to think that the estimates from our regressions are plausible and accurate. First, nearly all universities remained open through March 11 (Mangrum and Niekamp, 2020), when the last games in our sample were played. Second, because our results reveal larger (and statistically significant) effects for deaths, we suspect evidence that our estimated effect of games is biased by unobserved local factors correlated with the number of teams in the MSA. We report these results in Table 7. Column 1 repeats our main specification, where we include a dummy for MSAs with two or more NCAA teams. In column 2, we replace the dummy with a count of the number of teams in the MSA. Column 3 includes the log of teams in the MSA. The results are robust across all three specifications, suggesting that the dummy for two or more teams is effectively controlling for any local factors correlated with number of teams. At the same time, consistent with the evidence in Fig. 5, these results provide no evidence that multicollinearity between number of teams and games leads to unstable or noisy estimates of the effects of March games in the college sample.

To further explore whether our results are biased by local characteristics, we examine the four additional variables discussed above: average temperature in March; 2019 state flu deaths per capita; number of passengers per capita arriving in an MSA on flights from Italy during the first quarter of 2020 (Q1 2020); and the number of COVID-19 tests per capita conducted in the state by the end of May 2020 Fig. 8.

The balancing regressions in Table 4 provide no evidence that these local factors are correlated with the number of games in the MSA in the college sample. Table 8 shows estimates from augmented regressions that include these additional variables as covariates in our full model. Consistent with the balancing table results, the coefficient on games is not affected by the inclusion of any of these additional local factors. Taken together, these results provide strong support that in our sample of MSAs without professional teams, each NCAA game increases COVID-19 deaths in the surrounding MSA. We find no evidence that our results are biased by omitted local variables. And in the college sample, we can be confident that the connection between games and the downstream severity of the epidemic is not driven by NYC, as it is excluded from this sample.

Table 7
Effect of NCAA March games in 2020 – alternative measures of NCAA teams.

|                  | (1)  | (2)  | (3)  |
|------------------|------|------|------|
| **Panel A: Cases per 1000** |      |      |      |
| Games in MSA     | 0.068| 0.070| 0.069|
|                  | (0.055)| (0.068)| (0.065)|
| 2+ NCAA teams in MSA | 0.192| 0.209|      |
|                  | (0.209)|      |      |
| Linear teams     | 0.078|      |      |
|                  | (0.156)|      |      |
| Log teams        |      | 0.156|      |
|                  |      | (0.264)|      |
| Logged population in MSA | -0.412***| -0.397***| -0.402***|
|                  | (0.148)| (0.143)| (0.146)|
| Logged population density in MSA | 0.290***| 0.299**| 0.297**|
|                  | (0.138)| (0.147)| (0.144)|
| Constant         | -0.239| -0.561| -0.406|
|                  | (1.792)| (1.710)| (1.720)|
| Demographic controls | X  | X  | X  |
| N                | 402  | 402  | 402  |

| **Panel B: Deaths per 1000** |      |      |      |
| Games in MSA     | 0.247***| 0.282***| 0.275***|
|                  | (0.080)| (0.085)| (0.088)|
| 2+ NCAA teams in MSA | -0.018|      |      |
|                  | (0.301)|      |      |
| Linear teams     | -0.231|      |      |
|                  | (0.174)|      |      |
| Log teams        |      | -0.194|      |
|                  |      | (0.339)|      |
| Logged population in MSA | -0.371**| -0.323**| -0.331**|
|                  | (0.146)| (0.139)| (0.142)|
| Logged population density in MSA | 0.662***| 0.685***| 0.685***|
|                  | (0.170)| (0.172)| (0.174)|
| Constant         | -1.857| -2.382| -2.441|
|                  | (2.236)| (2.231)| (2.259)|
| Demographic controls | X  | X  | X  |
| N                | 402  | 402  | 402  |

