Estimation of direct net effects of events

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Marcus Roller
University of Bern,
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Abstract

I provide three estimation strategies for the estimation of direct net effects of events and the respective substitution effects. I apply the strategies to estimate the effect of fairs on overnight stays in Basel. I show that deseasonalizing by year day fixed effects is superior to month and week fixed effects and semi-parametric deseasonalizing. I find that fairs increase the overnight stays in nights during fairs by 17% and by 8% and 4% in the preceding nights. The net effect of fairs on overnight events is only one fourth of the gross effect. These results demonstrate that the distinction between net and gross effects is crucial also for the estimation of direct effects of events. The study therefore contributes to the literature on the estimation of economic effects of events which recently has focused on this distinction for indirect effects.

1 Introduction

Tourism is often subsidized arguing that the economic benefits exceed the private gains of the involved actors (see e.g. European Commission, 2016). This is also the case for events like festivals or fairs.[1] In order to justify such policies, policy makers need reliable estimates of the economic impacts of the subsidized item. There exists a large literature in tourism economics how to estimate such economic effects in general (see e.g. Kronenberg et al., 2018; Martínez-Roget et al., 2013; Tohmo, 2018; Kim et al., 2015).[2] These general methods can also be applied to assess the impacts of events on the local economy (see e.g. Van Wyk et al., 2015). The literature thereby distinguishes direct economic effects of events, i.e. effects that are directly generated by the spending of visitors, and indirect economic effects that occur due to trade relations of directly affected actors with other actors in the economy. Thus, indirect effects are always functions of the initial direct economic effects. Furthermore, literature distinguishes between gross and net effects. Gross effects capture the contribution of events to the economy and net effects capture the impact of events on the economy (Dwyer, 2015). Both only equal if there are neither price nor substitution effects.

Recent developments mainly focussed on the distinct estimation of indirect gross and net effects(see e.g. Dwyer, 2015). Despite the importance of distinguishing between gross and net effects (Dwyer, 2015), the initial direct effects are usually estimated only as gross effect by surveys (see e.g. Van Wyk et al., 2015). But survey data neglects any substitution effects and therefore likely overestimates the impact in the presence of substitution effects and price effects. The estimation of direct net effects however demands the estimation of counter-factional scenarios which in the case of events demands also data on all non-event related touristic activities which is naturally not included in surveys gathered at event sites. However, recent developments in digitization make new data sources available that allow a more rigorous estimation of economic net effects.Therefore, I derive three methods based on event study design (see e.g. Schmidheiny and Siegloch, 2019) that allows to study economic net effects of events using high frequency data: A parametric approach with month and week fixed effects, a parametric approach with year day fixed effects, and a semi-parametric approach with and without year day fixed effects. Additionally, I suggest a method that allows to estimate gross and substitution

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[1] In Basel for example the canton is even the largest shareholder of the fair company (Kanton Basel, 2013).
[2] Methodological overviews are provided by Dwyer and Forsyth (1997) and Burfisher (2017)

effects without survey data.

I test the methods studying the direct net effect of fairs on overnight stays and attraction visits by overnight visitors in Basel. Fairs are of specific interest because they are usually highly subsidized and attract potentially many tourists to a city for a short time period. If the cities are small compared to the number of visitors of a fair, they can even hit capacity limits. It is at least likely that fair overnight visitors substitute some of the tourists usually visiting the city due to increased prices. I show that a sophisticated method of deseasonalizing is needed to estimate direct net effects. The parametric approach with year day fixed effects delivers plausible results under least restrictive assumptions. The parametric approach with month and week fixed effects delivers partly implausible results which are likely caused by endogeneity issues. The semi-parametric approach with month and week fixed effects has strong identifying assumptions but might be suitable also for shorter time-series that do not allow the inclusion of year day fixed effects.

I find that fairs in Basel increase the overnight stays in nights between fair days on average by 17% and by 8% and 4% in the preceding nights. They do not affect the overnight stays the nights following fairs. Robustness checks indicate that my results are unlikely to be generated by favourable fair dates that accidentally coincide with visitor peaks. Applying two different methods, I show that the gross effect on overnight stays is about four times the estimated direct net effect. This implies a substitution effect of three fourth of the gross effect. My effects are estimates on quantities. For economic effects, the ratio is likely to be lower due to price effects. Yet, it still illustrates the importance of distinguishing net and gross effects when estimating initial direct economic effects of events.

Therefore, this study contributes to the field of methods estimating economic effects of events by providing estimation strategies that allow the identification of direct net and substitution effects. The superior strategy demands high-frequency data on the relevant economic outcomes. But such data becomes more and more available offering a chance to use the strategy also for full economic impact analyses (see e.g. Brown et al., 2020).

2   Related literature

Assessing economic effects of tourism and events has a long tradition in the literature (see e.g. Dwyer and Forsyth, 1997). The basic and still popular model for measuring economic effects of tourism or single events is the input-output model (IO) (see e.g. Kronenberg et al., 2018; Martínez-Roget et al., 2013; Tohmo, 2018). Methodological overviews are provided by Dwyer and Forsyth (1997), Mistilis and Dwyer (1999), and Miller and Blair (2009). The method generally involves two steps: The first step is the assessment of the direct effects of a shock on the economy. A shock can for example be an exogenous shock in inbound tourism for a country or an event. Such direct effects are expenditures for overnight stays, restaurants, equipment, etc. induced by the event. They are usually assessed by surveys asking the spending behaviour of tourists or event visitors (see e.g. Kim et al., 2015; Van Wyk et al., 2015). The second step is the assessment of the indirect effects on the economy. These are expenditures of hotels etc. at their suppliers induced by their increased sales and the iteration of them. These indirect effects are not directly measured but estimated using input-output tables that link expenditures and trades between industries. Hence, knowing the direct effects on all industries, factors retrieved from these input-output linkages allow calculating overall economic effects including the indirect effects.

The second step using input-output factors in order to estimate indirect economic effect builds on several strong assumptions. Among others the model assumes that the prices of inputs and outputs are fixed, i.e. any demand or supply shock will not change the relative prices in the economy. Furthermore, it assumes linear economics of scale and unlimited supply or unlimited capacities (Dwyer, 2015). These assumption are not very plausible especially when the direct effects are comparably large (Dwyer et al., 2004). Computable general equilibrium (CGE) models can overcome these short-comings of the IO models but at the cost of much higher complexity (Dwyer, 2015). Unlike the IO models, CGE models allow for flexible prices and do not impose unlimited capacities and supply. An extensive methodological overview is provided by Burfisher (2017). The assessment of the direct effects is step 1 is unaffected by this model change. Generally, the indirect and overall economic effects are lower using the CGE models instead of the IO models (see e.g. Dwyer et al., 2005).

In recent years these CGE models became more popular (see e.g. Dwyer, 2015; Van Wyk et al., 2015) but did not entirely replace the IO models. Beyond the mentioned higher complexity of the model, there is a second reason for this development: The effects that they measure are different in nature. While the IO models are capable to answer the question which share of the economic activity is due to tourism or a certain event, CGE models answer the question what would happen to the economic activities if there would be no tourism or a certain event had not taken place. Thus the IO models result in the contribution of tourism or an event to the economy and the CGE models in the impact of tourism or an event on the economy (Watson et al., 2007). Hence, there is not one model that is superior to the other but researches have to choose the correct model to answer the respective question.

Recent developments in estimating indirect and overall economic effects involve dynamic input-output tables (Kronenberg et al., 2018) and explicitly modelling and collecting data on the supply side (Kim et al., 2015).

