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Do tax incentives affect business location and economic development? Evidence from state film incentives☆

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ABSTRACT

I estimate the impacts of recently-popular U.S. state film incentives on filming location, film industry employment, wages, and establishments, and spillover impacts on related industries. I compile a detailed database of incentives, matching this with TV series and feature film data from the Internet Movie Database (IMDb) and Studio System, and establishment and employment data from the Quarterly Census of Employment and Wages and Country Business Patterns. I compare these outcomes in states before and after they adopt incentives, relative to similar states that did not adopt incentives over the same time period (a panel difference-in-differences). I find that TV series filming increases by 6.3–55.4% (at most 1.50 additional TV series) after incentive adoption. However, there is no meaningful effect on feature films, and employment, wages, and establishments in the film industry and in related industries. These results show that the ability for tax incentives to affect business location decisions and economic development is mixed, suggesting that even with aggressive incentives, and "footloose" filming, incentives can have little impact.

1. Introduction

Governments provide numerous incentives to encourage firms to choose their region for business or to spur economic development. These incentives vary, but common strategies include tax credits, grants, financing, enterprise and empowerment zones, and state taxation rates in general. These incentives are increasingly common, having more than tripled since 1990 (Bartik, 2017). An in-depth analysis by the New York Times found 1,874 incentive programs across the U.S., with a total cost of $80.4 billion per year.[1] Bartik (2017) projects that, for the entire nation in 2015, state and local business incentives had an annual cost of $45 billion.

Studying the economic impacts of incentives is essential both because of their popularity, especially recently, but also because their effectiveness is still not fully known. Reviews of the literature by Wasylenko (1999), Buss (2001), and Arauzo-Carod et al. (2010) note that the effect of incentives on firm location and economic development is still ambiguous. Some studies find at least moderate positive effects of incentives on firm location (e.g., Bartik, 1985; Bartik, 1989; Walker and Greenstreet, 1991; Papke, 1991; Wu, 2008; Strauss-Kahn and Vives, 2009), while others find a small positive effect or no effect at all (e.g., Schmenner, 1982; Plaut and Pluta, 1983; Carlton, 1983; Schmenner et al., 1987; Blair and Premus, 1987; Dabney, 1991; Lee, 2008).

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[1] See http://www.nytimes.com/interactive/2012/12/01/us/government-incentives.html (accessed 3/15/14).

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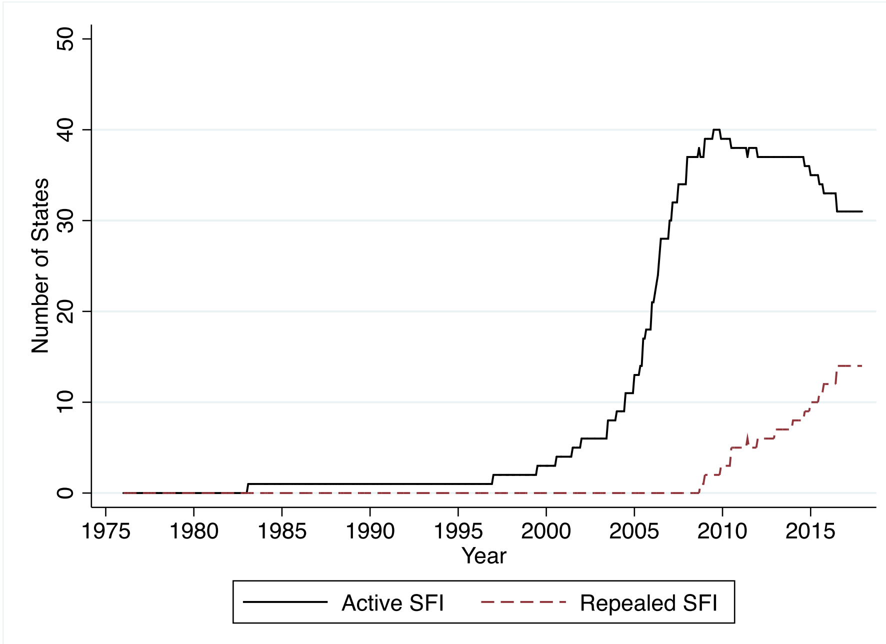