Sample is all counties in MSAs with NCAA teams and no NHL/NBA teams. Standard errors are clustered by MSA. *Statistical significance at the 10% level; **significance at the 5% level; ***significance at the 1% level. Dependent variables are cases/deaths per 1000 people. Cases and deaths are measured through May 31st. Column 1 is the main specification; column 2 replaces 2+ dummy with linear teams; column 3 replaces 2+ dummy with logged teams.
that our results are being driven primarily by non-students. This could reflect non-students attending the games, as well as students infecting other students who then transmit the virus to non-students in other settings outside of the game. Third, it seems likely that students were even less likely than the rest of the population to engage in social distancing, increasing the likelihood of transmission within the student population and to non-students. Fourth, for the average school in our sample, more than 80% of students are in state, suggesting that many of them remained in the university’s MSA, even after in-person classes were halted.

To further investigate the validity of our results, we merge in data on in-state and out-of-state enrollment from the Integrated Postsecondary Education Data System (IPEDS) for a set of 203 universities in our sample that report these data to IPEDS. We then aggregate enrollments within counties, and calculate the percentage of college students in the county that are in-state. Finally, we split this sample into those counties with above and below the median percentage in-state enrollment, and we run our main specification on each sub-sample.

The results, which we report in Table 9, show that for counties with above the median in-state enrollment, games have a positive effect on both cases and deaths. For counties with below the median in-state enrollment, games have no effect on cases or deaths. These results suggest that our estimates are driven by students that remain in the MSA.

6.4. Spillovers and attendance effects

To further explore the effects of games on COVID outcomes, we conduct two final analyses. First, we examine whether attendance affects virus outcomes. Specifically, we examine whether aggregate attendance from games played in March in a given MSA increases cases in the MSA. We do this for both our professional and college samples. We report these results in Table 10. The results show that attendance at NBA/NHL games has a positive effect on both cases and deaths. In contrast, we do not find an effect for NCAA games. These results should be interpreted cautiously because the ticket sales data we use are likely an imperfect proxy for true attendance.

Second, we examine whether the effect of games on the severity of the COVID-19 epidemic is different for counties where the games are actually played as opposed to the other counties in the MSA. Therefore, Table 11 reports results for counties where the game occurred and counties that are in the MSA but did not host a game. The results reveal that the effect of a game is just as large in the surrounding counties as it is in the county where the game is actually played.

We also tested whether NCAA results were different for games in county as opposed to games in MSA but not in county. Although the results are quite noisy, they suggest that the effect of NCAA games is actually larger outside of the county where they were held. This seems consistent with many students leaving campus, but remaining in the MSA where the school is located.

7. Discussion

A key challenge in identifying the causal effects of gatherings and social distancing is a fundamental simultaneity: bans on large gatherings may reduce case rates and mortality, but high case rates and mortality may also cause people to avoid large gatherings. We break this simultaneity by exploiting plausibly exogenous variation in the scheduling of sporting events across counties and MSAs. Team schedules were all determined prior to the arrival of the virus, and even variation in the number and type of professional sports teams across cities seems relatively disconnected from the early dynamics of the epidemic. Empirically, we bolster this assumption by controlling for local population, population density, demographic characteristics, and the presence of multiple teams. Our identification strategy rests on the assumption that after adjusting for these observed covariates, places that hosted more games in early 2020 were not systematically more likely to experience a more severe epidemic for other reasons.

We find that hosting one additional NBA or NHL game resulted in an additional 7520 cases and 658 deaths in the MSA where the game was played. In contrast, we find that each men’s college basketball games only resulted in an additional 35 deaths per MSA. The smaller effect in the NCAA sample are due to the fact that the MSAs with college basketball teams, but without professional sports teams, are much smaller than MSAs with NHL/NBA teams. In addition, these smaller MSAs also have lower death rates.

