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Agglomeration Spillovers from Native Nations: Evidence from Casino Reopenings*

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Abstract

We quantify agglomeration spillovers created by tribally-owned casinos located on federally recognized reservations by comparing changes in visitor counts among businesses located near a casino that reopened after COVID-19 stay-at-home orders were lifted and businesses located near a casino that remained closed. We find large and robust effects of casino reopening on visitor counts to businesses within one and a half miles away from reopened casino. The spillovers are largely isolated to the hospitality industry. We also find that nearby, off-reservation businesses saw an increase in visitors when a nearby casino reopened. Taken together, nearby businesses located both on- and off-reservations benefit from the shared demand created by tribal casinos.
Keywords: Spillovers, gaming, agglomerations, tribal jurisdiction, pandemic

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*The views expressed here are my own and do not necessarily represent those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

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1 Introduction

The spatial concentration of industrial activity has long been recognized as a key feature of urban economic development. Agglomeration increases productivity through knowledge spillovers, economies of scale, and network effects while reducing transportation, search, and matching costs (Davis and Dingel, 2019; Krugman, 1991; Marshall, 1890). But despite the well-established evidence for agglomeration spillovers in urban settings and industrialized sectors (Ellison et al., 2010; Glaeser and Gottlieb, 2009; Greenstone et al., 2010), the existence and magnitude of such spillovers remain important open questions for Native Nations and rural communities in the United States.

Tribes often face substantial economic, legal, and institutional challenges, leading to underdeveloped infrastructure, underfunded social services and limited access to capital. In addition, many American Indian reservations are located in rural areas that are geographically and socially isolated (Snipp, 1989). Yet, against the backdrop of these development challenges, tribally-owned gaming operations have become a critical source of income and economic growth for Native Nations since the 1990s. As of 2022, revenue from the Indian gaming industry hit a record of $40.9 billion from 519 gaming operations owned by 244 federally recognized tribes (NIGC, 2023). Economists and policymakers have shown that these gaming establishments provide a rare source of rural economic development by attracting tourists, creating jobs, and generating significant revenue for tribal governments, which can be then reinvested in community development (Aguilar et al., 2024). Beyond employment and revenue generation, they could also stimulate the growth of nearby businesses, such as hotels, restaurants, and retail stores.

Identifying agglomeration effects is of both pragmatic and theoretical interest. For tribal policymakers, they should know how local investments affect the community they serve. Yet the impact of local investments is theoretically unclear. Theory posits that local investments can benefit neighboring businesses from agglomeration spillovers (Greenstone et al., 2010). In our case, this would mean a casino brings foot traffic not only to itself but also draws visitors to nearby businesses. However, customers may substitute spending at businesses closest to a casino for spending elsewhere. In this case, agglomeration spillovers may be offset by what refer to as the "agglomeration shadow" (Anisfeld and Rosenthal-Kay, 2024). Interestingly, despite the theoretical and policy significance, there is little empirical research to causally identify agglomeration spillovers from large investments in rural communities.

In this paper, we estimate agglomeration spillovers by using the staggered reopenings of tribal casinos on federally recognized reservations during the COVID-19 pandemic as a natural experiment to identify the existence and extent of agglomeration spillovers. Tribal casinos provide a unique setting for causal inference. The Indian Gaming Regulatory Act (IGRA), signed in 1988, granted authority to tribal governments to own and operate gaming operations. As a result, tribes decided when their casinos would reopen once shelter-in-place orders were relaxed. This allows us to compare customer activity among businesses located near a casino that reopened after COVID-19 stay-at-home orders were lifted and businesses located near a casino that had yet to reopen.[1] We also determine which industries, if any, benefit from shared demand created by foot traffic at a nearby casino.

Using high-frequency mobile phone location data that tracks foot traffic to geocoded business establishments, we measure the number of weekly visitors to businesses between March and December 2020. This time frame encompasses the periods of closing and reopening for many tribal casinos. We exploit the differential reopening dates across roughly 210 reservation casinos, and our key identifying assumption is that the average change in visitors to nearby businesses in the comparison group reflects the counterfactual change in visitors to businesses near reopened casinos if the nearby casino had never reopened. Our main empirical method computes estimates of the average treatment on the treated using an outcome regression approach proposed by Callaway and Sant'Anna (2021). We also estimate

[1] A tribally owned casino, at least a Class III casino, can only open after a compact is signed with the state. However, once opened, tribes, rather than states, have the authority of day-to-day gaming operations (Crepelle, 2021). While tribes may abide by local state regulations, the scope of the state's authority in Class III casinos will be laid out in the Class III compact. Unlike Class III casinos, tribes have complete authority over Class II casinos. As a consequence, a tribe's decision to reopen can differ from the state's reopening plans and can differ between tribes within the same state.

spillover effects within concentric rings of various sizes around each casino.

We find businesses located within a mile and a half of a reservation casino benefit from agglomeration spillovers. Not surprisingly, the largest spillovers exist among businesses located closest to a casino. Spillover effects decay after one and a half mile and become negative as we move further away from a casino. However, within a relatively large area of three miles around a casino, the overall effect of a casino reopening on neighboring business foot traffic is positive.

Consistent with many other casino-related papers, we find that the growth in visitors after a casino reopening is largely isolated to leisure and hospitality businesses. We do find evidence of spillovers on nearby retail businesses such as gas stations and grocery stores which is a novel finding in the gaming literature. However, these reopening effects, along with those effects on businesses in the insurance, finance and professional services sectors, are sensitive to small violations of parallel trends. In addition, unlike many papers, we find that businesses located outside of a reservation benefit from locating near a reservation casino. In particular, when isolating off-reservation hospitality businesses, we estimate that casino reopenings increase foot traffic by roughly 34% at these establishments. This particular result shows that casinos are not only instrumental in driving economic development on reservations, but they also act as hubs or anchor institutions for neighboring nontribal economies.

Our findings on agglomeration spillovers from large tribal investments have at least two important policy implications. First, our results inform resource allocation and government revenue administration. In Indian Country, tribal and state governments often have overlapping tax authority on the same businesses or activities. Without state-tribal tax compacts, states and tribes have the legal jurisdiction to tax the same economic activity twice, impeding economic development (Cowan, 2021; Crepelle, 2019; Cowan, 2004). Our findings show that large-scale tribal investments on reservations could be a catalyst for regional economic development, thereby generating a positive externality for off-reservation establishments.

This interconnectedness provides additional rationale and incentive for closer economic co-operation between tribal and state governments.[2]

Second, our results have implications for place-based development policies in Native Nations. While IGRA has been recognized historically as the largest place-based policy to spur economic development in Native American communities, the social and economic impact of Indian gaming operations has been disputed. Prior findings have shown that casino openings are associated with higher rates of bankruptcy, more violent crime, and greater rates of auto thefts and larceny (Mathes, Mathes; Evans and Topoleski, 2002; Grinols and Mustard, 2006). Our quasi-experimental method shows that the indirect benefits generated by casinos need to consider when evaluating the welfare implications of these large place-based investments.

The layout of the paper is as follows. We discuss the data and sample criteria in Section 2. We then discuss the empirical strategy used to identify the role of casino reopenings on local business activity in Section 3. The results are presented in Section 4 and we conclude in Section 5.

2 Data

2.1 Foot Traffic

We use mobile device-based location tracking data to measure the impact of casino reopenings both at the casino itself and at businesses located outside a casino's premises. For our context, foot traffic data have two advantages over alternative business datasets such as the Business Employment Dynamics (BED) (Decker and Haltiwanger, 2023), Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES), and the Quarterly Census of Employment and Wages (QCEW) (Han et al., 2023). First,

[2]There is a larger literature in political science on the effects of tribal gaming revenues on state and federal government relations. See, e.g., Evans (2014); Light and Rand (2005); Wilkins and Stark (2017); Boehmke and Witmer (2012); Mason (2001).

foot traffic data are measured at a relatively higher frequency, which allows us to measure visit counts at establishments on a week-by-week basis. Since many casinos reopened on different weeks within the same month, weekly data are critical when identification is based on staggered casino reopening dates.[3] Second, foot traffic data contains precise latitude and longitude coordinates for each establishment. This allows us to measure spillovers using exact distances from a casino. This is a relatively unique feature of foot traffic data since most establishment-level datasets use administrative boundaries (e.g., BED data are aggregated to the state, QCEW data are aggregated to the county, and LODES data are aggregated to the census block).

The foot traffic data were collected by Advan (previously owned by SafeGraph). Advan derives their weekly establishment-level visit counts from individuals who opt-in to their partner network of roughly 1,000 mobile apps. After receiving opt-in consent, Advan observes cellphone locations "in the background," which means phone locations are tracked even when the app is not in use. According to Advan, roughly one of four smartphones, which equates to roughly 100 million monthly users, comprises the raw data. The median smartphone user produces 100 data points (or pings) per day. Given its high frequency and large sample, foot traffic data are commonly used in Covid-19 research (see, e.g., Fairlie et al., 2022; Pesavento et al., 2020; Hansen et al., 2022).

Visitor counts are collected from smart phone owners who downloaded certain apps. As a result, sampling bias is a potential concern. Several papers have documented the Advan's sample properties. Some studies measure sampling bias by comparing mobile location counts to known counts. For example, Coston et al. (2021) compare device-based location tracking data to North Carolina voter rolls and found that mobile tracking data are less likely to contain older and non-White individuals. However, when comparing Advan data across the entire U.S., most studies find that Advan data are well balanced. For example, when comparing the geographical distribution of Advan mobile devices throughout the U.S. to

[3]Thus, while measured at spatially precise levels, establishment data in LODES could not be adopted since it is measured annually.

county demographic characteristics, Li et al. (2024) find minor sampling biases across many demographic dimensions. This is consistent with other studies that find small sampling biases across counties (Chen and Rohla, 2018; Squire, 2019). Thus, most studies conclude that sampling bias in mobile location data do not pose a significant threat to inference.

To illustrate the properties of the devices in *our* sample, we first track trends in monthly sampling rates for devices residing in counties containing tribal casinos from March 2020 to December 2020.[4] We define the sampling rate as the total number of devices in a county containing a tribal casino divided by county adult population (since devices owned by individuals aged <16 are dropped by Advan).

Trends in the sampling rate from March 2020 to December 2020 are shown in Figure 1. The sampling rate in the counties with tribal casinos located on reservations hovers around 9 percent in each month and does not fluctuate considerably. For a comparison, this sampling rate is roughly twice as large as the five-year American Community Survey (which aims for a 5 percent sample of the U.S. population).

To assess how well Advan data represent the population in our focus counties, we estimate the correlation between county population of interest and the county device count. Figure 2 shows that the number of devices is strongly correlated with the county population (R^2=0.976). This result is similar to Squire (2019) and Li et al. (2024) who also find high correlations with devices and population counts at the county level for the U.S. as a whole.