While the distinction between economic impacts and contribution has been acknowledged in estimation indirect and overall economic effects, the assessment of direct economic effects in the tourism literature lacks strict methodological distinction between both although scholars are aware that this distinction is equally valid in this context (see e.g. Dwyer, 2015). Even very recent studies estimating the effects of events on the economy base their effects on survey data collected at the attendees and the organizers (see e.g. Van Wyk et al., 2015). This method captures the contribution, i.e. the gross effect of events because it attributes each dollar spent to the event. It does not ask how would the dollars have been spent if the event had not taken place. A valid strategy of estimating direct net economic effects of events seems to be missing in the literature. The reason might rather be a historic lack of data availability than an actual lack of methods from the general economic literature. I address this gap by suggesting an empirical framework that allows to estimate direct effects of events on any measure that is available on a daily basis.

There is a very wide range of studies addressing the economic contribution or their impacts on the economy. Many of them focus on single events like the London 2012 Olympics (Blake, 2005), the football world cup in South Africa in 2010 (Saayman and Rossouw, 2008; Bohlmann and Van Heerden, 2008) which all were studies predicting the effects using the above mentioned models. Daniels (2004) investigates sport events but focusses on the effects on wages. Dwyer

et al. (2005) estimate the economic effects of the Australian Formula One Grand Prix both using IO and GCE models demonstrating that the results can differ by more than the factor of two depending on the model choice. Van Wyk et al. (2015) and Saayman and Rossouw (2011) both investigate festivals in South Africa. Van Wyk et al. (2015) demonstrates the importance of using a CGE model but also relies on survey data for estimating the direct effects. Other studies investigate the MICE sector. Kasagranda et al. (2017) and Celuch et al. (2018) take a country perspective for Slovakia and Poland. Celuch et al. (2018) estimates the contribution of the meeting industry on the Polish Economy. Studies focussing on local effects of fairs are rather rare. Penzkofer (2017), AUMA (2018), Penzkofer (2018), and Hochheim and Penzkofer (2019) all estimate economic effects for fairs in Germany using IO models and survey data. Hence, they all estimate the contribution of these fairs to the economy rather than their impact. However, for fairs which are usually highly subsidized, it is rather interesting for policy makers to know what the economy would look like if the fair did not take place. Or speaking differently, what are the economic costs of cutting subsidies? Hence, in my empirical application, I focus on the direct impact of fairs on overnight stays and the usage of local attractions. Thereby, I compare the direct contribution and the direct impact of fairs on overnight stays and demonstrate that the difference is sizeable and the distinction therefore important.

This study contributes to the methodological literature of estimation the impact of events by providing an estimation strategy for direct net economic effects that in combination with CGE models can allow the estimation of the actual impact of events rather than their economic contribution.

3   Empirical strategy

3.1   Parametric strategy

The final goal of the empirical strategy is to estimate the direct net effect of events on any economic outcome variable. I suggest and adapted version of the event study design approach by Schmidheiny and Siegloch (2019) and estimate the following equation using OLS with daily

data:

$$Y_t = \alpha + \beta_0 M_t + \sum_{l=1}^{L} \beta_{-l} M_{t-l} + \sum_{f=1}^{F} \beta_f M_{t+f} + \gamma X_t + u_t \tag{1}$$

Y_t is an outcome variable at date t.[3] M_t is an indicator that equals one for date t if there is an event on date t and zero else. The coefficient estimate $\hat{\beta}_0$ will therefore capture the effect of the event on the respective outcome variable. M_{t-l} is an indicator that equals one for date t if there is an event on date $t - l$ and zero else. The coefficient estimate $\hat{\beta}_{-l}$ will therefore capture the effect on the outcome variable on the lth day after the event. M_{t+f} is an indicator that equals one for date t if there is an event on date $t + f$ and zero else. The coefficient estimate $\hat{\beta}_f$ will therefore capture the effect on the outcome variable on the fth date before the event. X_t is a vector of controls. It contains the same set of dummies for other events that we are not interested in capturing extraordinary demands caused by these events. Furthermore, it contains a year fixed-effect capturing the long-run trend, month fixed effects capturing the seasonality, and weekday fixed effects capturing the usual pattern during a week. Yet, all these controls cannot mitigate the fact that the timing of events is not random which can cause potential endogeneity issues.

3.2 Parametric strategy with year day fixed effects

If researches have multiple years of observations and the events of interest do not always take place at the same day in the year, they can include year day fixed effects, S_t, in equation 1:

$$Y_t = \alpha + \beta_0 M_t + \sum_{l=1}^{L} \beta_{-l} M_{t-l} + \sum_{f=1}^{F} \beta_f M_{t+f} + \gamma \tilde{X}_t + \gamma S_t + u_t \tag{2}$$

Unlike with date fixed effects, these allow us to compare for example the first Monday in each year and not the first of January that is in one year a Monday and the next year a Tuesday. All effects are then identified for events that change their year day. The endogeneity issues here are much less severe because the general seasonal timing does not effect the estimates. The identifying assumption is that the date adjustments of events is not related to the expected

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[3]Unless otherwise mentioned, I use the natural logarithm of overnight stays as dependent variable to directly estimate percentage effects.

outcome on the target date. This is clearly the case for regular events that fore example take place always on the first Sunday in June. Such events jump six days all 5 or 6 years by construction. Note that month or weekday effects drop out by construction and are not contained in $\tilde{X}_t$.

3.3 Semi-parametric strategy

Trying to capture the seasonality by month dummies however places parametric restrictions and leads to discontinuities at the start and end of a month. A more sophisticated approach is adjusting the time series with a local polynomial smooth in principal following the approaches usually used to identify bunching behaviour in densities (see e.g. Kleven and Waseem, 2013). In particular, I estimate the following equation using OLS:

$$\Delta \tilde{Y}_t = \alpha + \beta_0 M_t + \sum_{l=1}^{L} \beta_{-l} M_{t-l} + \sum_{f=1}^{F} \beta_f M_{t+f} + \gamma X_t + \Delta \tilde{u}_t \tag{3}$$

where

$$\Delta \tilde{Y}_t = Y_t - \tilde{Y}_t$$

$\tilde{Y}_t$ is the prediction from a local polynomial smooth of Y_t on t excluding the b dates before and the five dates after a fair or an event. The advantage is that it captures the usual level of outcome locally around the event date and that there are no discontinuities at the start and end of a month. Formally, we can approximate the outcome variable Y_s around date t by a Taylor polynomial of order p:

$$Y_s \approx m(s|t,\phi) = \phi_0 + \phi_1[s-t] + \phi_2[s-t]^2 + ... + \phi_p[s-t]^p \tag{4}$$

where

$$\phi_0 = Y_t$$

$$\phi_1 = Y_t'$$

$$\vdots$$

$$\phi_p = Y_t^p$$

Y_t^p is the pth derivative of Y_t with respect to t. Hence, the polynomial captures the level and the curvature of the function locally. This is much more precise and flexible than using month fixed effects. Formally, I solve the following minimization problem for each date t:

$$\min_{\phi} \sum_{s}^{T} [Y_s - m(s|t, \phi)]^2 K_h[s - t] \tag{5}$$

where $K_h[s-t]$ are Epanechnikov kernel weights with bandwidth h if date s is outside the $2b$ day window around the event dates and zero else. This also allows us to estimate the polynomial for the dates within that window if the bandwidth is larger than the $2b$ days. The advantage of this method is that it is less restrictive on the demanded data then the year day fixed effects and offers a more sophisticated deseasonalizing of the data than the paramentric strategy. Yet, the identification is similar to the parametric approach, i.e. the non random timing of events is more likely to lead to endogeneity issues than in the strategy with year day fixed effects.