---

Fig. 8. 2019 flu deaths and 2020 games. Notes: Each point in the graph represents one of the 295/402 counties located in an MSA where at least one county is home to at least one NHL or NBA/NCAA team (the NHL/NBA 296 county sample had one county which did not merge with 2019 flu deaths data). The horizontal axis reports the combined number of NHL and NBA games/NCAA games played in the MSA where the county is located between March 1, 2020 and March 12, 2020. The vertical axis is the number of flu deaths in 2019. The slope of the fitted line is 70.45 in the left panel and — 3.64 in the right panel.
Standard errors are clustered by MSA. *Statistical significance at the 10% level; **significance at the 5% level; ***significance at the 1% level. Dependent variables are cases/deaths per 1000 people. Cases and deaths are measured through May 31st.

### Table 8

|                                | (1)       | (2)       | (3)       | (4)       | (5)       |
|--------------------------------|-----------|-----------|-----------|-----------|-----------|
| **Panel A: Cases per 1000**    |           |           |           |           |           |
| Games in MSA                   | 0.068     | 0.0966    | 0.0718    | 0.0595    | −0.0122   |
|                               | (0.0555)  | (0.0628)  | (0.0543)  | (0.0580)  | (0.0530)  |
| Average air temperature        |           |           |           |           |           |
|                               | −0.0415***|           |           |           |           |
|                               | (0.0130)  |           |           |           |           |
| 2019 state flu death rate      | 49.9851** |           |           |           |           |
|                               | (22.6338) |           |           |           |           |
| Passengers from Italy Q1 2020  |           |           |           |           | 0.0000***|
|                               |           |           |           |           | (0.0000)  |
| **Panel B: Deaths per 1000**   |           |           |           |           |           |
| Games in MSA                   | 0.1503*** | 0.1512*** | 0.1619*** | 0.1554*** | 0.1365*** |
|                               | (0.0513)  | (0.0535)  | (0.0536)  | (0.0581)  | (0.0489)  |
| Average air temperature        |           |           |           |           |           |
|                               | −0.0053   |           |           |           |           |
|                               | (0.0119)  |           |           |           |           |
| 2019 state flu death rate      | 37.0990** |           |           |           |           |
|                               | (16.0200) |           |           |           |           |
| Passengers from Italy Q1 2020  |           |           |           |           | 0.0000***|
|                               |           |           |           |           | (0.0000)  |

Sample is all counties in MSAs with NCAA teams and no NHL/NBA teams. Column 1 is the main NCAA regression results; column 2 includes temperature as a covariate; column 3 includes the 2019 flu death rate as a covariate; column 4 includes Italian passengers as a covariate; column 5 includes testing per population as a covariate. Standard errors are clustered by MSA. *Statistical significance at the 10% level; **significance at the 5% level; ***significance at the 1% level. Dependent variables are cases/deaths per 1000 people. Cases and deaths are measured through May 31st.

We use estimates of the value of a statistical life (VSL) to construct a rough estimate of the social cost of an additional game. For example, using an EPA VSL estimate of $11.5 million, our analysis indicates that each NHL/NBA game played generated more than $7.5 billion in fatality costs, while each college basketball game generated about $391 million in fatality costs. However, because the vast majority of COVID-19 deaths occur among the elderly, using a lower VSL may be more appropriate. Using an age-adjusted VSL of $2 million implies that each NHL/NBA game cost about $1.3 billion in fatalities, and each NCAA game cost about $68 million in fatalities. Using this much more conservative VSL, our results indicate that the 135 NHL and NBA games played in March 2020 created more than $175 billion worth of fatalities, while the roughly 128 NCAA games created about $8.7 billion worth of fatalities.

The average ticket price for an NHL or NBA game is about $150 (thehockeywriters.com, YahooFinance). Roughly 17,800 fans attended the average NHL and NBA game in our sample. This implies that the average NBA/NHL game generated about $2.7 million in total spending from live attendance. In other words, fatality costs per game ($1.3 billion) are almost 500 times greater than spending per game. Even assuming that spending on tickets comprises only half of consumer spending at games, the fatality costs are more than 200 times greater. For NCAA basketball games, SeatGeek estimates an average ticket price of about $35. Roughly 6500 fans attend the average NCAA game, yielding total spending per NCAA game of about $228,000. Again, even assuming additional spending at games equal to spending on tickets, fatality costs per game ($68 million) are roughly 300 times greater than spending.