While there is no consensus on the extent of casino spillovers[5], the majority of papers find that spillovers in local job creation from casinos are concentrated within the leisure (two-digit NAICS = 71) and hospitality service (two-digit NAICS=72) industries (Anisfeld and Rosenthal-Kay, 2024; Humphreys and Marchand, 2013; Scavette, 2023a; Walker and Sobel, 2016). The only other paper that uses a quasi-experiment design to study casinos is Aguilar

[4]Advan computes the home location of a device by analyzing six weeks of data during nighttime hours (6PM— 7AM). When a sufficient amount of data are collected, the device is assigned a home lat-lon coordinate (technically, a Geohash-7 variable).

[5]For example, some papers identify employment effects across all industries in specific cases (Sheng and Gu, 2018; Scavette, 2023b). These papers that find broad effects from casinos lack a quasi-experimental design; therefore, the direct effect of casinos cannot be ascertained.

et al. (2024). They exploit variation in the year of establishment across many reservations and find large and persistent employment effects on reservation businesses as a whole. The employment effects within the hospitality sector are significant, but they also find spillovers on non-hospitality reservation businesses.

For these reasons, we will focus our attention on the demand spillovers among neighboring businesses in all industries, though we expect the largest effects to be located in the leisure and hospitality service sectors (which we denote simply as hospitality businesses). Since foot traffic data generally serve as a proxy for consumer spending, we would like to focus our attention on industries where foot traffic and consumer spending are highly correlated (especially during the Covid-19 pandemic). Couture et al. (2022), who uses both mobile phone locations and card transaction data, find a strong correlation between foot traffic at leisure and hospitality venues and store-level revenues, while smaller to no correlation between foot traffic and store-level revenues at grocery stores (especially during the early months of the pandemic).

2.2 Casino Locations

We rely on Casino City's gaming database[6] to identify the names and addresses of each tribally owned casino that was open prior to March 2020, the start of the Covid-19 pandemic. According to our calculations, there were 525 tribally owned casinos located anywhere in the world at this time (Harwell et al., 2022). We trim the sample by dropping the following casinos: those located outside of federally recognized reservations, those that closed multiple times during the pandemic, one of the seven casino pairs that share the same address (or neighbor each other), those without published closing and reopening dates, those without associated foot traffic data and those whose initial reopening date were after December 2020 (which corresponds to the last month before some casinos closed for a second time). Our final sample contains 210 tribal casinos (for summary statistics on casino characteristics, see

[6]https://www.gamingdirectory.com/covid-19/.

Appendix Table A1).

The location of each casino in our final sample is shown in Figure 3. A large number of tribal casinos are located in California, Minnesota and Wisconsin because those states contain a large number of number of federally recognized tribes. On average, these casinos are located in counties with half the population living in urbanized areas. In fact, 19% of the casinos are located in counties without an urbanized place. We also include both Vegas-style casinos and smaller casinos ("gasinos" and "racinos") in our sample.

To determine the extent of casino spillovers, we create "great circle" buffers around each casino. We initially create a buffer of size 0.50 miles and subsequently increase the buffer by 0.50 miles until we reach three miles.[7] Limiting the spillovers to within three miles of a casino is an arbitrary cutoff but, given our goal is to quantity agglomeration effects, we want to focus on businesses that potentially benefit from casinos. We consider all establishments located inside a casino concentric ring as "treated" when the nearby casino has reopened. The benefit of this identification strategy is that there are likely no spillover effects between units located in two different geographic areas.[8]

2.3 Casino Reopening Dates

We also use data collected by Casino City's gaming directory to assign closing and reopening dates for each casino in our sample. Figure 4, Panel A shows the distribution of closing dates for casinos in our sample and Panel B shows the distribution of reopening dates. The majority of tribal casino closing dates were tightly clustered during the week of March 16. This corresponds closely to March 11, 2020, when the World Health Organization characterized COVID-19 as a pandemic.

There is more heterogeneity in reopening dates. The vast majority of casinos reopened

[7] To get a sense of the size of spatial spillovers from papers that use a quasi-experimental design, Qian et al. (2023) find spillovers from large grocery store openings are highly localized and concentrated within 0.1 miles. Anisfeld and Rosenthal-Kay (2024) find that urban casinos are concentrated in businesses, especially those in the leisure and hospitality service industries, within only eight minutes of a casino.

[8] We drop the small number of establishments that are located inside multiple buffers; thus, each establishment is unique to a buffer.

during different weeks in May and June of 2020.[9] The most reopening occurred during the week of June 1 when approximately 45 tribal casinos in our sample reopened.

We perform a simple balance test to determine if local demographic and economic conditions varied between areas near early casino reopenings compared to areas near later casino reopenings.[10] Figure 5 plots the distribution of the propensity scores that predict the timing of a casino reopening based on the local demographic and economic conditions.[11] We see that the two distributions overlap, suggesting that local demographic and economic conditions are similar in areas near early and late casino reopenings.

3 Empirical Strategy

We are interested in estimating the effect of tribally owned casino reopenings on visits to the casino itself and to nearby businesses, which is known as the average treatment effect on the treated (ATT),

$$ATT = E[Y_{i,t}(1) - Y_{i,t}(0)|D_i = 1]$$

In our context, $\mathrm{E}[Y_{i,t}(1)|D_i = 1]$ is the average number of visitors to establishment i at a post-treatment period t that are located near a casino that reopened after being closed due to the COVID-19 pandemic ($D_i = 1$). The second term, $\mathrm{E}[Y_{i,t}(0)|D_i = 1]$ is the average number of visitors at the same establishment in the same post-treatment period had the

[9] Those not shown, after January 2021, some casinos closed (and reopened) for a second time. The second wave of closures was often short-lived: e.g., the median length of the second wave of closures was only 24 days compared to the initial wave of 85 days. To avoid complications with interpreting spillovers among casinos who closed and reopened several times, we limit the weeks in our sample from the week starting March 23, 2020, to the week ending December 13, 2020 (a total of 38 weeks). As shown in Appendix Figure A1, nationwide COVID-19 deaths were relatively stable throughout this period and predate the surge in COVID-19 deaths driven by the alpha variant.

[10] For this exercise, we define an early reopening if a casino reopened before the median reopening date (June 1, 2020). All other casinos are considered later reopenings.

[11] We assign census block groups to each casino and adopt the five-year 2015–2019 ACS to measure the local conditions. In particular, we predict treatment timing using the following variables: median household income, the American Indian/Alaska Native share of the total population, median age, poverty rate and total population.

nearby casino not reopened. We observe the first term but cannot observe the later.

However, as long as the trends in potential outcomes between the treatment and comparison groups are the same, then the standard difference-in-difference estimator,

$$\delta^{2\times2} = \text{ATT} = \underbrace{(E[Y_{i,t=2}|D_i = 1] - E[Y_{i,t=1}|D_i = 1])}_{\text{change for treated group}} - \underbrace{(E[Y_{i,t=2}|D_i = 0] - E[Y_{i,t=1}|D_i = 0])}_{\text{change for comparison group}}$$

can recover the ATT.

While there are many new approaches to estimate ATT under differential timing (Cunningham, 2021), we adopt an empirical approach proposed by Callaway and Sant'Anna (2021), referred to as CS. This method uncovers the treatment group- and time-specific average treatment on the treated, ATT(g,t), for treatment group g at time t. This method computes every valid 2x2 diff-in-diff comparison for each treatment group and uses the size of each treatment group as weights to compute the overall ATT (Goodman-Bacon and Cunningham, 2019).

In our preferred model, comparison groups are always the "not-yet-treated" groups located anywhere in the U.S. When using "not-yet-treated" units as the comparison groups, the unconditional $\widehat{ATT(g,t)}$ for treatment group g in periods $t \geq g$ is:

$$\widehat{\text{ATT(g,t)}} = \frac{\sum_j \Delta y_{j,g-1,t} 1\{G_j = g\}}{\sum_j 1\{G_j = g\}} - \frac{\sum_j \Delta y_{j,g-1,t} 1\{G_j = 0, D_t = 0\}}{\sum_j 1\{G_j = 0, D_t = 0\}} \tag{1}$$

where $\Delta y_{j,g-1,t}$ = $y_{j,t}$ - $y_{j,g-1}$, G_j=g is the set of treatment groups that were treated in week g, and D_t equals one when unit j is treated in time period t, zero otherwise. If treatment group g has yet to be treated, then G_g=0 and D_t=0. Thus, the comparison group is the average change in outcomes among units that have yet to be treated in period t. To estimate ATT(g,t), we adopt the outcome regression (OLS) approach proposed by Callaway and Sant'Anna (2021).

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4 Results

We first determine if the published reopening dates correspond with an increase in foot traffic at a newly reopened casino. We expect to see a jump in foot traffic at newly reopened casinos since the control group contains all not-yet-reopened casinos (technically, closed to the public).[12] By estimating dynamic effects, we can also determine if there are any differences in visitor trends between treatment and comparison groups before casinos reopened.

4.1 Direct Effects on Casino Visits

Using the number of visitors at a casino as our outcome, we display the event-time ATT's using the approach developed by Callaway and Sant'Anna (2021) in Figure 6, Panel A. We display event-time CS estimates and their 95% uniform confidence intervals for ten weeks before and after a casino reopened.

Figure 6, Panel A shows that the number of visitors to casinos increased sharply after Covid-19 reopenings. During the first ten weeks after reopening, weekly casino visitors increased by around 340 people in the Advan panel, or 325 percent relative to the number of visitors during the pre-reopening period. This large effect does not decay for the first ten weeks of reopening.

Figure 6, Panel A also reveals a small differential trend in the pre-period: i.e., we see a relative increase in visitors to casinos that were planning to reopen. This increase in foot traffic could reflect the use of additional staff to prepare for reopening to the public. To the extent that the Advan panel contains casino employees, we could be observing a *causal* anticipatory effect. Under this scenario, then the preexisting differential trend in casino visits, especially from periods $t-2$ to $t-1$, would not necessarily be considered a violation

[12] Advan data documentation states that closed businesses can still have visit counts. If employees in the Advan panel visit the location, then Advan will count that visit (the duration of the visit must last at least four minutes to count as a visit). Measurement error in mobile location data is also highly likely. For example, if someone parks their car near a casino, that person maybe counted as a visitor if their phone pings in the casino's polygon. Thus, in our data, we observe visitors at closed casinos. Fortunately, as shown in Figure 6, measurement error appears classical in nature.

of parallel trends (that is, unless we thought casino employees would have visited the casino if otherwise). If reopenings cause employees to return prior to the public reopening, then one solution is to compare all post-treatment effects to period $t-2$ instead of $t-1$. When we do this in Panel B, the preexisting differential trends decrease substantially (though we can reject the null of no pre-trend because the error bands are so small). Fortunately, the largest violation in parallel trends in the pre-period is relatively small (only six visitors per week). If we allow the post-treatment violation of parallel trends to equal twice the size of the maximum violation of parallel trends in the pre-period, thus, assuming $\bar{M}$=2 using Roth et al. (2023)'s terminology, the lower-bound of the 95% confidence interval for the estimate of the event-time parameter in event time 9 is 287 visitors (as compared to 312 visitors when assuming parallel trends holds). As a result, for the rest of the paper, we will compare all estimates to period $t-2$.