Notes: SFIs include only cash rebates, grants, refundable tax credits, or transferable tax credits for motion picture production, and do not include states with only sales tax exemptions or other small incentives. A state has an active SFI if an SFI exists in the state and is accepting applicants. A state has a repealed SFI if the state previously had an active SFI, but no longer has one, or if the state has suspended its SFI, either temporarily or permanently.

Fig. 1. Number of U.S. States with an active or repealed state film incentive (SFI).

A particularly useful context to study to determine the effect of incentives is the rapid diffusion of state film incentives (SFIs), which many U.S. states offer to encourage filming.[2] The most common and generous forms of SFIs are grants, cash rebates, or refundable or transferable tax credits for filming or motion picture production.

Studying SFIs is illuminating for a few reasons. First, the film industry is one where filming itself is relatively insensitive to locational characteristics, relative to businesses in general deciding where to locate. In the film industry, filming locations are relatively substitutable because the majority of scenes can be shot anywhere.[3] Relative to other industries, filmmakers also tend to be less sensitive to local labor and input market characteristics as they usually bring their skilled workers (e.g., principal actors, directors, and managers) with them, and hire locally for less skilled workers (e.g., camera operators, extras) (Tannenwald, 2010; Luther, 2010). Filming also requires much less physical capital investment. Filming is thus relatively "footloose" even given the large agglomeration economies in motion picture production more broadly.[4] Cost is becoming the most important decision in where to film, trumping even creative concerns (Christopherson and Rightor, 2010).[5]

This contrasts with firms in general who base business locations on a broader set of factors (Arauzo-Carod et al., 2010): agglomeration economies, wages, skills or education of the labor force, city population or density, land price and availability, energy costs, building costs, accessible markets for customers or suppliers, union activity or labor laws, climate, local economic conditions, and local public goods. Firms often consider incentives after first selecting finalist locations based on the above factors (Schmenner et al., 1987; Blair and Premus, 1987; Greenstone et al., 2010). This was especially highlighted in the search for Amazon's HQ2.

Second, these incentives are incredibly common and aggressive. This makes it likely that there are detectable effects of SFIs, both because the aggressive subsidies should lead to more substantial effects, and because the large amount of variation provides more statistical power. SFIs went from being almost non-existent before the 1990s to peaking in July 2009 with 39 states, plus the District of Columbia, having an SFI (Fig. 1). There is also increasing variation from states repealing these incentives, 14 states as of 2017. In addition, states with existing SFIs often increased their subsidy rates (Fig. 2).[6] A typical SFI since 2009 subsidies between 20 and 30% of "qualified expenditure" on filming and motion picture production. Given the popularity and strength of SFIs, expenditure on them is significant, with an estimate of $1.5 billion in the fiscal year 2010 (Tannenwald, 2010).

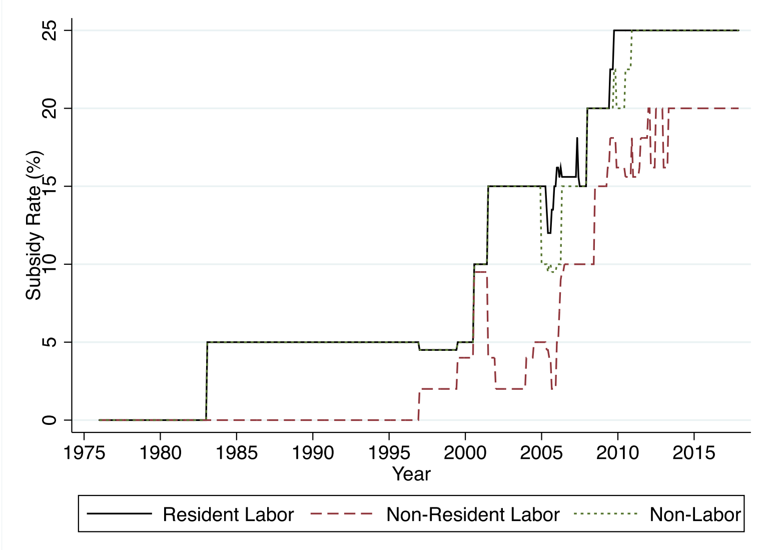
[2] Incentives for filming are equally popular at both the federal and provincial levels in Canada (Lester, 2013) and are also popular internationally. See https://www.productionincentives.com/(accessed 2/21/19) for a useful map and comparison tool.