4 Data

I test the three suggested estimation strategies estimating the effect of fairs on overnight stays in Basel (Switerland) from 01/01/2015 to 12/31/2019. Fairs are often subsidised events and large compared to the capacities of cities which makes the assumption of no substitution effects of traditional methods unlikely to hold. Overall, 101 fairs took place in this time span which leads to 20 fairs per year. The fairs lasted 4.3 days on average, thus at least exhibitors are very likely also to stay overnight. Table 1 provides the descriptive statistics about these fairs.

Table 1: Descriptive statistics fairs

Year	Number	Duration				Visitors				Exhibitors			
		Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
2015	19	4.42	2.69	1.00	10.00	37,730	45,453	1,050	150,000	259	359	38	1,500
2016	25	4.12	2.49	1.00	10.00	35,109	42,202	800	145,000	283	346	45	1,500
2017	20	4.55	2.63	1.00	10.00	40,100	45,104	300	144,365	250	319	40	1,300
2018	16	4.56	2.50	1.00	10.00	41,271	43,566	1,362	124,300	246	284	23	1,046
2019	21	4.05	2.25	1.00	10.00	35,389	53,262	1,288	236,619	241	180	42	605
Total	101	4.32	2.47	1.00	10.00	37,625	45,209	300	236,619	257	300	23	1,500

Notes: This table presents the descriptive statistics for the fairs that took place in Basel from 01/0/2015 to 12/31/2019. Standard deviations in parenthesis. Data source: Statistisches Amt (2020).

Table 2 contains the descriptive statistics for the overnight stays in the respective period in Basel. The overnight stays are composed of hotels (1 to 5 stars) and other accommodations. The overnight stays in other accommodations more than double from 2016 to 2017 due to the registrations of Airbnb apartments. Since all empirical strategies contain year fixed effects, this is not an identification issue.

Table 2: Descriptive statistics overnight stays

Overnight stays					
Year	All	Others	1 to 2 star	3 star	4 to 5 star
2015	1,201,796	29,452	194,474	421,999	555,871
2016	1,217,677	53,837	198,166	449,554	516,120
2017	1,328,047	128,890	203,484	501,348	494,325
2018	1,386,499	127,007	210,590	524,979	523,923
2019	1,423,486	121,922	207,257	529,253	565,054
Total	6,557,505	461,108	1,013,971	2,427,133	2,655,293

Occupancy rates (in percent)					
Year	All	Others	1 to 2 star	3 star	4 to 5 star
2015	61.97	35.68	50.66	65.08	65.95
2016	61.36	45.84	50.50	64.65	64.91
2017	60.95	59.94	49.40	63.00	64.40
2018	62.77	59.70	53.10	65.52	64.87
2019	64.43	59.77	56.93	64.80	68.06
Total	62.29	52.18	52.12	64.61	65.64

Notes: This table presents the descriptive statistics for the overnight stays in Basel for the years 2015 to 2019. The category others captures all non-hotel accommodation. Data source: Statistisches Amt (2021).

Bringing the fair data and the overnight stay data together, we can plot the daily overnight stays as in panel (a) of figure 1 for 2019. The dark gray bars mark fair dates while the light gray bars mark dates with other events that are likely to influence the number of overnight stays. The solid black line are the daily overnight stays. One can clearly see that they fluctuate a lot. On the one hand there is a seasonality, i.e. there are more overnight stays in summer than in the winter. Second, there are typically more overnight stays during the week than on weekends. Obviously, there are several peaks of which most seem to coincide with fairs or events. Thus, we have first visual evidence that the fairs actually increase the overnight stays as do the events The same holds if we consider the occupancy rate as depicted in panel (b). We also see that several fairs coincide with occupancy rates above 90% where the overnight stays are close to the overall capacity limit ob Basel's accommodation.

Figure 1: Overnight stays 2019

(a) Overnight stays
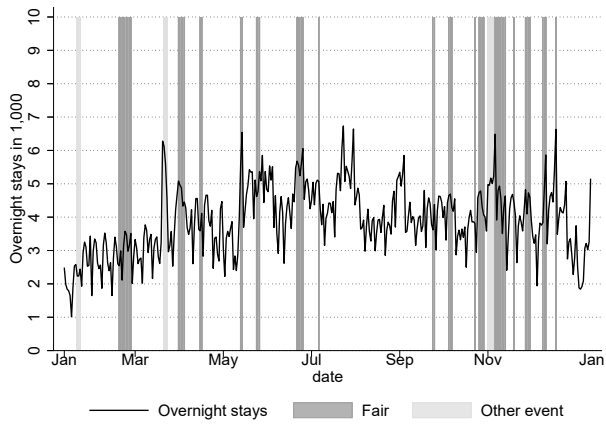
(b) Occupancy
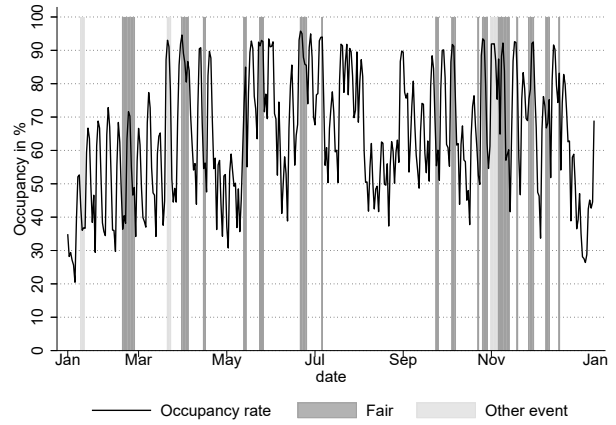
Notes: Panel (a) shows the total daily overnight stays in Basel for the year 2019. Panel (b) shows the overall daily occupancy rate of the available accommodation in Basel for 2019.
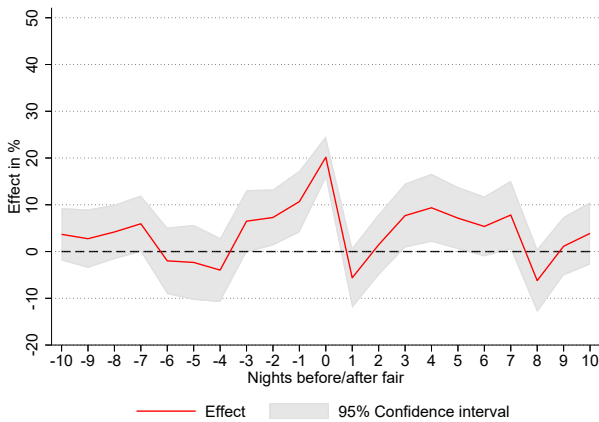
5 Results

5.1 Net effects

Panel (a) of figure 2 presents the results for equation 1 using the natural logarithm of daily overnight stays as dependent variable and with only event controls and a time window of +/-10 days around fairs. The estimate for 0 estimates the average percentage effect of fairs on overnight stays for nights between fair days. Hence, it estimates that in these nights the overnight stays increase by 20% compared to nights without fairs. The estimates are also significantly positive up to three days before fairs and as of the third night after a fair. The latter seem surprising but might actually be caused by the non-random timing of fairs. Panel (b) shows the results including additionally year fixed effects, month fixed effects and weekday fixed effects. The results do not change very much except that the lead and lag estimates are smoother.