4.2 Spillover Effects from Casino Reopenings

Given that we find a large, permanent effect of casino reopenings on direct casino visitors during the first ten weeks after reopening, we now turn to estimating the impact of casino reopenings on businesses located outside a casino's premises. Similar to our initial analysis, we use Callaway and Sant'Anna (2021)'s outcome regression approach to estimate treatment effects. We also report the robustness of our estimates using a procedure developed by Roth et al. (2023) to account for potential violations in post-treatment parallel trends. All standard errors are bootstrapped and clustered among businesses by casino rings (i.e., the errors are clustered among units within the same concentric ring around a casino).

We first estimate how far we can observe agglomeration spillovers from casino reopenings for all businesses.[13] We bin businesses into 0.5 mile rings around each casino and report the spillover effects for each bin in percent terms. Each treatment effect is a group-average

[13]Technically, we consider all businesses in the Advan net of establishments linked to naics code involving agriculture, construction, and social services (such as medical care, schools, government services). The remaining business contain the following two-digit naics code: 44,45,58,51,52,52,53,54,55,56,71,72, and 81.

estimate which compares businesses near reopened casinos within the same distance as businesses located near not-yet-reopened casinos.

Those estimates are shown in Figure 7. The spillover effects are positive and statistically significant at the 5% level within 1.5 miles around a casino. We observe that casino reopenings increased visitor counts by 70% within a half mile around a casino, 30% around businesses between one-half and mile around a casino and 20% around businesses between one and one-half mile around a casino. After 1.5 miles, the spillovers decay to become statistically indistinguishable from zero. The spillover effects among businesses located between 2.5 and 3 miles away from a casino are negative and statistically significant; however, the overall spillover effect within the entire three mile radius of a casino is positive but statistically insignificant (ATT = 0.102, s.e. = 0.100).

The spillover estimates in Figures 7 rest on the parallel trends assumption. To test whether businesses near reopened and not-yet-reopened casinos have similar trends in visitor counts prior to a casino reopening, we compute CS estimates of the event-time parameters and plot those estimates in Figure 8. While many of the individual pre-period estimates are statistically indistinguishable from zero, we reject the null of no pretrends between periods $t-10$ and $t-2$ (p-value=0.004). Thus, visitor counts are growing at different rates between the treatment and control group prior to casino reopening. To formally test whether our post-treatment estimates are robust to violations in parallel trends, we plot how sensitive our spillover effects are to violations of parallel trends in Appendix Figure A2. This figure shows that if we assume the worst violation in the pre-period doubled in the post-treatment period, we would still conclude that casino reopenings increased foot traffic at nearby businesses for at least up to ten weeks.

We next estimate the event-time parameters and conduct the same sensitivity check for violations of parallel trends by major industry. Those industries are: (1.) hospitality (two-digit naics=71 and 72); (2.) retail trade (two-digit naics=44 and 45); (3.) professional services (two digit-naics=51-56,81) and transportation (two-digit naics = 48). Those estimates of the event-time parameters are located in Figure 9. Panel A shows a large break in hospitality visitors after reopening. During the first ten weeks of reopening, visitors to hospitality businesses located within one and a half miles away increased by 65%. We observe, however, pretrend differences between the treatment and control group. In particular, we reject the null of no pretrends over the weeks $t-10$ to $t-2$ (p-value of H_0: no pretends is 0.028). The pretrends suggests that, prior to reopening, customers are visiting hospitality businesses in the treatment group at a faster rate than the hospitality businesses in the control group. However, as shown in Appendix Figure A3, when we use a procedure based on Rambachan and Roth (2023) and assuming $\bar{M}$=2, we can still reject the null of no effect from the third week after reopening on.

Figure 9, Panel B shows that the casino reopening effect was smaller among retail businesses than nearby hospitality businesses. Assuming no violations in parallel trends, casino reopenings increased foot traffic to neighboring retail businesses by roughly 42%. However, the small bounds around each pre-treatment estimate means we still reject the null of no pretrends (p-value = 0.003). Using the same sensitivity approach as earlier, we test whether the break in visitor counts caused by a casino reopening is robust to violations of parallel trends. Appendix Figure A4 shows that we cannot reject the null of no effect from casino reopening at any post-treatment week if the post-treatment violation is twice as large as the worst violation in parallel trends in the pre-period. The breakdown value of $\bar{M}$ is one in this case; thus, we can claim positive spillover effects if we assume that the violation of parallel trends in the post-period is the same size as the violation of parallel trends in the pre-period.

A similar story exists with both professional sector businesses and transportation-related businesses (see Figure 9, Panels C and D). We see very small differences in pretrends among professional service businesses in the treatment and control groups. However, the post-treatment effects are too small (and estimated too imprecisely) to withstand small violations in parallel trends (see Appendix Figures A5 for more information). The spillover effect on transportation-related businesses is slightly positive, but the pretrend differences contain wide confidence intervals, which leads to a relatively low breakdown value of 0.5 (Rambachan and Roth, 2023). Thus, of all industries analyzed, the largest and more robustly estimated spillover effects occurred among nearby hospitality businesses.

Given this result, we investigate how far agglomeration effects on hospitality businesses spread. Those spillover effects are shown in Figure 10. The spillover effects on hospitality businesses located within 0.50 mile of casino were very large (ATT = 1.28 log points). This implies that visitors to these businesses increased by three-fold after a nearby casino reopened. The spillover effects decreased to between 0.4-0.5 log points as we move further away from a casino until they become statistically indistinguishable from zero after one and a half miles. We find no evidence of an agglomeration shadow within three miles of a casino reopening. Taken together, our CS estimates and robustness checks point to a large increase in visitors to hospitality businesses caused by casino reopenings. The increase in visitors to other nearby businesses are statistically significant, but are sensitive to changes to identifying assumptions.

4.3 Spillovers across Reservation Boundaries

Last, we consider whether these observed spillover effects from casino reopenings were isolated to on-reservation businesses or whether local businesses located outside a reservation boundary also benefited from agglomeration spillovers. Consistent with our earlier results, we focus on hospitality businesses located within one and a half miles from a casino.

To determine the effect of casino reopenings across tribal jurisdictional boundaries, we compute the overall CS estimate of the average treatment effect on the treated by using every treatment group's ATT estimate in every post-treatment period. These treatment effects are located in Table 1. Our overall spillover effect on off-reservation hospitality businesses located within a mile and a half of a casino was 0.34 log points (41 percent). We fail to reject the null of no pretrends and the breakdown value of $\bar{M}$ is 1.5; thus, when violations of parallel trends are larger than 1.5 times the maximum violation in the pre-period, then we cannot reject the null of no effect. Taken together, this is compelling evidence that tribal casinos generated benefits in non-tribal communities.

We also find spillover effects among on-reservation hospitality businesses; though, the shear number of on-reservation businesses is substantially less than the number of nearby, off-reservation hospitality businesses. The breakdown value is slightly smaller, which is likely a function of wider error bands in the pre-period. Nonetheless, we find evidence that both on- and off-reservation hospitality businesses benefit from agglomeration spillovers. Thus, large place-based investments by tribes are benefiting businesses located both inside and outside of their tribal jurisdiction.

5 Conclusion

In our paper, we use novel data from mobile phone locations and exploit the differential reopening dates of tribal casinos to estimate the spatial spillovers from casino operations. We find large and permanent effects from casinos on foot traffic to nearby businesses, especially those in casino-related industries like restaurants and hotels. This break in visitors, especially among hospitality businesses, at the time of a casino reopening is too large to be explained away by differing pretrend paths. While the spillover effects are local, we estimate agglomeration spillovers in neighboring, non-reservation areas.

Very few papers focus on tribally owned and tribally run businesses such as gaming operations. Though often overlooked, tribes provide an important source of rural investments. Despite these investments, tribes and states have often conflicted over such items as resource ownership and tax authority. As a result, tribal and state economic activity is often characterized by policymakers as a zero-sum. This paper provides one of the few analyzes that show how large investments by tribes have spillovers that benefit nearby businesses located both on and off reservations.

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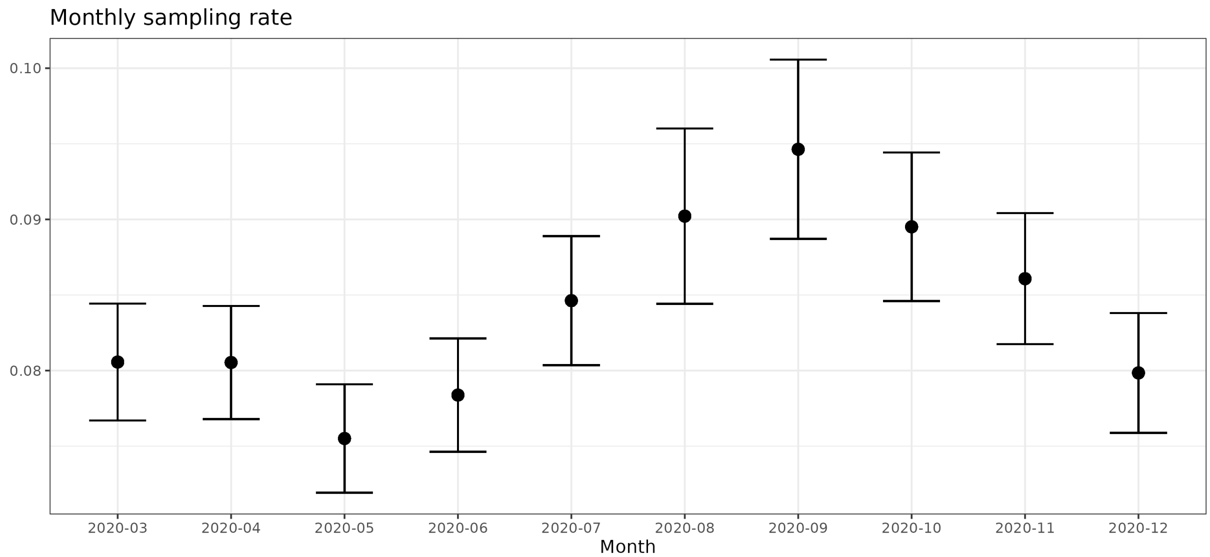


Figure 1: **Sampling Rates in Counties of Interest**

Notes: The monthly number of devices presiding in each county containing a tribal casino located witin a reservation are taken from Advan's panel of tracked devices. Since Advan removes devices used by individuals aged<16, we divide the total device count by the county's adult population. County population was taken from the 2015-2019 ACS (Steven Ruggles and Schouweiler, 2024).