[3] While filmmakers often require some scenes at iconic landmarks or city-identifying locations, filmmakers can use many strategies to fake the location, as discussed in Button (2018 a).

[4] Agglomeration economies for the film industry are large and are behind the concentration of this industry in Greater Los Angeles and Greater New York City (Florida et al., 2011). See Button (2018 a) for a more detailed discussion of agglomeration economies in the film industry.

[5] For example, filmmakers are often told to change their scripts to fit new locations selected by management (see, e.g., http://online.wsj.com/articles/SB10001424052748703816204574489153078960792 (accessed 10/13/14).) and independent filmmakers are expected to have SFI funding established before pursuing private financing (see, e.g., http://independentfilmblog.com/why-film-investors-dont-want-you (accessed 10/13/14).).

[6] This variation in SFIs is considerable relative to the variation in general state tax rates. For example, from 2000 to 2012 there were 146 changes in state SFIs but only 49 changes in state sales tax rates, 45 changes in state corporate tax rates, and ten changes in state investment tax credits.



Notes: See the notes to Figure 1. Resident (non-resident) labor includes payroll for (non-) state residents and non-labor includes non-payroll expenditures. See Appendix A and Online Appendix C for additional details. Medians are calculated only over the set of states with SFIs. States with an SFI that does not cover a particular type of qualified expenditure (typically non-resident labor) are included as a zero in the calculation.

Fig. 2. Median subsidy rates of SFIs over time, by categories of qualified expenditures.

Because filming is relatively "footloose," SFIs are aggressive, and there is significant variation in SFIs, studying the effect of SFIs on the film industry provides a "most likely" "crucial case" case study (Gerring, 2012) that informs the study of incentives and business location more broadly. That is if SFIs are "most likely" to affect filming location, but they do not, then this suggests that other incentives are also unlikely to affect business location, given that locational decisions in other industries are less flexible.

In addition to telling us how incentives affect business location in general, studying SFIs also tell us about the effectiveness, or lack thereof, of tax incentive or economic development strategies more broadly. There is an extensive literature examining incentives, such as enterprise zones (e.g., Neumark and Kolko, 2010; Bondonio and Engberg, 2000; Freedman, 2013; Briant et al., 2015), empowerment zones (e.g., Hanson, 2009; Hanson and Rohlin, 2013; Krupka and Noonan, 2009), tax-increment financing, (e.g., Anderson, 1990; Dye and Merriman, 2000), foreign trade zones (e.g., Rogers and Wu, 2012), and other regionally-targeted incentives such as the New Markets Tax Credit (Freedman, 2015). Some of these are case studies of incentives targeting specific industries (e.g., Moretti and Wilson, 2014; Swenson, 2017; Thom, 2018 a; Thom, 2018 b; Weinstein, 2018; Button, 2018 a). Studying SFIs also contributes to a small, but growing, literature examining how incentives can affect specific industries and if they can create an industry cluster (e.g., Porter, 2000; Rosenthal and Strange, 2004; Moretti and Wilson, 2014; Swenson, 2017; Weinstein, 2018; Thom, 2018 a; Button, 2018 a.)