Figure 2: Effect of fairs on overnight stays
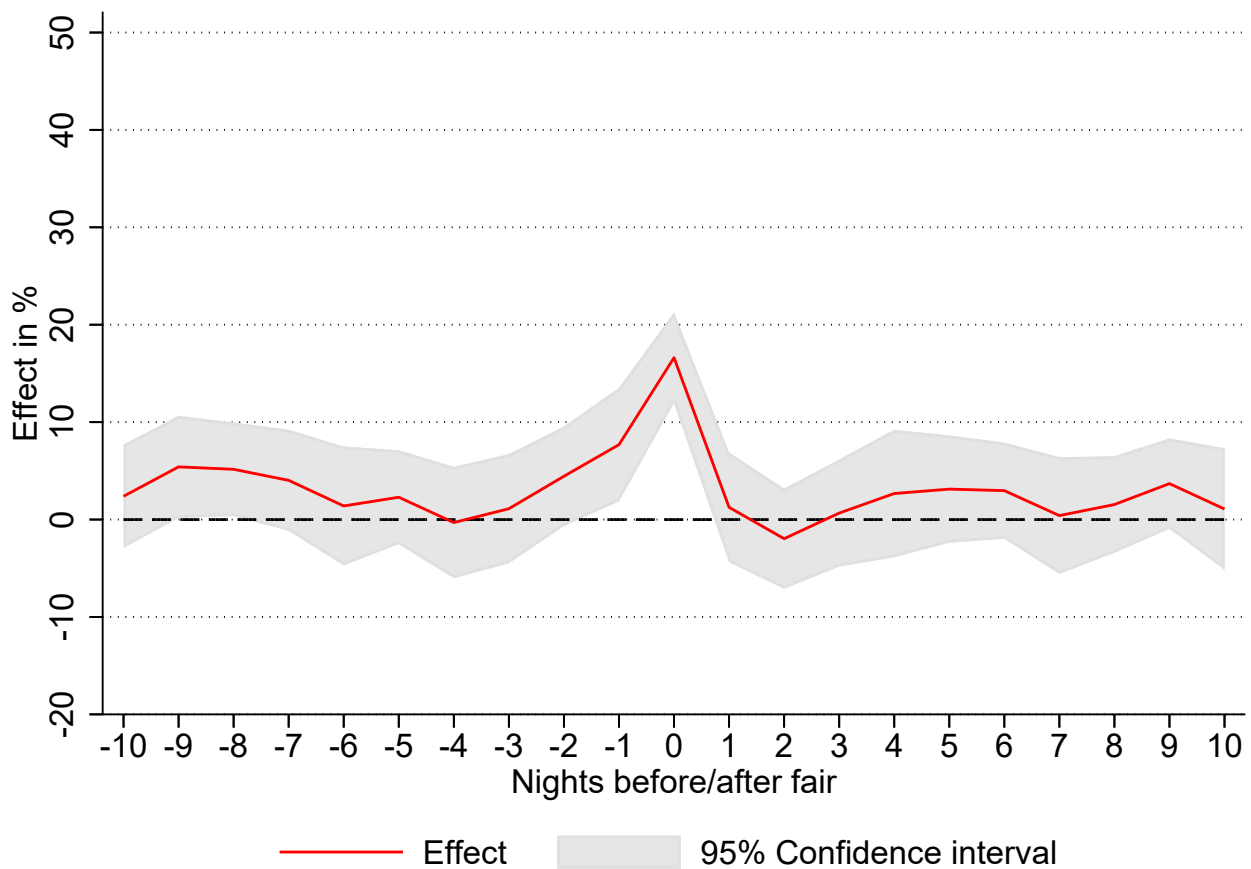**(a)** without controls   **(b)** with controls
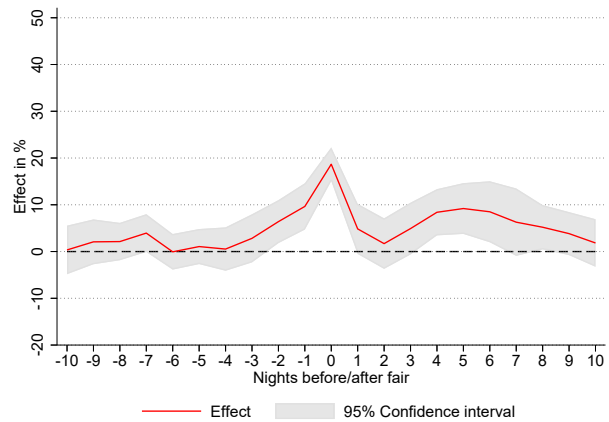
Notes: This figure presents the estimates of the average percentage effect of fairs on overnight stays in Basel from 01/01/2015 to 12/31/2019. -1 refers to the night before a fair and +1 to the night following the last fair day. 0 refers to nights between two fair days. Panel (a) presents the results from the parametric specification (see equation 1) without any controls. Observations: 1,826 days. Year day clustered standard errors. Panel (b) presents the results from the parametric specification (see equation 1). Observations: 1,826 days. Year day clustered standard errors.

Controlling by month fixed effects might not be enough because it can neither perfectly capture seasonal pattern nor perfectly address endogeneity issues arising from non random fair dates. Therefore, I also estimate the parametric specification in equation 2 which adds season day

fixed effects that can account for any seasonality in the data. Figure 4 presents the results. Indeed, the positive estimates for the days following a fair disappeared while the fair effect stayed almost the same (17%). The two nights before the fairs are also significantly positive with an increase of 7.7% in nights before fairs and of 4.5% two nights before. I find no significant effect after the fair. This suggests that probably exhibitors or visitors arrive early to prepare the fair but do not stay longer contradicting any bleisure hypotheses.

Figure 3: Effect of fairs on overnight stays with year day fixed effect

Notes: This figure presents the estimates of the average percentage effect of fairs on overnight stays in Basel from 01/01/2015 to 12/31/2019. -1 refers to the night before a fair and +1 to the night following the last fair day. 0 refers to nights between two fair days. It presents the results from the parametric specification with year day fixed effects (see equation 2). Observations: 1,826 days. Year day clustered standard errors.

The semi-parametric approach using equation 3 leads to very similar results as figure 3 indicates. Panel (a) presents the results from the estimates using equation 3. The estimated coefficient during fairs is almost the same as in the parametric specifications and we clearly see significantly

more overnight stays the nights before fairs. The positive estimates four days after the fair however indicate that also the semi-parametric approach captures a certain timing effect of fairs. If we estimate the effect using equation 3 but with year fixed effect, the estimated effects get very close to the parametric specification with year day fixed effects. Yet the point estimate for fair nights is slightly lower.