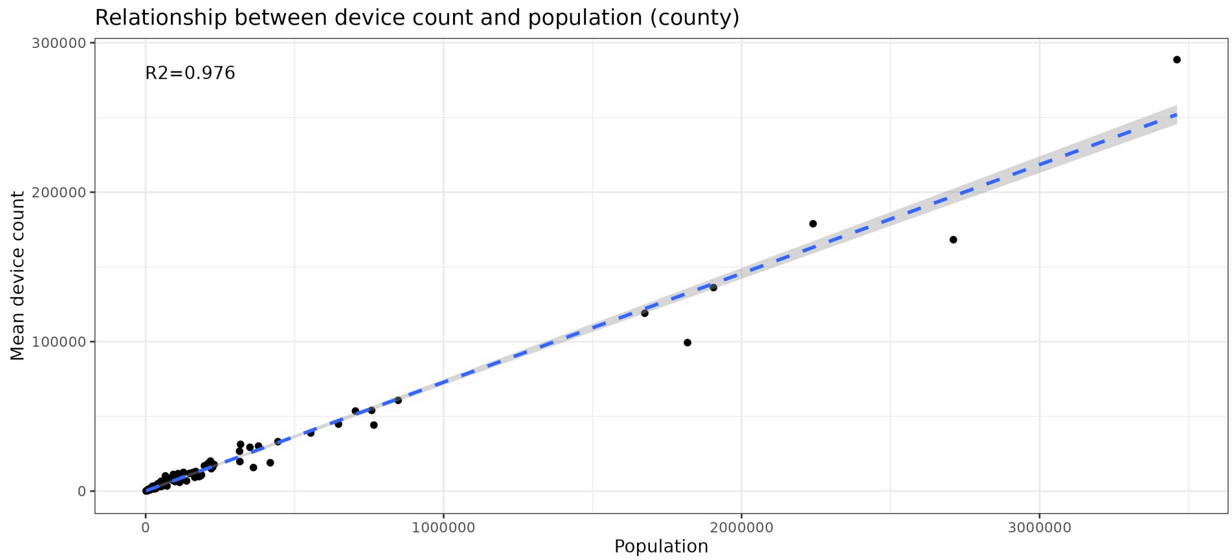


Figure 2: **Correlation between County Population and County Device Count**

Notes: The average number of devices tracked by Advan is taken from April 2020 to January 2021. Devices are geolocated to a specific county using Advan's proprietary model. Since Advan removes devices used by individuals aged<16, we divide the total device count by the county's adult population. County population was taken from the 2015-2019 ACS (Steven Ruggles and Schouweiler, 2024).

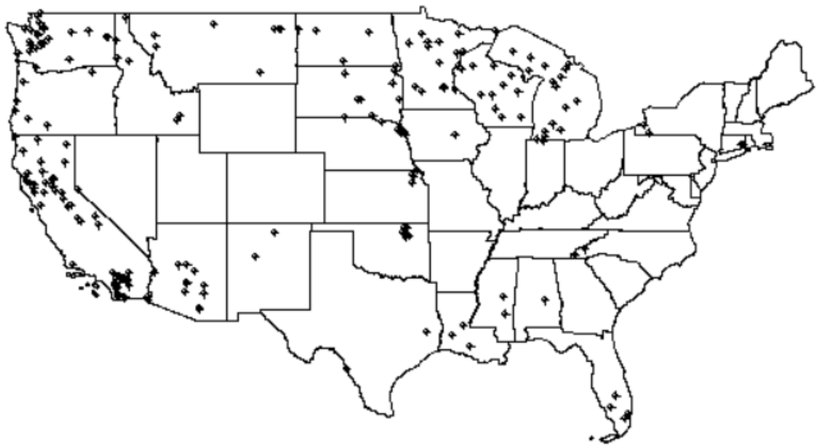
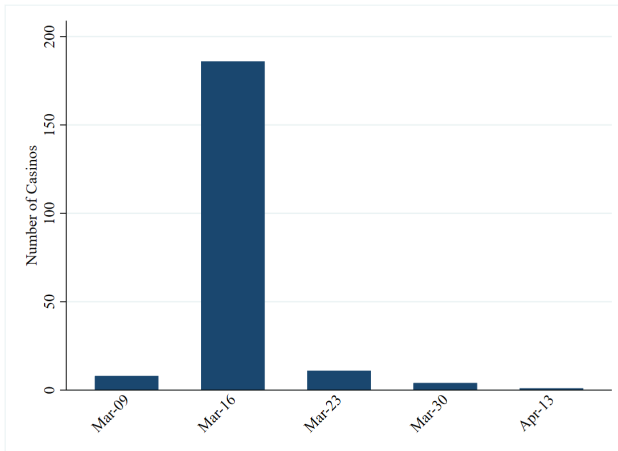
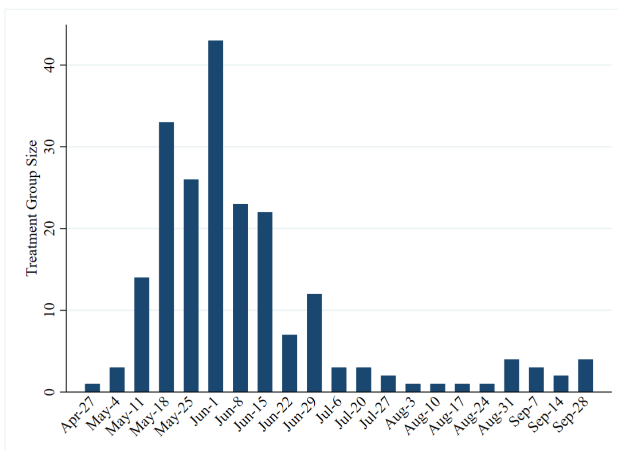


Figure 3: **Sample of Tribally Owned Casinos**

Notes: This map contains the sample of tribal casinos in our sample. See Section 2 for details. The source data came from Casino City's Gaming Directory.



(a) COVID-19 Closing Dates



(b) COVID-19 Reopening Dates

Figure 4: Closing and Reopening Dates of Tribal Casinos

Notes: Panel A contains the closing dates and Panel B contains the reopening dates (by week of reopening). The source data came from Casino City's gaming directory.

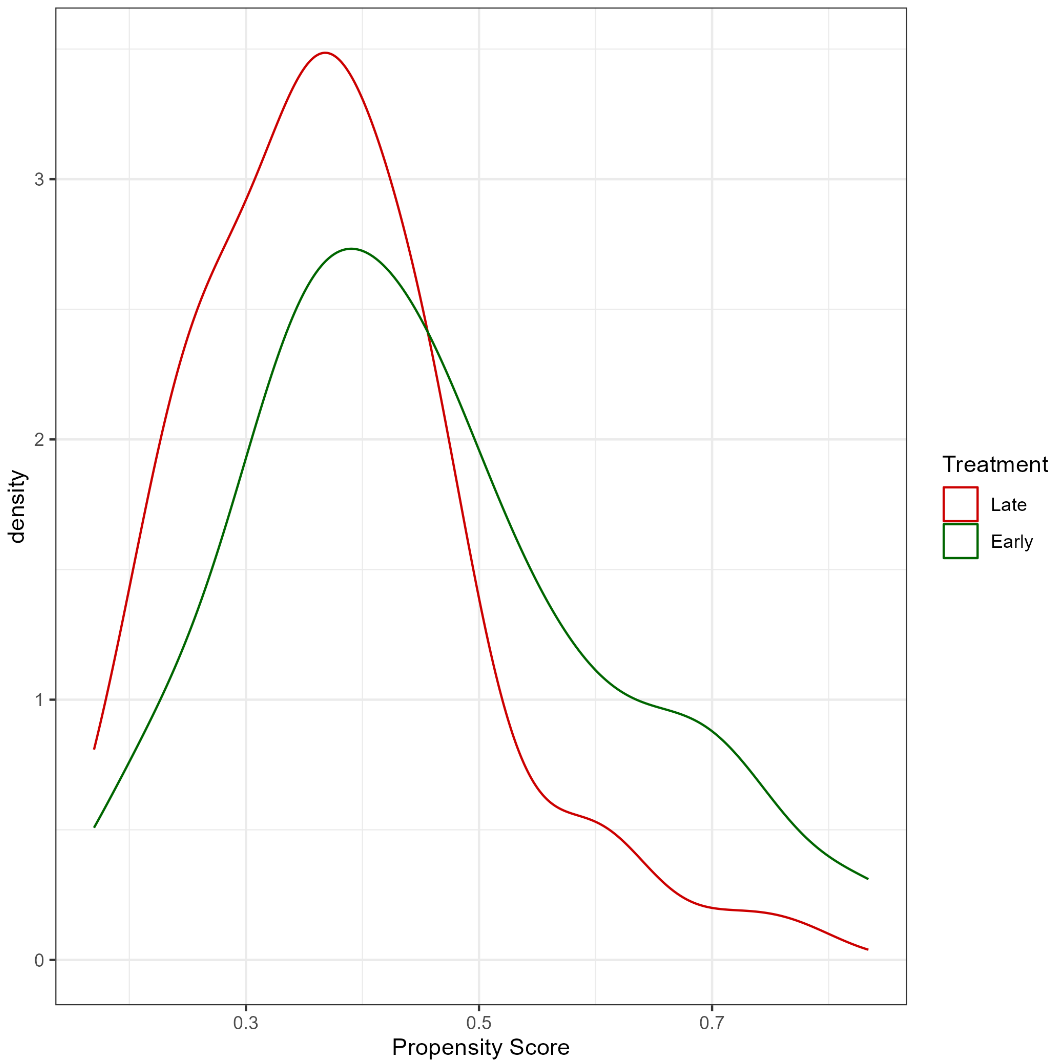
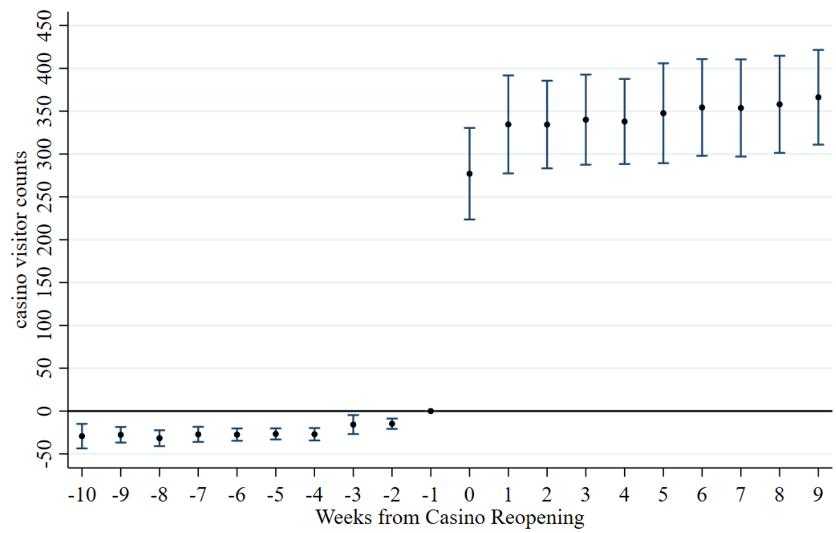
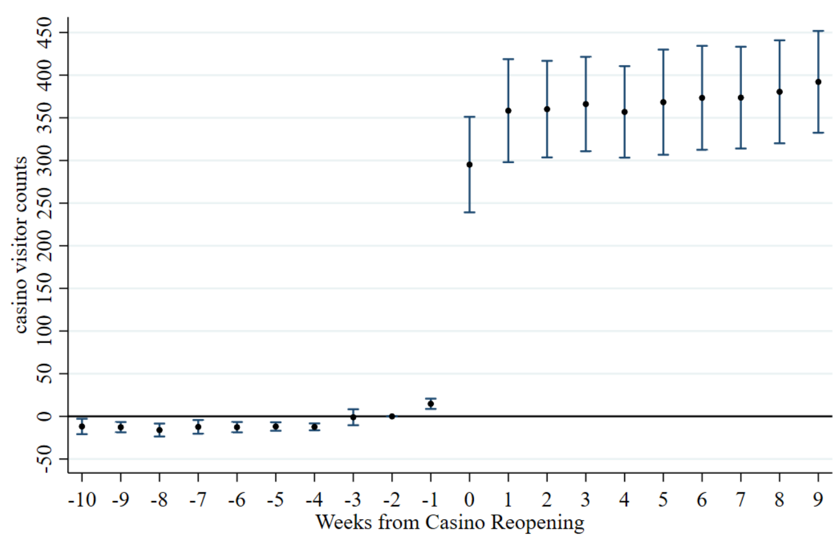