One implication is that restricting fans from attending games will likely yield substantial public health benefits. Per-game attendance at NFL games and many major college football games is about four times higher than for NHL or NBA games, which might be viewed as a substantial risk factor. On the other hand college and NFL football teams only play about 15–20% as many games as NHL and NBA teams, and the vast majority of NFL and NCAA football stadiums are open air. To the extent that football games are played outdoors, there is a theoretical case that football games could be safer than indoor basketball and hockey games.

More generally, our study is based on data generated from games...
Table 9
Effect of NCAA March games in 2020 – splitting sample by in-state enrollment.

|                  | Low in-state enrollment (cases) | High in-state enrollment (cases) | Low in-state enrollment (deaths) | High in-state enrollment (deaths) |
|------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| Games in MSA      | – 0.022                         | 0.188*                          | – 0.001                         | 0.255***                        |
|                  | (0.077)                         | (0.097)                         | (0.123)                         | (0.088)                         |
| 2+ teams         | 0.491*                          | – 0.177                        | 0.060                           | 0.251                           |
|                  | (0.292)                         | (0.396)                         | (0.359)                         | (0.372)                         |
| Logged population in MSA | – 0.045                        | – 0.168                        | – 0.271                        | 0.086                           |
|                  | (0.151)                         | (0.269)                         | (0.196)                         | (0.239)                         |
| Logged population density in MSA | 0.351**                        | 0.153                           | 0.552**                         | – 0.419                         |
|                  | (0.162)                         | (0.227)                         | (0.221)                         | (0.305)                         |
| Constant         | 7.011                           | – 0.077                        | 15.490*                         | – 12.674*                       |
|                  | (6.064)                         | (5.792)                         | (8.011)                         | (6.747)                         |
| Demographic controls | X                             | X                               | X                               | X                               |
| N                | 102                             | 101                             | 102                             | 101                             |

Standard errors are clustered by MSA. *Statistical significance at the 10% level; **significance at the 5% level; ***significance at the 1% level. Dependent variables are cases/deaths per 1000 people. Cases and deaths are measured through May 31st. Cases/deaths low in-state enrollment columns are specifications for counties with below median in-state students. Cases/deaths high in-state enrollment columns are specifications for counties with above median in-state students.

Table 10
Attendance regressions.

|                | (1) | (2) |
|----------------|-----|-----|
| **Panel A: Cases per 1000** |     |     |
| Attendance (1000s) | 0.0102*** | – 0.0000 |
|                  | (0.0028) | (0.0000) |
| 2+ teams in MSA  | 0.4525 | 0.3062* |
|                  | (0.3444) | (0.1782) |
| Logged population in MSA | – 0.7718*** | – 0.9364*** |
|                  | (0.2710) | (0.1515) |
| Logged population density in MSA | 0.7911** | 0.2874*** |
|                  | (0.3941) | (0.1373) |
| Constant         | – 8.9392* | – 0.5719 |
|                  | (4.5111) | (1.7180) |
| Demographic controls | X | X |
| N                | 296 | 402 |

| **Panel B: Deaths per 1000** |     |     |
| Attendance (1000s) | 0.0134*** | – 0.0000 |
|                  | (0.0035) | (0.0000) |
| 2+ teams in MSA  | 1.0809** | 0.3986 |
|                  | (0.4502) | (0.2669) |
| Logged population in MSA | – 1.0124*** | – 0.3193* |
|                  | (0.3169) | (0.1755) |
| Logged population density in MSA | 0.7980 | 0.6148*** |
|                  | (0.5076) | (0.1842) |
| Constant         | 8.5970 | – 2.7969 |
|                  | (7.3308) | (2.8565) |
| Demographic controls | X | X |
| N                | 296 | 402 |

Column 1 reports results for the professional sample; column 2 reports results for the NCAA sample. Standard errors are clustered by MSA. *Statistical significance at the 10% level; **significance at the 5% level; ***significance at the 1% level. Dependent variables are cases/deaths per 1000 people. Cases and deaths are measured through May 31st.