Figure 4: Effect of fairs on overnight stays- semi-parametric estimation
(a) With month and weekday fixed effects   **(b)** With year day fixed effect
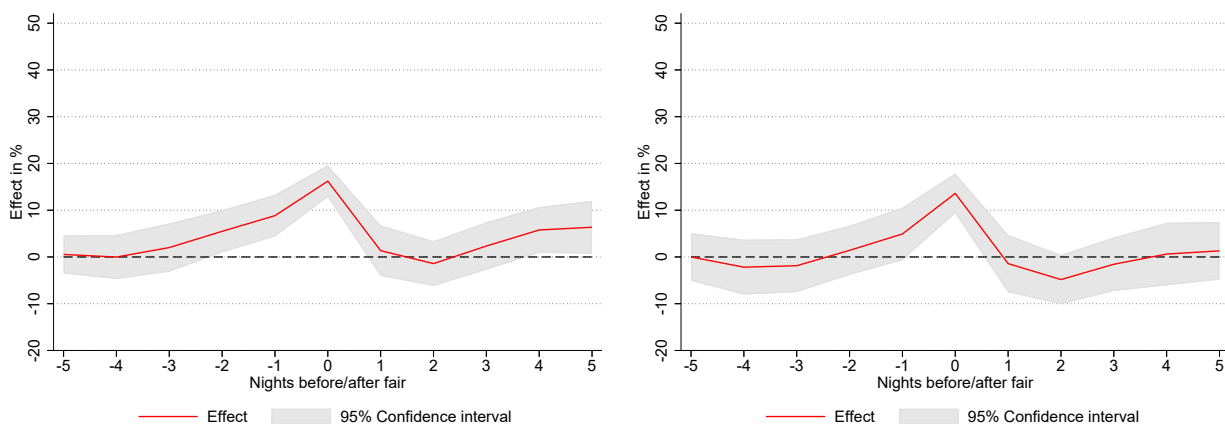
Notes: This figure presents the estimates of the average percentage effect of fairs on overnight stays in Basel from 01/01/2015 to 12/31/2019. -1 refers to the night before a fair and +1 to the night following the last fair day. 0 refers to nights between two fair days. Panel (a) presents the results from the semi-parametric specification (see equation 3) with month and weekday fixed effects using a local polynomial smooth of degree 3, Epanechnikov-kernel weights, and a bandwidth of 90 days excluding -5/+5 day windows around fairs and events. Observations: 1,826 days. Year day clustered standard errors. Panel (b) presents the results from the semi-parametric specification (see equation 3) with year day fixed effect using a local polynomial smooth of degree 3, Epanechnikov-kernel weights, and a bandwidth of 90 days excluding -5/+5 day windows around fairs and events. Observations: 1,826 days. Year day clustered standard errors.

Overall, one can conclude that a sophisticated process of deseasonalizing is demanded to estimate direct net effects of events.[4] In my application, I prefer the parametric specification with season day fixed effects alone because it puts less restrictions on the size of the estimated time-window around fairs[5] and has least restrictive identifying assumptions.

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[4]For results for other events refer to table A.2 and A.1 in the appendix

[5]There is a trade-off between the length of the leads and lags and the estimation of the counterfactual distribution because the effect window is cut out of this estimation.

5.2 Heterogeneity

The data allows to split the effect into different accommodation categories. Hence, I estimated equation 2 using only hotel overnight stays. The estimates are very similar as using all overnight stays (see panel (a) of figure 5) which is caused by the fact that overnight stays in other accommodation account for less than 10% of all overnight stays. The estimates using only overnight stays in other accommodations are positive for almost the entire time window as indicated in panel (b) of figure 5. But the confidence bands are very large such that I would not over interpret the significant estimates at the tails. The effect during fairs is very similar to hotels. Thus, there is no specific accommodation category profiting more or less from fairs.

Figure 5: Effect of fairs on overnight stays with year day fixed effect
(a) Hotels   **(b)** Other
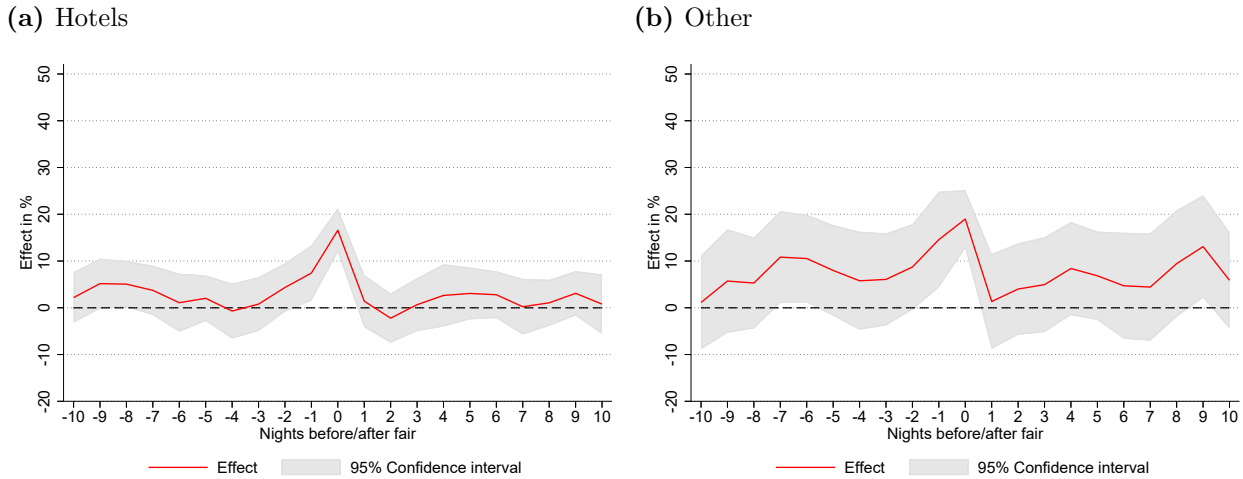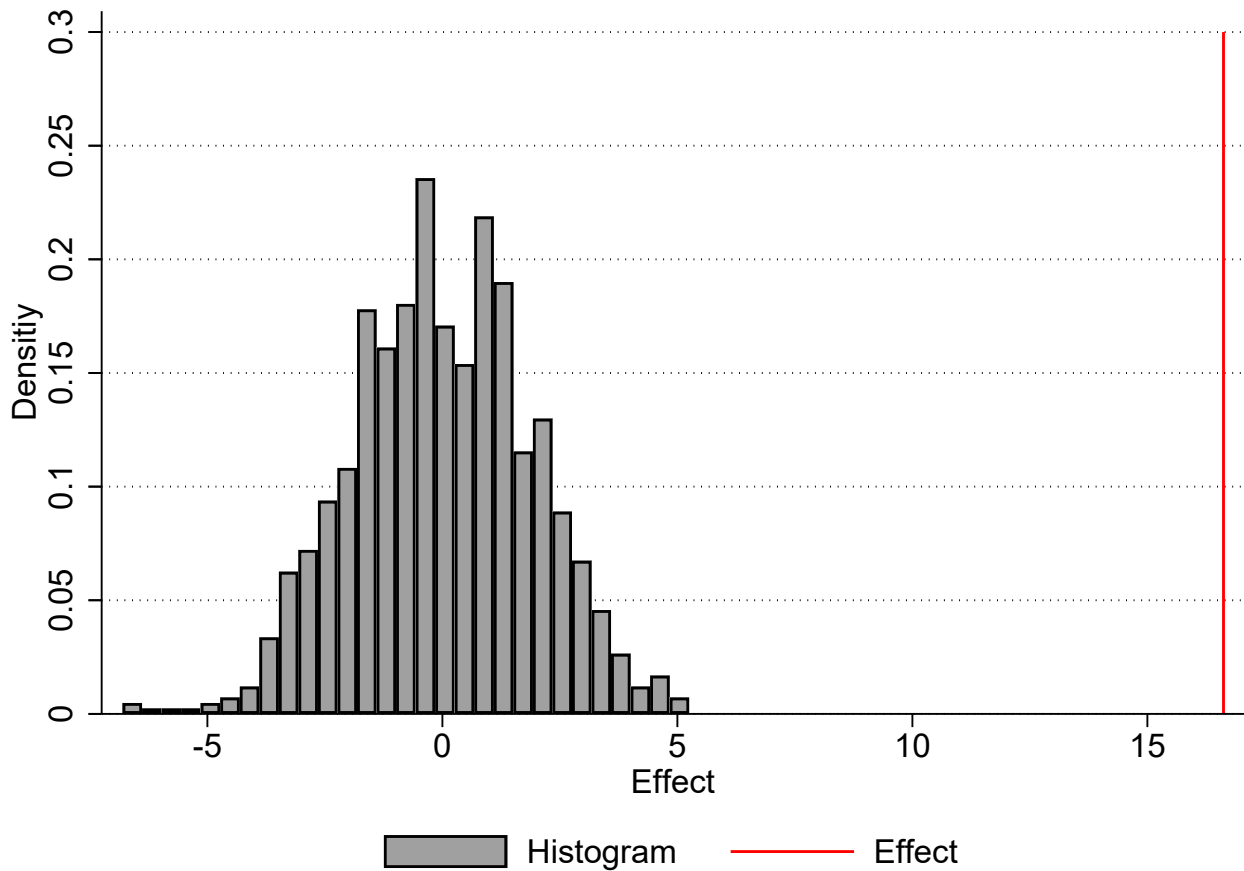