However, this case study of SFIs and the film industry tells us more about the effectiveness of incentives that attempt to generate clusters or that target specific industries. This is especially the case if those industries are similarly footloose, whereby costs also trumps other locational factors that affect production. This could include, for example, call centers or manufacturing that relies more on lower-skilled work. SFIs also operate similarly to many job creation tax credits (e.g., Neumark and Grijalva, 2017; Chirinko and Wilson, 2010) in that both incentives provide significant incentives to increase employment. SFIs tell us less about incentives that are focused on specific geographic areas (e.g., enterprise zones, empowerment zones, and foreign trade zones.)

In this study, I estimate the effect of SFIs on filming location for both TV series and feature films, the effect on the film industry itself (employment, establishments, wages), and the effect on related industries. I compiled a unique database of all SFIs since their inception up until 2017. I combine this SFI database with two databases that track filming locations: the Internet Movie Database (IMDb), which provides 16,593 TV Series and 61,480 feature films, and the Studio System database, which provides 1,563 TV series and 8,968 feature films. To estimate effects on employment, establishments, average weekly wages, and total wages in the film industry, I use data from the Quarterly Census of Employment and Wages (QCEW) and County Business Patterns (CBP). I also use QCEW data to capture the impact on spillover industries, such as independent artists, payroll services, hospitality, caterers, transportation rentals, costumes, and non-residential building leasing.[7]

To estimate the causal effect of SFIs on these outcomes, I use panel regression with two-way fixed effects. This is akin to a difference-in-differences research design where states that adopt SFIs are compared, before and after they adopt SFIs, to similar states that do not adopt or have not yet adopted. This panel regression approach provides a much more convincing estimate of the impacts of SFIs by controlling for both time-invariant state characteristics and national trends in motion picture production. I start by estimating the average effects of SFIs after adoption, and then I estimate the effects of SFIs over time (an event study). I then explore the assumptions behind my difference-in-differences research design: policy exogeneity, the parallel paths assumption, and the stable unit treatment value assumption (SUTVA). Finally, I explore heterogeneous effects by studying if the effects of SFIs vary by the timing of their adoption, their subsidy rates, and by the size of the existing film industry (to measure agglomeration economies).

I find evidence that SFIs have a large and mostly robust effect on the filming location of TV series, but I find little evidence

[7] I focus on the impacts on specific industries rather than data aggregated over all industries for two reasons. First, this better estimates the policy-relevant question of if incentives affect the targeted industry. Second, using aggregate data over all industries severely reduces the statistical power to detect economic impacts, as many uncontrolled factors affect aggregate state economies.

Table 1
Summary statistics for the main data: SFI database, IMDb and studio system filming data, and QCEW and CBP data for the motion picture production industry.

Variable	Years	Freq.	Mean	Median	Std. Dev.	Min	Max	N
(a) State Film Incentives								
SFI	1976–2017	M	0.23	0	0.42	0	1	25,704
Repealed	1976–2017	M	0.03	0	0.18	0	1	25,704
(b) IMDb								
# TV Series	1976–2017	A	7.7	1	36.5	0	588.4	2,142
# Feature Films	1976–2017	A	28.7	6.8	94.0	0	1,246.9	2,142
(c) Studio System								
# TV Series	1984–2017	A	3.2	0	18.5	0	216.0	1,734
# Feature Films	1984–2017	M	0.4	0	1.6	0	32.3	20,808
(d) QCEW Motion Picture Production								
Employment	1978–2017	M	3,299	611	14,503	0	145,897	20,508
Establishments	1978–2017	Q	289	91	890	0	10,579	7,413
Ave. Weekly Wages	1978–2017	Q	$730	$529	$934	$16	$15,051	7,397
Total Wages	1978–2017	Q	$18.3 m	$2.30 m	$118 m	$715	$2.87b	7,397
(e) CBP Motion Picture Production								
Employment	1986–2016	A	2,248	334	11,759	9	175,756	1,523
Establishments	1986–2016	A	209	67	608	2	5,726	1,523