Figure 5: **Propensity Scores, by Early/Late Reopening Status**

Notes: The probability of reopening early (i.e, before the median reopening date for all casinos) is estimated using a Probit model. The covariates were median household income, share of total population that are American Indian/Alaska Native alone or in combination with other races, median age, poverty rate, and total population.



(a) Assuming No Anticipation



(b) Allowing for Limited Anticipation

Figure 6: **The Direct Effect of Casino Reopenings on Casino Visitor Counts**

Notes: These figures plot the event-time ATTs, along with their 95% confidence interval. The outcome is raw visitor counts at casinos. The pre-treatment mean is 80 visits/weeks. All estimates in the top panel are referenced to period $t-1$ and all estimates in the bottom panel are referenced to period $t-2$. We exploit the variation in treatment timing to estimate the event-time parameters. As a result, the comparison group are not-yet-treated casinos. The uniform 95 percent confidence intervals are based on a multiplier bootstrap procedure clustered by state.

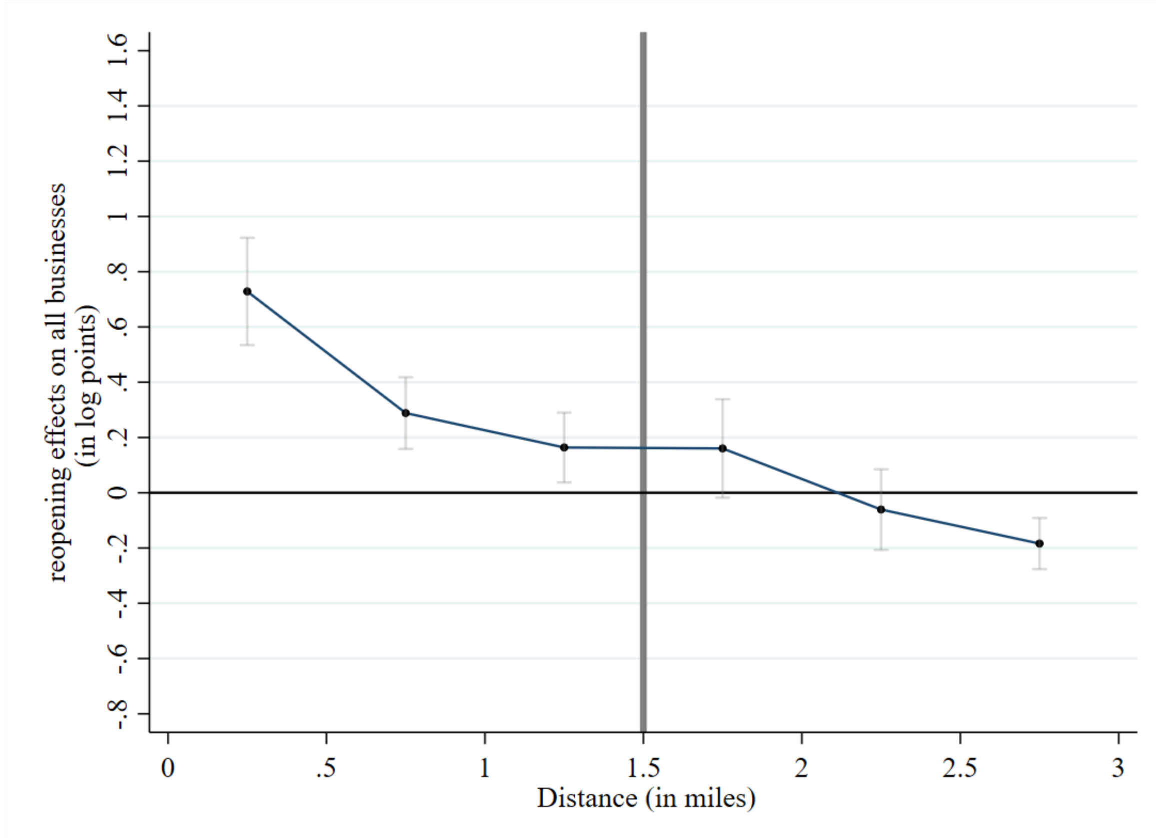


Figure 7: **Spillover Effects, by distance from casino**

Notes: The figure plots the group-average treatment effects from casino reopenings on nearby businesses in each concentric ring of size 0.5 mile. Thus, the first dot represents the average treatment effect on the treated among all businesses located between 0 and 0.5 miles from a casino. The businesses included come from the following two-digit naics code = 44,45,48,51,52,53,54,55,56,71,72,81. Estimates of the group-time parameters are computed using Callaway and Sant'Anna (2021)'s outcome regression approach. The comparison group is not-yet-treated casinos located anywhere in the U.S. We allow for limited anticipation by comparing all estimates to period $t - 2$. The 95 percent confidence intervals are based on standard errors from a multiplier bootstrap procedure clustered at the state level.

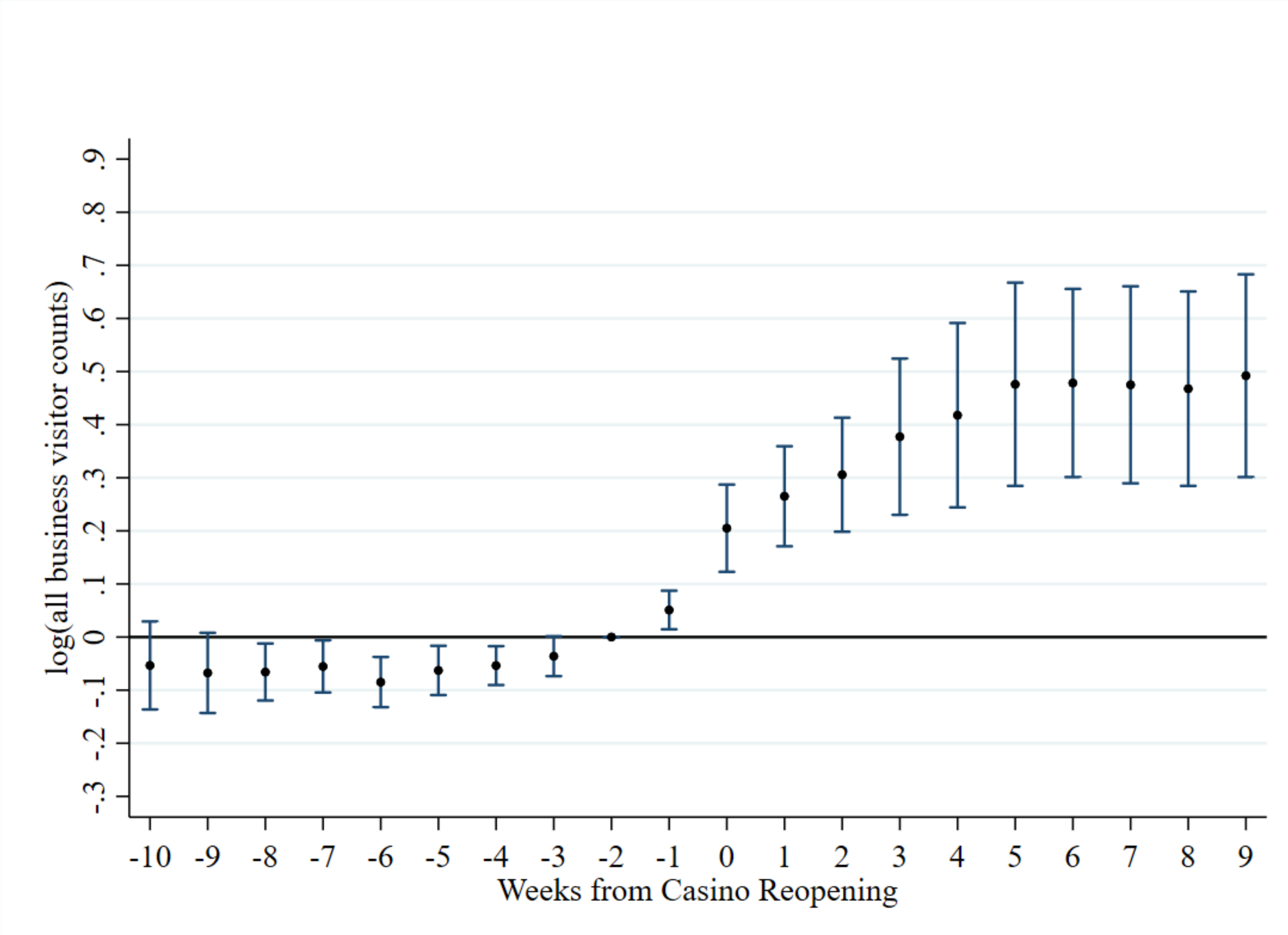
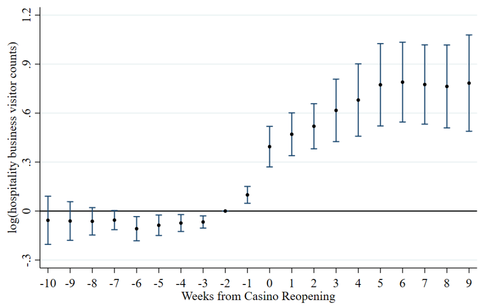
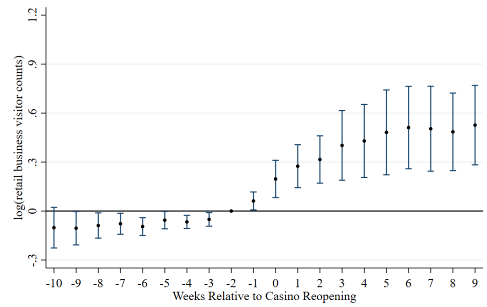