Table 11
Spillover regressions.

|                | (1) | (2) |
|----------------|-----|-----|
| **Panel A: Cases per 1000** |     |     |
| Games in county | 0.148*** | 0.081 |
|                  | (0.052) | (0.055) |
| Games in MSA but not in county | 0.161*** | 0.170 |
|                  | (0.048) | (0.117) |
| 2+ teams in MSA | 0.484 | 0.224 |
|                  | (0.351) | (0.169) |
| Logged population in MSA | – 0.743** | – 0.373*** |
|                  | (0.293) | (0.144) |
| Logged population density in MSA | 0.780* | 0.247* |
|                  | (0.407) | (0.137) |
| Constant         | – 8.456* | – 1.198 |
|                  | (4.829) | (1.801) |
| Demographic controls | X | X |
| N                | 296 | 402 |

| **Panel B: Deaths per 1000** |     |     |
| Games in county | 0.203*** | 0.097 |
|                  | (0.064) | (0.074) |
| Games in MSA but not in county | 0.204*** | 0.125 |
|                  | (0.062) | (0.112) |
| 2+ teams in MSA | 1.104** | 0.319 |
|                  | (0.462) | (0.277) |
| Logged population in MSA | – 0.937*** | – 0.305* |
|                  | (0.345) | (0.157) |
| Logged population density in MSA | 0.780 | 0.575*** |
|                  | (0.539) | (0.188) |
| Constant         | 7.578 | – 3.596 |
|                  | (7.579) | (2.643) |
| Demographic controls | X | X |
| N                | 296 | 402 |

Column 1 sample is all counties in MSAs with NHL/NBA teams. Column 2 sample is all counties in MSAs with NCAA teams and no NHL/NBA teams. Standard errors are clustered by MSA. *Statistical significance at the 10% level; **significance at the 5% level; ***significance at the 1% level. Dependent variables are cases/deaths per 1000 people. Cases and deaths are measured through May 31st.

played before social distancing policies and other adaptive behaviors were implemented. It is possible that sporting events would lead to less transmission if people were wearing masks and were seated in a socially distanced manner. Regardless, our estimates might represent a reasonable upper bound on the likely effect of large sporting events under higher levels of self-protective behavior. More broadly, our results may also help to guide policymakers as they face decisions regarding how to regulate gatherings ranging from more private events, such as weddings and funerals, to more public events, including trade and academic conferences.

Conflict of interest

There are no conflicts of interest to report.

References

Ahammer, A., Halla, M., Lackner, M., 2020. Mass gatherings contributed to early COVID-19 spread: evidence from US sports. COVID Econ. Vetted Real Time Pap. 30, 40–62.
Basketball Reference, 2020. 2019–20 NBA schedule and results. . (Accessed 4 January 2020). https://www.basketball-reference.com/leagues/NBA_2020_games-march.html.
Berry, C.R., Fowler, A., Glazer, T., Handel-Meyer, S., MacMillen, A., 2021. Evaluating the effects of shelter-in-place policies during the COVID-19 pandemic. Proc. Natl. Acad. Sci. U. S. A. 118 (15).
Cardazzi, A., Humphreys, B.R., Rusken, J.E., Soebbing, B., Watanabe, N., 2020. Professional sporting events increase seasonal influenza mortality in US cities. Available at SSRN 3628649.
Dave, D., McNichols, D., Sabia, J.J., 2020a. The contagion externality of a superspreading event: The Sturgis Motorcycle Rally and COVID-19. South. Econ. J.
Dave, D.M., Friedson, A.I., Matsuzawa, K., McNichols, D., Sabia, J.J., 2020b. Did the Wisconsin Supreme Court Restart a COVID-19 Epidemic? Evidence from a Natural Experiment. Technical Report. National Bureau of Economic Research.