Notes: This figure presents the estimates of the average percentage effect of fairs on overnight stays in Basel from 01/01/2015 to 12/31/2019. -1 refers to the night before a fair and +1 to the night following the last fair day. 0 refers to nights between two fair days. Panel (a) presents the results from the parametric specification with year day fixed effects (see equation 2) for hotels. Observations: 1,826 days. Year day clustered standard errors. Panel (b) presents the results from the parametric specification with year day fixed effects (see equation 2) for other accommodations. Observations: 1,826 days. Year day clustered standard errors.

5.3 Robustness

The major identification issue is that fairs are not randomly timed within a year which is addressed by the year day fixed effects. But the re-timing of fairs and the introduction and abolishment of fairs that drive the identification when I use year day fixed effects might neither be random but strategic regarding the overnight stays. To test whether the effects are likely

caused by favourable re-timing of fairs, I performed a bootstrap analysis: I randomly re-timed the fairs within each year keeping their duration constant and estimated equation 2. I repeated this procedure 1,000 times and plotted the distribution of the estimates for the nights between fair days, $\hat{\beta}_0$, in figure 6. The effects are centred around zero. The red line plots the actually estimated effect of 17%. All bootstrap effects are far below the estimated effect. Hence, I can rule out that my results are driven by strategic re-timing of fairs.

Figure 6: Effect of fairs on overnight stays - bootstrap

Notes: This figure presents the histogram of 1,000 bootstrap estimates of the average percentage effect of fairs on overnight stays in Basel from 01/01/2015 to 12/31/2019 from the parametric specification with year day fixed effects (see equation 2) using random fair start dates within the respective year.

5.4 Substitution effects

The estimated effects in section 5 are direct net effects. In this section, I estimate the magnitude of error using direct gross effects as an input for an economic effect analysis instead of direct net

effects. First, I annualize the results from estimating equation 2 in levels applying the following calculation:

$$\hat{B} = \underbrace{\frac{\sum_{t=1}^{T} M_t}{5}}_{\text{Fair nights per year}} \underbrace{\frac{\sum_{t=1}^{T} Y_t}{5}}_{\text{Overnight stays per year}} \hat{\beta}_0$$

$$+ \underbrace{\frac{\sum_{t=1}^{T} M_t}{5}}_{\text{Fair nights per year}} \underbrace{\frac{\sum_{t=1}^{T} Y_t}{T}}_{\text{Overnight stays per day}} \left[\sum_{f=1}^{F} \hat{\beta}_f + \sum_{l=1}^{L} \hat{\beta}_{-l} \right] \quad (6)$$

The result is a net effect of 66,500 additional overnight stays per year as presented in table 3. The gross and substitution effects are estimated using two different methods:

In *method 1*, the gross effect is calculated as 21% of the annual overnight visitors following the official statistics (BHP – Hanser und Partner AG, 2016) resulting in 275,415 overnight stays due to fairs. Hence, 208,915 overnight stays only substitute other overnight stays.

Table 3: Gross and substitution effects on overnight stays

Method	Gross effect	Net effect	Substitution effect	Share of net effect
1	275,415	66,500	-208,915	24.15%
2a)	148,885	66,500	-82,384	44.67%
2b)	251,532	66,500	-185,032	26.44%

Notes: The net effect is the annualized cumulative net effect over all fairs including the +/-10 day window around the fairs from the estimation of equation 2. Method 1: The gross effect is calculated as 21% of the annual overnight visitors following BHP – Hanser und Partner AG (2016). Method 2a): The substitution effect is the annualized cumulative net effect over all fairs including the +/-10 day window around the fairs from the estimation of equation 2 using the logarithm of attraction visits by overnight guests as dependent variable. Method 2b): The substitution effect is the annualized cumulative net effect over all fairs including the +/-10 day window around the fairs from the estimation of equation 2 using the logarithm of zoo visits by overnight guests as dependent variable.

In *methods 2a) and b)*, I estimate the substitution effect indirectly by exploiting data of the usage of the Basel Card which each legal overnight guests receives. The Basel Card grants discounts at various attractions in Basel. Each time the card is used it is scanned. The data at hand contains every single use of the Basel Card from 01/01/2018 to 05/14/2019.[6] If we assume that the fair visitors do not have any demand for attraction visits and that the different types of overnight visitors that usually visit Basel are equally likely to be substituted by fair, the effect

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[6]The data is confidential an was received from Basel Tourism directly. For descriptive statistic see table A.1 in the appendix.

on attraction visits reflects the substitution effect for overnight stays. Figure 7 presents the results of estimation equation 2 using the natural logarithm of the usage of the Basel Card as dependent variable. Panel (a) refers to method 2a) and shows that the attraction visits decrease two nights before fairs up to -30% on fair days. Applying equation 6 to the estimates for the attraction visits leads to an estimated substitution effect of -82,384 visitors. This implies that the gross effect is 148,885 which is much lower than the official statistics.