Figure 8: **Event-Study Estimates for all Neighboring Businesses within 1.5 miles of a casino**

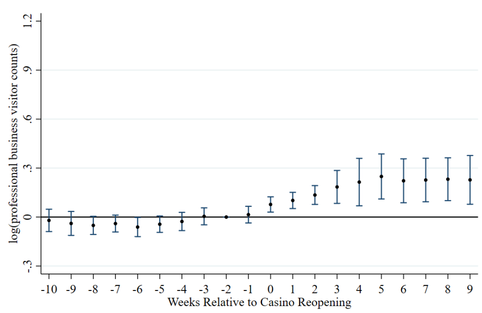
Notes: These figures plot the event-time ATTs for ten weeks before a casino reopened to the public and tens weeks after the reopening. The outcome is the log of raw visitor counts at all businesses within 1.5 miles of a casino. All estimates are referenced to period $t-2$. We exploit the variation in treatment timing to estimate the event-time parameters. As a result, the comparison group are not-yet-treated casinos. The uniform 95 percent confidence intervals are based on a multiplier bootstrap procedure clustered at the casino ring level.



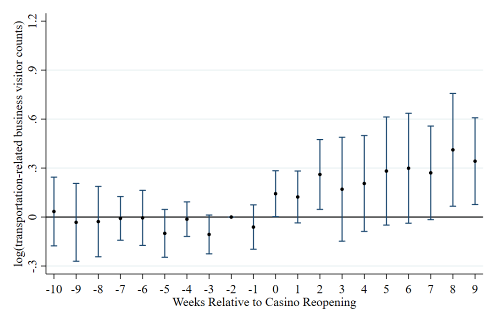
(a) Hospitality Sector



(b) Retail Trade



(c) Professional Services



(d) Transportation Sector

Figure 9: **Event-Study Estimates for Neighboring Businesses within 1.5 miles of a casino, by industry**

Notes: These figures plot the event-time ATTs for ten weeks before a casino reopened to the public and tens weeks after the reopening. Businesses are classified by industry based on their two-digit naics code. The outcome is the log of raw visitor counts at a business within 1.5 miles of a casino. All estimates are referenced to period $t - 2$. We exploit the variation in treatment timing to estimate the event-time parameters. As a result, the comparison group are not-yet-treated casinos. The uniform 95 percent confidence intervals are based on a multiplier bootstrap procedure clustered at the casino ring level.

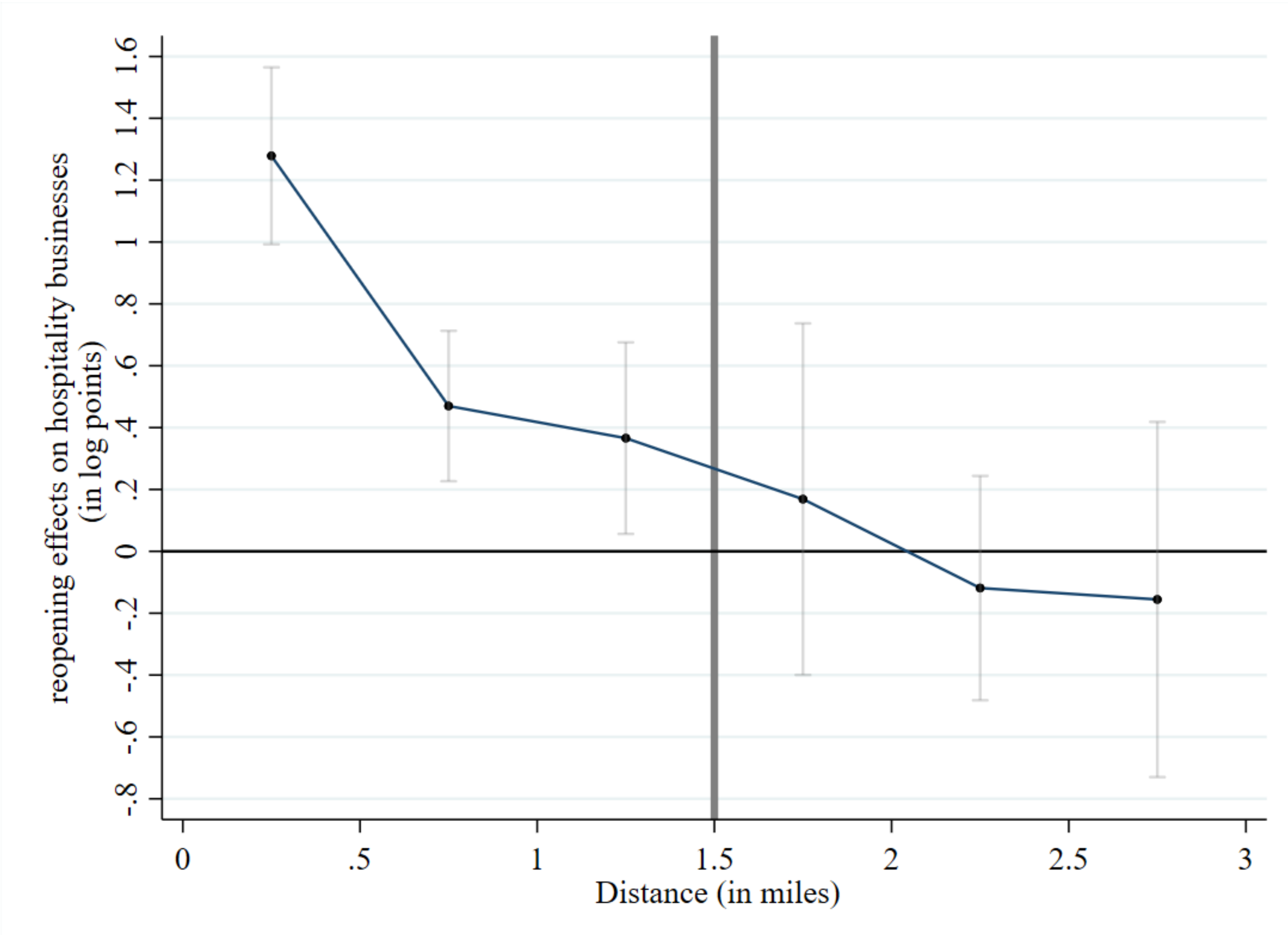


Figure 10: Spillover Effects on Hospitality Businesses, by distance

Notes: The figure plots the group-average treatment effects from casino reopenings on nearby businesses in each concentric ring of size 0.5 mile by industries. The industries are defined by their two-digit naics code: hospitality sector = 71,72. Estimates of the group-time parameters are computed using Callaway and Sant'Anna (2021)'s outcome regression approach. The comparison group is not-yet-treated casinos located anywhere in the U.S. We allow for limited anticipation by comparing all estimates to period $t-2$. The 95 percent confidence intervals are based on standard errors from a multiplier bootstrap procedure clustered at the state level.

Table 1: : The Effect of Casino Reopenings on Businesses located on- or off-Reservation

	Hospitality Sector	
	Off-Reservation Businesses (1)	On-Reservation Businesses (2)
Reopening Effect		
within 1.5 mile	0.340	0.492
	(0.081)***	(0.150)***
Breakdown Value of $\bar{M}$	1.5	1.0
Observations	69,200	18,803

Notes: The outcome of interest is logged weekly visitors at hospitality businesses. The overall reopening effect is estimated using Callaway and Sant'Anna (2021)'s outcome regression approach. The comparison group are businesses located in a not-yet-reopened casino. The standard errors are calculated from a multiplier bootstrap procedure clustered at the casino-ring level. The reopening effect is the weighted average of all post-treatment effects for all treatment groups in each period. The size of the treatment group is used as the weight. On-Reservation businesses are located on a federally recognized Native American reservation. All businesses in the sample are limited to those located within one and a half miles of a casino. *,**,*** show significance at the 10%, 5%, and 1% level, respectively.

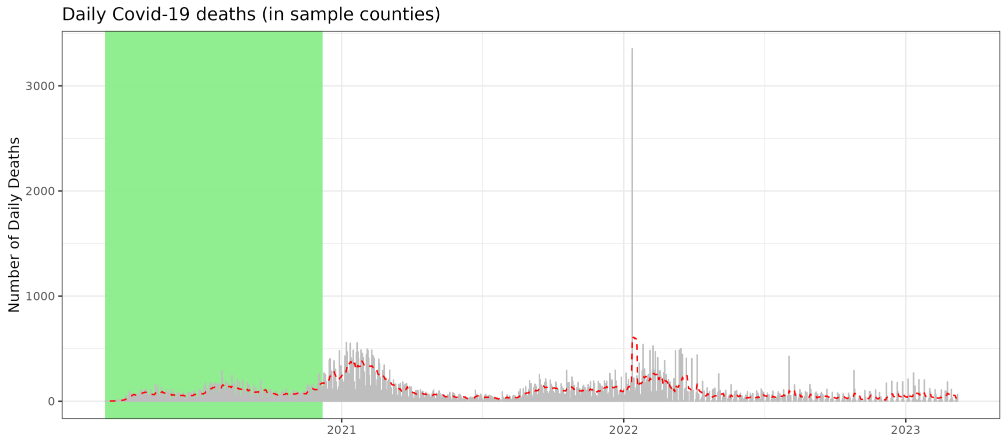


Figure A1: **COVID-19 Deaths, by Week**

Notes: The total number of Covid-19 deaths were taken from https://github.com/CSSEGISandData/COVID-19..