Notes: See Appendix A and Online Appendix C for additional details on SFI characteristics. A = annual frequency, Q = quarterly frequency, and M = monthly frequency. The variable *SFI* equals one for states that have an SFI program that is a refundable or transferable tax credit, a grant, or a cash rebate. The variable *Repealed* equals one if the state formerly had an SFI but it is no longer active, either temporarily or permanently. The IMDb sample includes 16,362 TV Series and 59,652 feature films. The Studio System sample includes 1,563 TV series and 8,968 feature films. The QCEW data is a combination of "Motion picture and video production" (NAICS code 512110) from 1990 to 2017, "Motion picture and video production" (SIC code 7812) from 1988 to 1989, and the sum of "Motion picture production, except TV" (SIC 7813) with "Motion picture production for TV" (SIC 7814), from 1978 to 1987. The CBP data uses the NAICS industry classification ("Motion picture and video production", NAICS 512110) from 1998 to 2016 and the SIC industry classification ("Motion picture and video production", SIC 7812) from 1986 to 1997.

that SFIs affect the filming location of feature films. Despite these impacts on filming, I do not find any meaningful effect on the size of the film industry. At best I find non-robust evidence of small increases in employment in motion picture production - at most an 18.2% increase, or 314 jobs on average, under extremely generous assumptions. I also find almost no evidence of any impacts on related industries that might get spillover benefits from motion picture production.

The rest of this paper is organized as follows. Section 2 discusses my data sources, Section 3 discusses my methodology, Section 4 presents and discusses the main results, Section 5 presents the results of numerous robustness checks, Section 6 extends the main model to investigate heterogeneous effects, Section 7 presents preliminary estimates of the effect of repealing SFIs, and Section 8 discusses the results and conclusions.

2. Data

To quantify the impacts of SFIs on filming, employment, and establishments, I use five sources of data. First is a unique panel database I compiled of SFIs in the U.S. states.[8] Second is filming location data from the Internet Movie Database (IMDb). Third is another database of filming location: Studio System. Fourth is Quarterly Census of Employment and Wages (QCEW) data on employment, establishments, average weekly wages, and total wages in the motion picture production industry, and related industries. Fifth is County Business Patterns (CBP) data on employment and establishments in the motion picture production industry.

2.1. *State film incentives database*

There are different types of incentives for filming or motion picture production at the state level.[9] The most common type, which I quantify in this analysis and title State Film Incentives (SFIs), are rebates, grants, refundable tax credits, or transferable tax credits. All these give a percentage of a motion picture production's "qualified expenditure" back to the production company.[10]