Figure 7: Effect of fairs on attraction use
(a) All   **(b)** Zoo
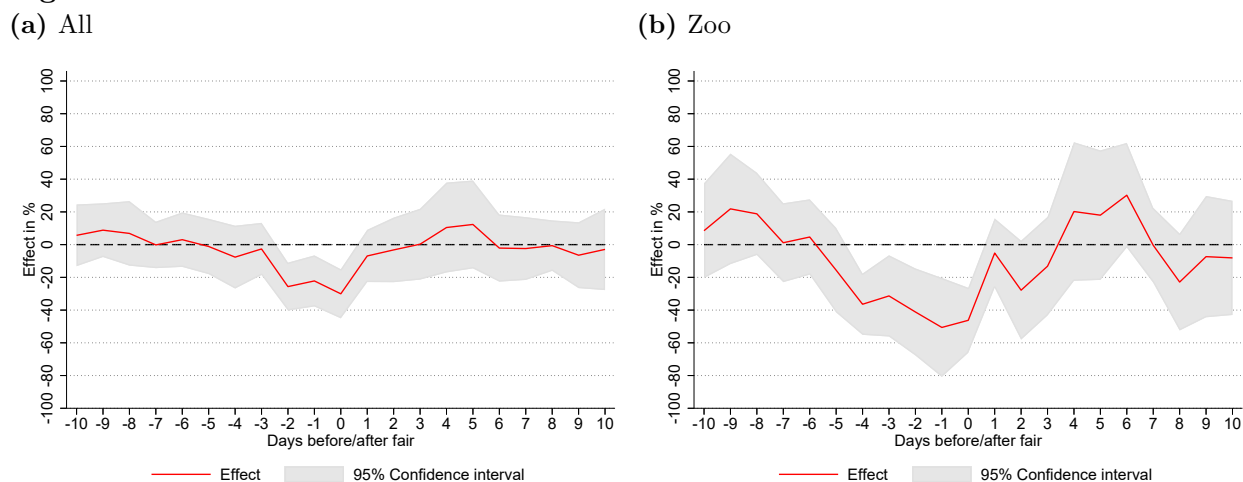
Notes: This figure presents the estimates of the average percentage effect of fairs on the attraction use by overnight guests in Basel from 01/01/2018 to 05/14/2019. -1 refers to the day before a fair and +1 to the day following a fair. 0 refers to fair days. Panel (a) presents the results from the parametric specification with year day fixed effects (see equation 2) for all attractions included in the Basel Card. Observations: 499 days. Year day clustered standard errors. Panel (b) presents the results from the parametric specification with year day fixed effects (see equation 2) for the zoo. Observations: 499 days. Year day clustered standard errors.

The assumption that fair visitors do not visit attractions does not entirely hold, since for example during the art fair, museums are rather complements to the fair. Hence, panel (b) refers to method 2b) and plots the effect only for the zoo, which is least likely to be visited by fair guests. This is also reflected in the larger effect on fair days which is almost -50%.[7] Applying equation 6 to the estimates for the zoo visits leads to an estimated substitution effect of -185,032 visitors. This implies that the gross effect is 251,532 which almost matches the official statistics from method 1.

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[7]On fair days where the overnight stays nearly hit the capacity limit ($> 80\%$ occupancy) normal visitors are quasi entirely substituted as figure A.2 shows.

Thus, the direct gross effect of fairs on overnight stays in Basel is about four times the net effect. Three fourth of the overnight stays only substitute other overnight stays. This demonstrates the importance also distinguishing between net effects and gross effects (impact and contribution) when estimating the direct effect of events. Every CGE model based estimation based on the gross effects would by far overestimate the the indirect impact.

6   Conclusion

In this paper, I studied the current methodological developments in assessing the economic impacts of tourism and touristic events. I showed that although there has been a lot of progress in estimating the indirect effects in recent years (see e.g. Dwyer, 2015; Kronenberg et al., 2018), there is less progress in the methods estimating the size of the initial shock, i.e. the direct economic effect (see e.g. Kim et al., 2015). Usually, literature regards gross effects from survey data as the initial shock (see e.g. Kim et al., 2015; Kronenberg et al., 2018; Van Wyk et al., 2015) but if it does not equal the net effect it has the potential to severely overestimate the direct effect and the indirect effect which is a function of the direct effect. Therefore, I derive three methods based on event study design (see e.g. Schmidheiny and Siegloch, 2019) that allows to study economic net effects of events using high frequency data: A parametric approach with month and week fixed effects, a parametric approach with year day fixed effects, and a semi-parametric approach with and without year day fixed effects.

I test the methods studying the direct net effect of fairs on overnight stays and attraction visits by overnight visitors in Basel. I show that a sophisticated method of deseasonalizing is needed to estimate direct net effects, i.e. the specifications with year day fixed effects deliver more plausible results under less restrictive assumptions. While the parametric approach with month and week fixed effects delivers partly implausible results, the semi-parametric approach with month and week fixed effects might be suitable also for shorter time-series.

I find that fairs in Basel increase the overnight stays in nights between fair days on average by 17% and by 8% and 4% in the preceding nights. They do not affect the overnight stays the nights following fairs. Robustness checks indicate that my results are unlikely to be generated by favourable fair dates that accidentally coincide with visitor peaks.

Using two different methods, I demonstrate that the gross effect of fairs on overnight stays in Basel is is about four times the net effect depending on the underlying assumptions. This ratio is quite large and might be lower for other direct economic effects like restaurant visit. It is also likely to be lower if one incorporates price effects. But we can clearly reject the assumption of the absence of price and substitution effects is made by traditional approaches for estimation direct economic effects. Thus, a clear distinction between net and gross effects is demanded also in the first stage of the estimation of economic effects of events in the case where events are large compared to the local capacities.

The method introduced in this paper is suitable for studying any direct economic effects of events but it is demanding on the respective data: For a comprehensive economic analysis one needs daily data on all relevant economic outcomes. Recent developments are in digitization make such data more and more available. Future research therefore should focus on new data sources that can be exploited to more adequately estimate direct economic effects of tourism or events.

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A   Appendix

A.1   Data

Table A.1: Descriptive statistics attraction visits

Year	All	Art museums	Museums	Zoo	Others
2018	95,460	42,693	25,225	20,322	7,220
2019	35,936	16,605	9,482	7,545	2,304
Total	131,396	59,298	34,707	27,867	9,524

Notes: This table presents the descriptive statistics for the attraction visits by overnight stayers using the Basel Card in the canton of Basel from 01/01/2018 to 05/14/2019 for different attraction categories. Art museums are the Kunstmuseum, the Fondation Beyeler, the Tinguely Museum, the Kunsthalle Basel, the Haus der elektronischen Künste Basel and the Kunsthaus Baselland. All other museums are contained in the second category. The Zoo is displayed separately and all other attractions are contained in Others.

A.2   Results

Table A.2: Estimates

Variable	I	II	III	IV	V
Fairnight(-10)	3.68	0.35	2.39		
	(2.86)	(2.65)	(2.71)		
Fairnight(-9)	2.75	2.08	5.41**		
	(3.19)	(2.44)	(2.67)		
Fairnight(-8)	4.19	2.14	5.16**		
	(2.97)	(2.04)	(2.45)		
Fairnight(-7)	5.95*	3.95*	4.03		
	(3.08)	(2.06)	(2.65)		
Fairnight(-6)	-1.99	-0.06	1.40		
	(3.64)	(1.94)	(3.11)		
Fairnight(-5)	-2.33	1.07	2.29	0.53	0.00
	(4.09)	(1.91)	(2.46)	(2.08)	(2.60)
Fairnight(-4)	-3.96	0.53	-0.31	-0.01	-2.18
	(3.49)	(2.37)	(2.92)	(2.40)	(3.00)
Fairnight(-3)	6.49*	2.83	1.11	2.01	-1.87
	(3.39)	(2.62)	(2.85)	(2.64)	(2.88)
Fairnight(-2)	7.28**	6.40***	4.45*	5.48**	1.42
	(3.06)	(2.34)	(2.61)	(2.31)	(2.68)
Fairnight(-1)	10.69***	9.65***	7.69***	8.83***	4.92*
	(3.36)	(2.53)	(2.97)	(2.28)	(2.87)
Fairnight(0)	20.17***	18.67***	16.62***	16.22***	13.60***
	(2.30)	(1.83)	(2.37)	(1.74)	(2.17)
Fairnight(1)	-5.61*	4.84*	1.26	1.34	-1.42
	(3.28)	(2.73)	(2.87)	(2.76)	(3.13)
Fairnight(2)	1.45	1.69	-1.96	-1.42	-4.83*
	(3.32)	(2.75)	(2.62)	(2.44)	(2.69)
Fairnight(3)	7.69**	4.91*	0.67	2.33	-1.56
	(3.49)	(2.82)	(2.80)	(2.59)	(2.92)
Fairnight(4)	9.36**	8.40***	2.67	5.77**	0.62
	(3.72)	(2.52)	(3.34)	(2.50)	(3.41)
Fairnight(5)	7.15**	9.20***	3.13	6.35**	1.31
	(3.39)	(2.77)	(2.81)	(2.89)	(3.15)
Fairnight(6)	5.37	8.51**	2.97		
	(3.27)	(3.33)	(2.52)		
Fairnight(7)	7.82**	6.28*	0.41		
	(3.74)	(3.68)	(3.05)		
Fairnight(8)	-6.21*	5.20**	1.54		
	(3.45)	(2.42)	(2.53)		
Fairnight(9)	1.14	3.83	3.69		
	(3.19)	(2.35)	(2.37)		
Fairnight(10)	3.89	1.83	1.08		
	(3.40)	(2.59)	(3.18)		
R2	0.17	0.56	0.77	0.39	0.68
N	1,826	1,826	1,826	1,826	1,826
Event controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	Yes	No	Yes
Month fixed effects	No	Yes	No	Yes	No
Weekday fixed effects	No	Yes	No	Yes	No
Year day fixed effects	No	No	Yes	No	Yes