Table A1: Pre-Pandemic Casino Characteristics

Variable	Mean	Std. Dev	[Min, Max]
Weekly Visits	1024.47	1314.61	[0, 11047]
Dwell Time (minutes)	119.22	63.68	[2, 468]
Distance from Home (miles)	32.67	45.70	[1.25, 693.64]
Employees	629.28	925.19	[4,8400]
Slots	897.03	933.47	[27,8543]
Parking spaces	1537.31	1916.19	[20, 13470]
Hotel Rooms	124.18	238.50	[0,2224]

Notes: The weekly visits are taken from January 2020. The casino characteristics are derived from matching the names and addresses of the casinos in Advan to the same information located by Casino City, a website that aggregates information on casinos.

Table A2: Sample Characteristics, within one and a half miles

Industry Group	N	Mean Visits	Std. Dev.	[Min, Max]
Hospitality	4,314	408.51	1270.93	[0,15461]
Retail Trade	6,121	186.29	753.11	[0, 12170]
Finance, Real Estate, Comm., Prof.	3,779	158.93	613.96	[0,11746]

Notes: Statistics taken from January 2020. Businesses are classified into five industries based on Miyauchi et al. (2021). "Hospitality" venues contain a two-digit NAICS code = 71,72. "Retail Trade" venues contain a two-digit NAICS code $\in$ (44,45). "Finance, Real Estate, Communication, Professional" contain a two-digit NAICS code $\in$ (51,52, 53, 54, 55, 56,91).

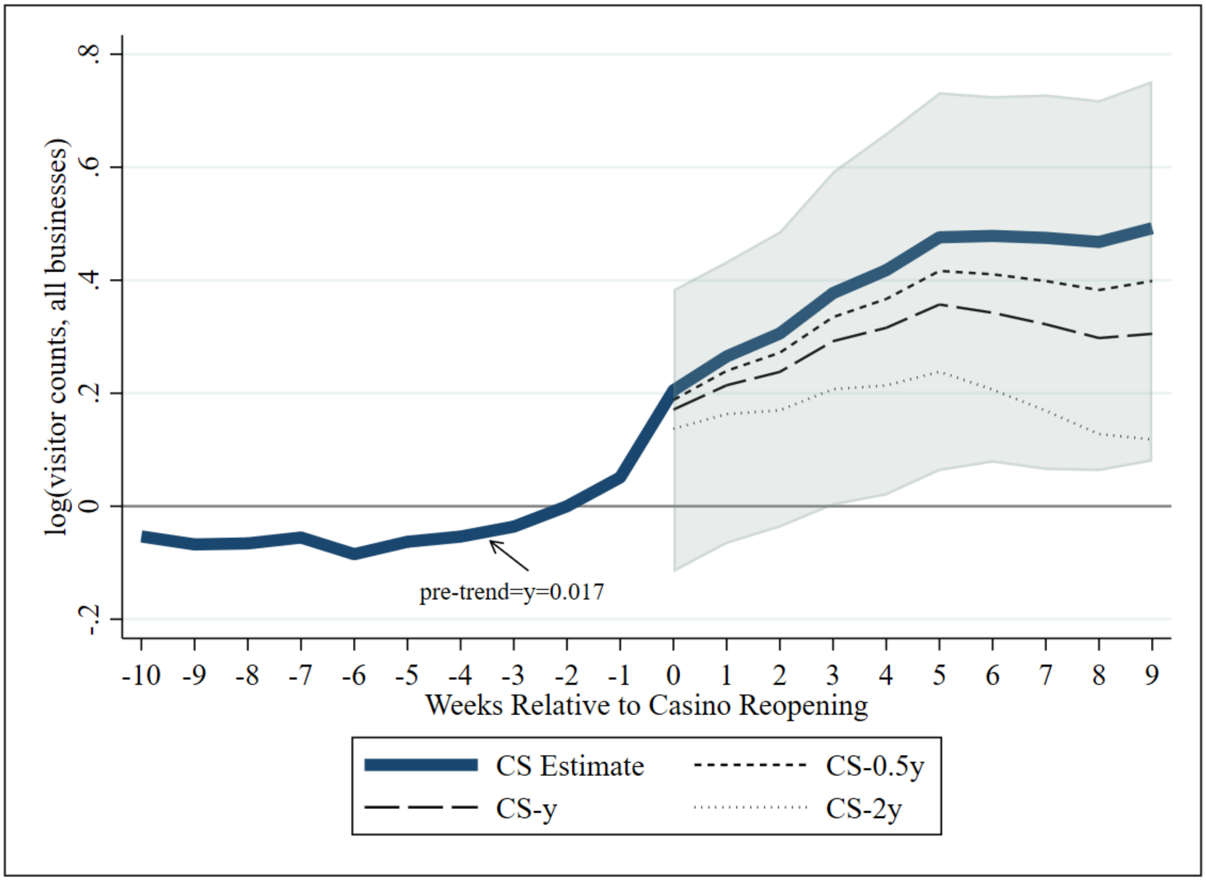


Figure A2: **Sensitivity to Violations of Parallel Trends, all businesses**

Notes: This figures shows how violations of parallel trends affects the post-treatment estimates. In the worst case, the estimated pretrend is equal to a differential change in log(visitor counts) of 0.017 per week. We compare the CS estimates (thick line) to three alternatives where each line equals the original estimate - m×y×t, where m is either 0.5, 1 or 2, y=0.017 and t is number of weeks since $t-2$. The shaded area is the 95% confidence interval developed by Rambachan and Roth (2023). This figure shows that even when we assume that the pre-trend doubles in the post-period, we would see statistically significant effects from casino reopenings at least five weeks after reopening.

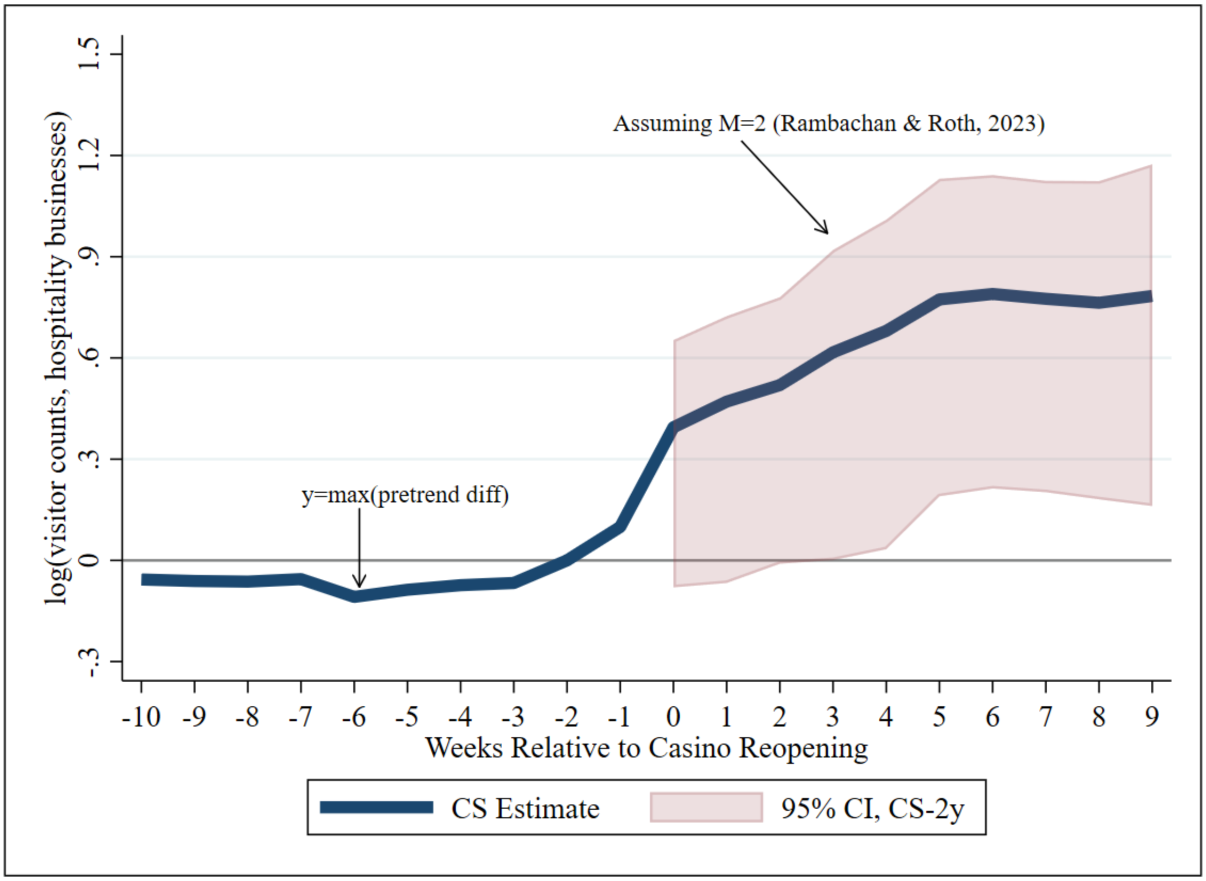


Figure A3: **Sensitivity to Violations of Parallel Trends, hospitality businesses**

Notes: This figures shows how violations of parallel trends affects the post-treatment estimates. In the worst case, the estimated pretrend is equal to a differential change in log(visitor counts) of 0.108. We plot the original CS estimates (thick line) and overlay the 95% confidence interval developed by Rambachan and Roth (2023). We assume that the violation of parallel trends in the post-treatment period is twice as large ($\bar{M}$=2) as the worst violation in the pre-period. Under this assumption, we still see statistically significant effects from casino reopenings after the third week after reopening.