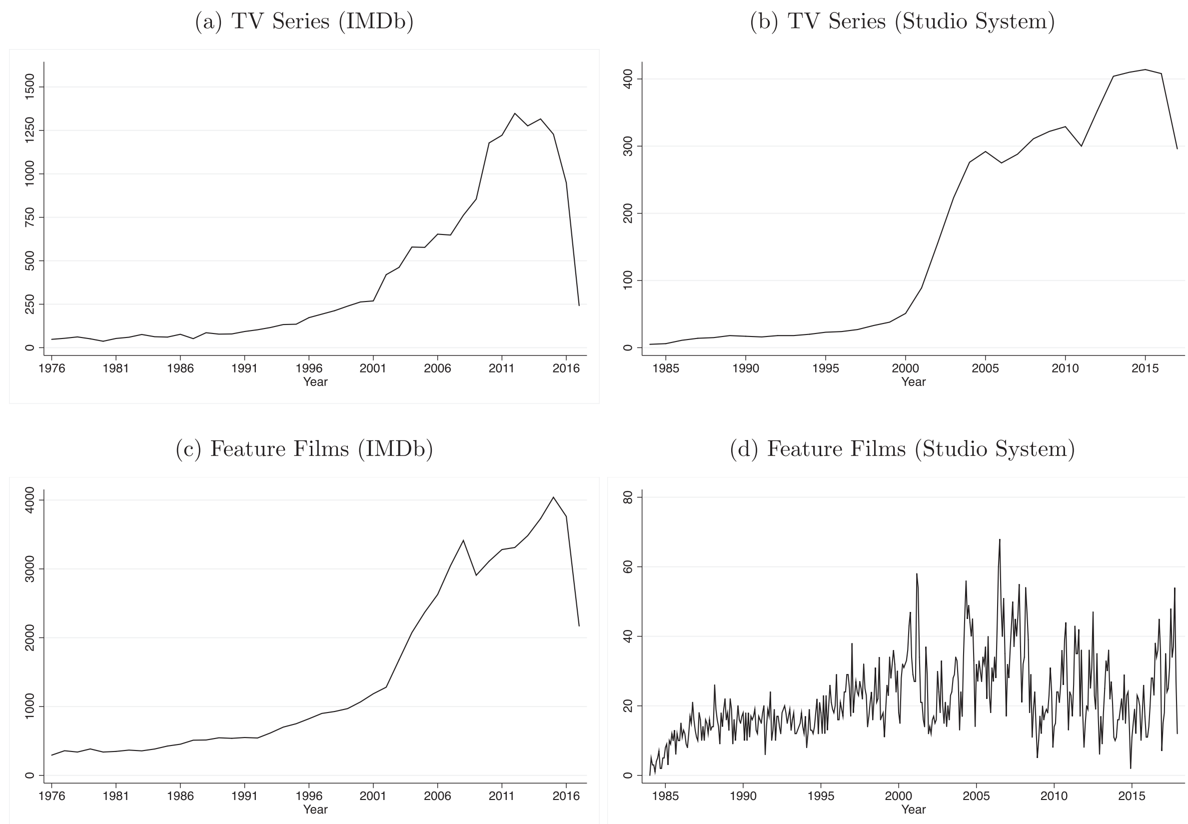
Online Appendix C details the history of SFIs in each state, and their features, for all states and the District of Columbia. I compiled this database by locating the relevant laws, via statutes in WestLaw, confirming changes in legislation over time using notes provided by WestLaw, and locating the actual acts, through HeinOnline, that amended these laws. In rare cases, supplementary sources such as government websites or consulting firm websites were used to confirm details that were not codified explicitly in law.

Table 1 presents summary statistics for my state film incentives database. From 1976 to 2017, across all states, 23% of states are

[8] Bartik (2017) does not include data on SFIs. The data I compiled on SFIs is also more detailed than other work, such Good Jobs Firsts' data (Mattera et al., 2011) or other research quantifying the impact of SFIs (Swenson, 2017; Thom, 2018 a).

[9] There are some incentives at the city or county level that I do not cover in this paper and are otherwise hard to study. These incentives are usually services such as permitting or discounts on police escorts.

[10] My focus on these stronger and more common incentives mirrors Adkisson (2013), Thom (2018 a), and Swenson (2017). The other less common and weaker state-level incentives that I do not quantify are the few tax credits that are neither transferable nor refundable, sales and use tax exemptions or rebates, and tax credits for investment in a motion picture production facility or capital program. Tax credits that are neither refundable nor transferable are relatively weak incentives since they only cover the filmmaker's low tax liabilities. They are also less common: tax credits that are neither refundable nor transferable constitute no more than 4.9% of observations where a state is observed with an incentive. These less common and weaker incentives are rarely discussed in debates about tax incentives for the film industry and were usually only used temporarily before states moved to the types of SFIs I analyze. I control for tax incentives that are neither refundable nor transferable in my analysis.



Notes: The IMDb sample includes 16,362 TV Series and 59,652 feature films from 1976 to 2017. The Studio System sample includes 1,563 TV series and 8,968 feature films from 1984 to 2017. Each series is an annual (or monthly, for Studio System feature films) sum of all productions in that year across all states that list at least one state of filming.