Notes: This table presents the estimates of the average percentage effect of fairs on overnight stays in Basel from 01/01/2015 to 12/31/2019. -1 refers to the night before a fair and +1 to the night following the last fair day. 0 refers to nights between two fair days. Year day clustered standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
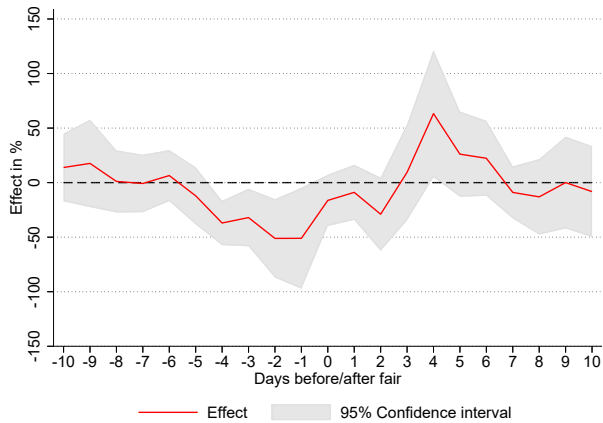
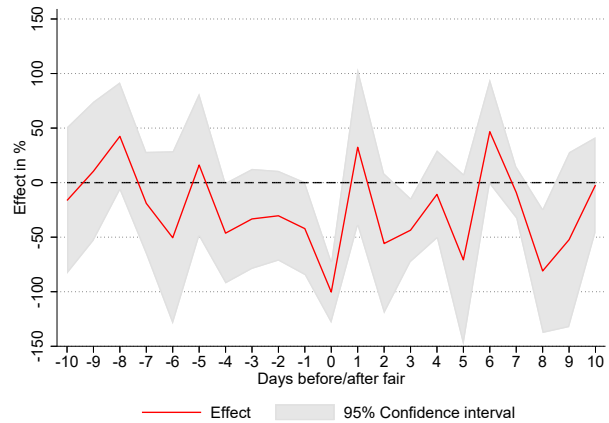**Figure A.1:** Effect of events on overnight stays
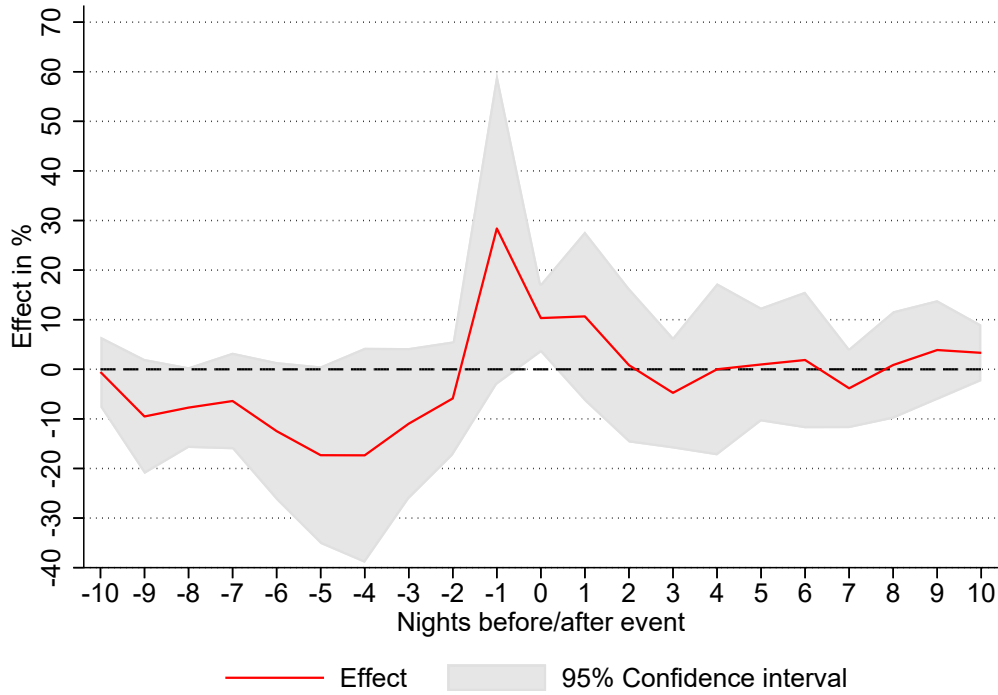
Notes: This figure presents the estimates of the average percentage effect of events on overnight stays in Basel from 01/01/2015 to 12/31/2019. -1 refers to the night before a fair and +1 to the night following the last fair day. 0 refers to nights between two fair days. Results from the parametric specification with year day fixed effects (see equation 2). Observations: 1,826 days. Year day clustered standard errors.

Figure A.2: Effect of events on zoo visits

(a) Low occupancy rate

(b) High occupancy rate

Notes: This figure presents the estimates of the average percentage effect of fairs on zoo visits by overnight guests in Basel from 01/01/2018 to 05/14/2019. -1 refers to the day before a fair and +1 to the day following a fair. 0 refers to fair days. Panel (a) presents the results from the parametric specification with year day fixed effects (see equation 2) for days with occupancy rates below 80%. Observations: 499 days. Year day clustered standard errors. Panel (b) presents the results from the parametric specification with year day fixed effects (see equation 2) for days with occupancy rates above 80%. Observations: 499 days. Year day clustered standard errors.

Center for Regional Economic Development (CRED)

University of Bern

Schanzeneckstrasse 1

P.O.Box

CH-3001 Bern

Telephone: +41 31 684 37 11

E-Mail: info@cred.unibe.ch

Website: http://www.cred.unibe.ch

The Center for Regional Economic Development (CRED) is an interdisciplinary hub for the scientific analysis of questions of regional economic development. The Center encompasses an association of scientists dedicated to examining regional development from an economic, geographic and business perspective.

Contact of the authors:

Marcus Roller

University of Bern

Schanzeneckstrasse 1

P.O.Box

CH-3001 Bern

Telephone: +41 31 684 37 11

Email: marcus.roller@cred.unibe.ch

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