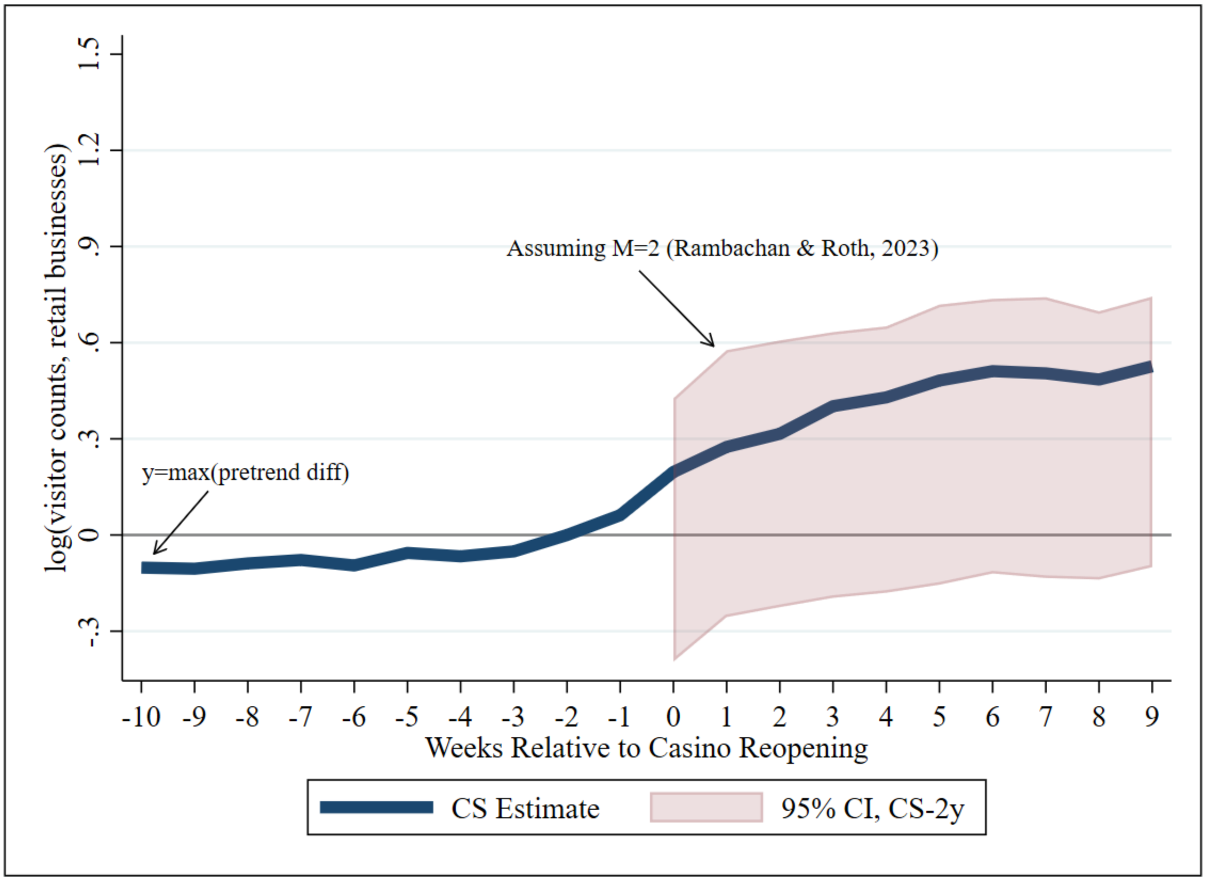


Figure A4: **Sensitivity to Violations of Parallel Trends, retail businesses**

Notes: This figures shows how violations of parallel trends affects the post-treatment estimates. We plot the original CS estimates (thick line) and overlay the 95% confidence interval developed by Rambachan and Roth (2023). We assume that the violation of parallel trends in the post-treatment period is twice as large ($\bar{M}$=2) as the worst violation in the pre-period. Under this assumption, we still see statistically significant effects from casino reopenings after the third week after reopening.

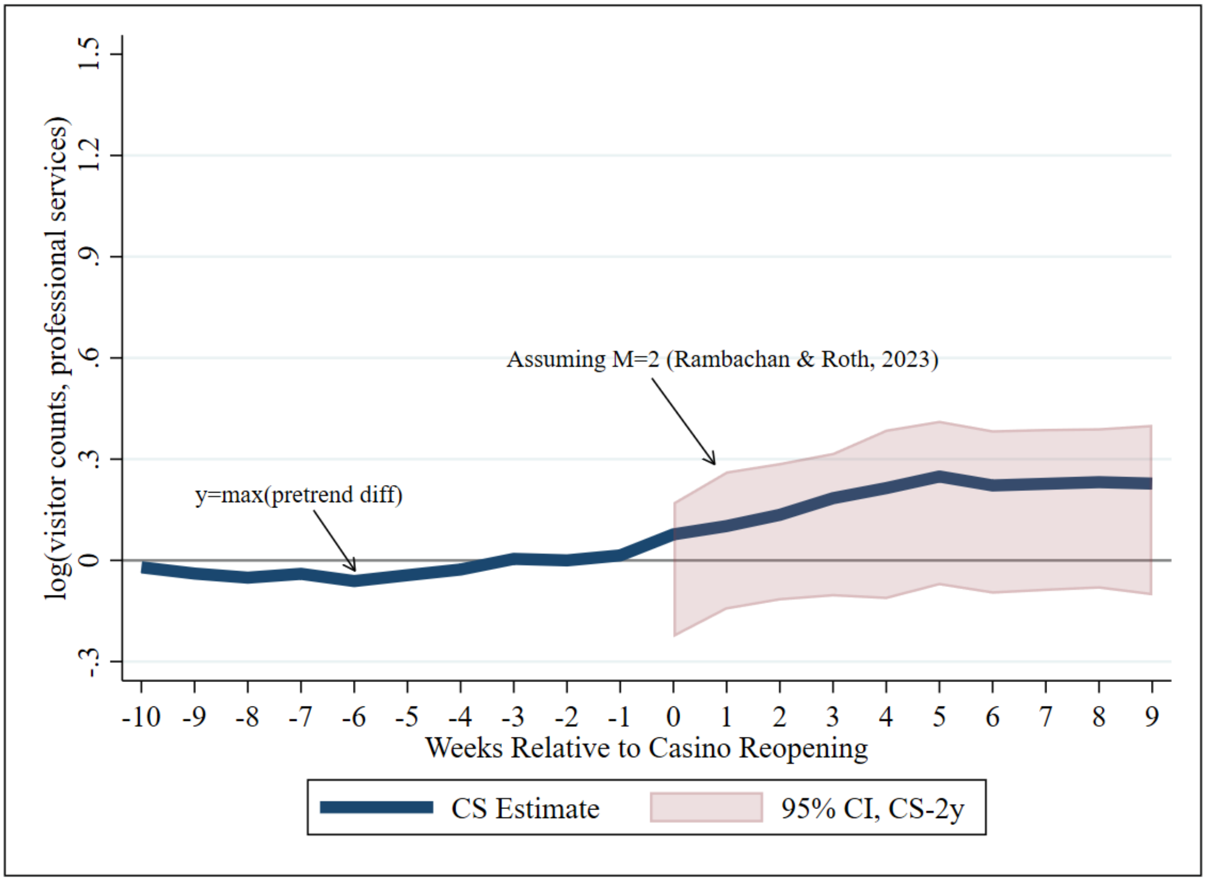


Figure A5: **Sensitivity to Violations of Parallel Trends, professional sector businesses**

Notes: This figures shows how violations of parallel trends affects the post-treatment estimates. We plot the original CS estimates (thick line) and overlay the 95% confidence interval developed by Rambachan and Roth (2023). We assume that the violation of parallel trends in the post-treatment period is twice as large ($\bar{M}$=2) as the worst violation in the pre-period. Under this assumption, we still see statistically significant effects from casino reopenings after the third week after reopening.

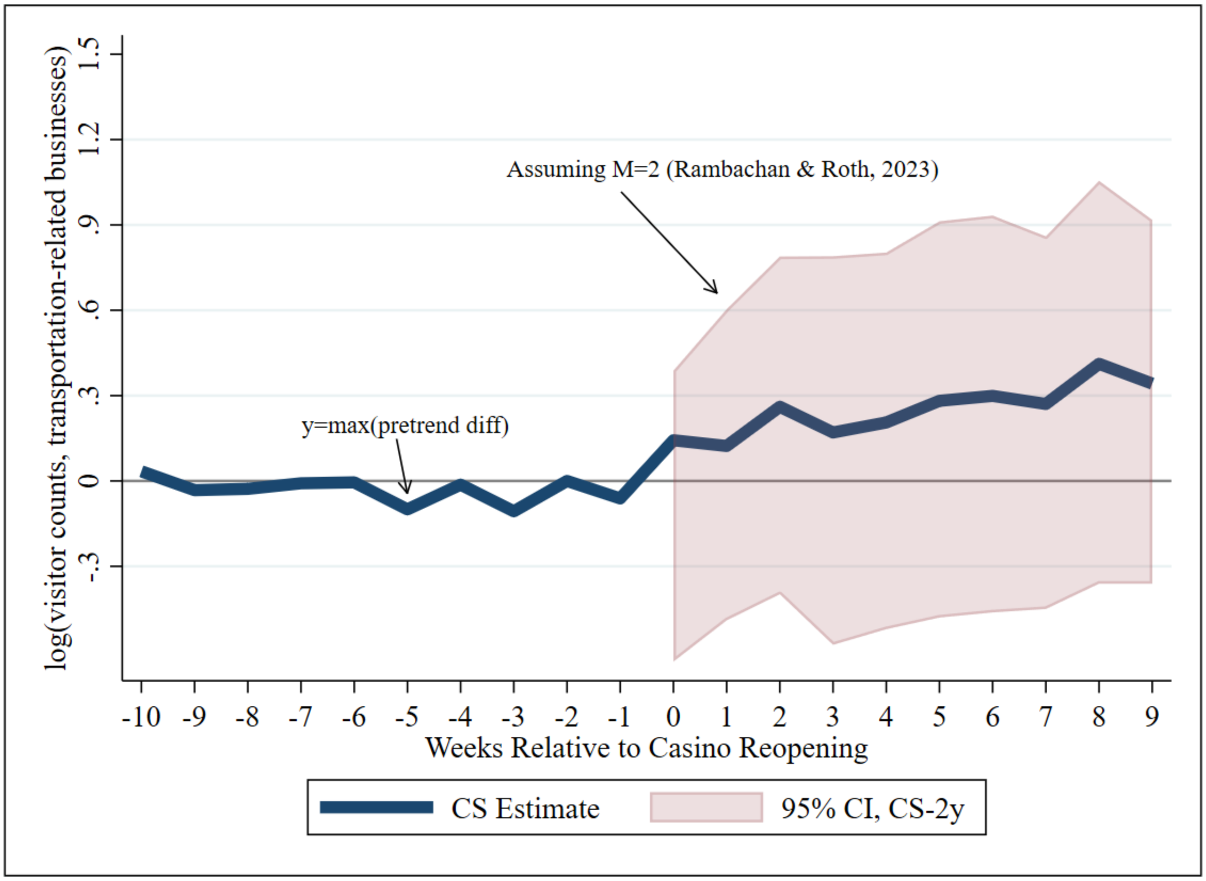


Figure A6: **Sensitivity to Violations of Parallel Trends, transportation-related businesses**

Notes: This figures shows how violations of parallel trends affects the post-treatment estimates. We plot the original CS estimates (thick line) and overlay the 95% confidence interval developed by Rambachan and Roth (2023). We assume that the violation of parallel trends in the post-treatment period is twice as large ($\bar{M}$=2) as the worst violation in the pre-period. Under this assumption, we still see statistically significant effects from casino reopenings after the third week after reopening.