Fig. 3. Filming by year.

observed with an SFI ($SFI = 1$), meaning that the state has an SFI that is accepting applications. 3% of states are observed where they had an SFI, but it was repealed or suspended either temporarily or permanently ($Repealed = 1$).[11] Appendix A contains information on SFI features, such as subsidy rates by category of qualified expenditure, and information on weaker incentives (tax credits that are neither refundable nor transferable) which I do not study since they are far less common and are weaker. However, I do control for these in my analysis.

2.1.1. *State film incentive characteristics*

The primary way that SFIs differ by state is in their subsidy rates for different categories of expenditure on inputs into filming. The subsidy rates almost always target three categories of expenditure: the payroll of state residents, the payroll of non-residents, and non-labor expenditures. Non-labor expenditures include a broad, and often non-exhaustive, list of spending on inputs such as set construction, wardrobe, photography, sound, lighting, rental fees, transportation, caterers, and lodging. Advertising and distribution are not included. Fig. 2 shows how these subsidy rates have increased over time, and Appendix Table A1 panel (a) presents summary statistics for these subsidy rates. Full details are in Online Appendix C.

The second way that SFIs differ is in their rate of refundability, that is, how much filmmakers receive beyond their often low state tax liabilities. Some SFIs are cash grants or rebates, which provide filmmakers with direct cash, but the majority of SFIs are tax credits, which are refundable, transferable, or neither. If a tax credit is refundable, it can be sold back to the state, though sometimes at a discounted rate. If a tax credit is transferable, it can be sold, through intermediary brokers, to other firms with tax liabilities to the state. These brokers typically take a cut of 20–30% of the credit (Luther, 2010; Christopherson and Rightor, 2010). In either case, the filmmaker can receive a benefit beyond their often low tax liabilities, a benefit not offered by tax credits that are neither refundable nor transferable. Appendix Table A1 presents summary statistics for the characteristics of SFIs.

2.2. *Internet Movie Database (IMDb) data*

The Internet Movie Database at IMDb.com is a popular online database with information on motion picture productions. IMDb includes information on over 5,310,913 titles.[12] I use text-based data files provided by IMDb to extract a sample of TV series (16,362) and feature films (59,652) that include all productions with a release date

[11] This includes the following 14 states, with this data current to the end of 2017: Alaska from July 2015 onward, Arizona from January 2011 onward, Florida from July 2016 onward, Idaho from July 2010 onward, Indiana from January 2012 onward, Iowa from December 2009 onward, Kansas in 2009 and 2010, and July 2012 onward, Maryland from October 2009 to June 2011, Michigan from October 2015 onward, Missouri from September 2014 onward, Montana from January 2015 onward, New Jersey from July 2010 onward, Vermont from June 2011 onward, and Wisconsin from January 2014 onward.

[12] See http://www.imdb.com/stats (accessed 10/7/18).

from 1977 to 2018 that list a filming location in a U.S. state.[13]

Unfortunately, the IMDb data does not uniformly include the filming year for either TV series or feature films. I use the year of release to estimate the filming year by assuming the filming year was one year before the release year.[14] For TV series, there is no comprehensive data on when each season of each TV series was filmed, but IMDb does provide years for which the series was in distribution.[15] For TV series, I assign the filming equally across the period when the TV series was in distribution.[16] Once I have assigned a production to states and years of filming, I then generate counts of the number of TV series and feature films filmed in each state and year.[17]

Fig. 3a presents the number of IMDb TV series per year, and Fig. 3c presents the number of IMDb feature films released per year. Both rise over time, which is a function of increased filming over time but also a function of the IMDb data being more complete for more recent years. The rise is most steep after about 2001. There is then a dip in productions in 2018 which reflects that data from 2018 is incomplete given that the year was not complete when I compiled the data in July 2018.

Table 1 panel (b) presents summary statistics for the IMDb data. The mean number of TV series filmed in each state and year is 7.7, but the median is one, reflecting that most filming is concentrated in states like California[18] and New York.[19] At least some TV series filming occurs for about two-thirds of all state-year observations. For feature films, the mean state-year has 28.7 feature films, with a median of 6.8. 93% of state-year observations have at least one feature film.