Dave, D.M., Friedson, A.I., Matsuzawa, K., Sabia, J.J., 2020c. When Do Shelter-in-Place Orders Fight COVID-19 Best? Policy Heterogeneity Across States and Adoption Time. Working Paper. National Bureau of Economic Research.

ESPN, 2020. NCAAM teams. (Accessed 4 January 2020). https://www.espn.com/mbb/teams.

Friedson, A., McNichols, D., Sabia, J., Dave, D., 2020. Did California’s Shelter in Place Order Work? Early Evidence on Coronavirus-Related Health Benefits. Working Paper.

Gautret, P., Steffen, R., 2016. Communicable diseases as health risks at mass gatherings other than Hajj: what is the evidence? Int. J. Infect. Dis. 47, 46–52.

Gitter, S.R., 2017. The H1N1 virus and Mexican baseball attendance. Athens J. Sports 4 (4), 263–275.

Gourieroux, C., Monfort, A., Trognon, A., 1984. Pseudo maximum likelihood methods: applications to Poisson models. Econometrica: J. Econom. Soc. 701–720.

Gupta, S.K.I., Wing, C., 2020. Mandated and Voluntary Social Distancing during the COVID-19 Epidemic. Brookings Papers on Economic Activity (Conference Draft).

Gupta, S., Nguyen, T.D., Lozano Rojas, F., Raman, S., Lee, B., Bento, A., Simon, K.I., Wing, C., 2020. Tracking Public and Private Response to the COVID-19 Epidemic: Evidence from State and Local Government Actions. Technical Report. National Bureau of Economic Research.

Hockey Reference, 2020. 2019–20 NHL schedule and results. (Accessed 4 January 2020). https://www.hockey-reference.com/leagues/NHL_2020_games.html.

Kapoor, R., Rho, H., Sangha, K., Sharma, B., Shenoy, A., Xu, G., 2020. God is in the rain: the impact of rainfall-induced early social distancing on COVID-19 outbreaks. Available at SSRN 3605549.

Mangrum, D., Niekamp, P., 2020. Jue insight: college student travel contributed to local COVID-19 spread. J. Urban Econ. 103311.

Nguyen, T.D., Gupta, S., Andersen, M., Bento, A., Simon, K.I., Wing, C., 2020. Impacts of State Reopening Policy on Human Mobility. NBER Working Paper (forthcoming).

Nishiura, H., Oshitani, H., Kobayashi, T., Saito, T., Sunagawa, T., Matsui, T., Wakita, T., Suzuki, M., 2020. Closed Environments Facilitate Secondary Transmission of Coronavirus Disease 2019 (COVID-19). medRxiv.

Prince, Jeffrey, Simon, Daniel H., 2020. The Effect of International Travel on the Spread of Covid-19 in the US. Available at SSRN.

Qian, H., Miao, T., LIU, L., Zheng, X., Luo, D., Li, Y., 2020. Indoor Transmission of SARS-CoV-2. medRxiv.

Stoecker, C., Sanders, N.J., Barreca, A., 2016. Success is something to sneeze at: influenza mortality in cities that participate in the super bowl. Am. J. Health Econ. 2 (1), 125–143.

The New York Times, 2020. Coronavirus (COVID-19) data in the United States. (Accessed 8 April 2020). https://github.com/nytimes/covid-19-data.

Weeden, K.A., Cornwell, B., 2020. The small-world network of college classes: implications for epidemic spread on a university campus. Sociol. Sci. 7, 222–241.

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT Press.

Zielinski, A., 2009. Evidence for excessive incidence of infectious diseases at mass gatherings with special reference to sporting events. Prz. Epidemiol. 63 (3), 343–351.