2.3. Studio System data

Studio System (formerly Baseline) is a proprietary industry database of TV series and feature films. The content is not user-generated like IMDb; instead, it is carefully managed by professionals to ensure data quality and completeness. Compared to IMDb, the Studio System data is more reliable, contains more information about each production, but contains fewer productions, partly because it only focuses on nationally-distributed TV series or feature films.

I extract a database of 1,563 TV series[20] and 8,968 feature films between 1985 and 2018 and where all TV series are filmed in at least one US state. I use a similar process as with the IMDb data to allocate these TV series and feature films.[21]

Fig. 3b presents the number of TV series per year and Fig. 3d presents the number of feature films per year. For TV series, before 2001, there are 50 or fewer TV series active each year, and this jumps up to about 300 per year from about 2005 to 2011, and then jumps up to 400 from about 2012 to 2016. Like the IMDb data, productions drop in the final year reflecting that the year had not completed yet when I extracted the data. For feature films, filming dates are available at a monthly frequency, and, unsurprisingly, filming varies seasonally by month. Feature films in the Studio System data do increase slightly over time but are relatively constant at around 28 films per month.

Table 1 panel (c) presents summary statistics for the Studio System data. Compared to the IMDb data, there are fewer productions. The mean number of TV series (feature films) is 3.2 (0.4), with a median of zero.[22] 35% (23%) of state-year (state-month) observations have some TV series (feature film) filming.

2.4. Quarterly Census of Employment and Wages (QCEW) data

The Quarterly Census of Employment and Wages (QCEW), collected by the Bureau of Labor Statistics, provides data on employment and establishment counts, average weekly wages, and total wages, at different levels of industry specificity. In all cases, I only use the estimates for private industry, which excludes government enterprises. Estimates by industry are reported by six-digit North American Industry Classification Code (NAICS) system (1990–2017) and the four-digit Standard Industry Classification (SIC) system (1976–1989 or 1978 to 1989).[23]

To quantify impacts on the film industry, I use estimates for “Motion picture and video production” (NAICS 512110) from 1990 to 2017 and “Motion picture and video production” (SIC 7812) from 1988 to 1989. For 1978 to 1987, estimates are listed separately for TV and non-TV (“Motion picture production, except TV” (SIC 7813), “Motion picture production for TV” (SIC 7814)). I sum these estimates to get employment, establishment, and total wage counts, and calculate average weekly wages as the weighted mean of average weekly wages for “except TV” and “for TV,” weighted by employment counts.[24] Note that the motion picture and video production industry does not include motion picture distribution or exhibition, or sound recording, which all fall under separate NAICS or SIC codes.

Table 1 panel (d) presents summary statistics for employment, establishment, total wages, and average weekly wages. At the mean (median)

[13] I extracted this data on 8/4/18. IMDb categorizes productions into mutually-exclusive groups: TV Series, TV Episode, TV Miniseries, TV Movie, TV Special, Movie, Video, Short, or Videogame. I ignore the TV Episodes category because it provides separate data on some notable episodes, but it does not cover the vast majority of TV episodes or series. Results using TV Episodes and TV Miniseries, however, are similar to TV Series and are available upon request. I exclude the categories of TV Special, Short, Video, and Video Game as they are rarely targeted by incentives, as made clear in state statutes. There are, however, some states that do subsidize video game production, but an analysis of video game production is a separate question that requires better data far beyond what I have collected here. I also exclude the Video category since this category is catch-all for anything not already categorized. Finally, I fold the TV Movie category data into the Movie category data since both are similar (TV Movies are just distributed on TV rather than in theaters), and I re-title this category “Feature Films.”

[14] As described later in the paper for the Studio System feature films data, which has filming dates, most filming occurs the year before the release year.

[15] The mean years of distribution is 3.8 (standard deviation of 4.0).

[16] For example, for a series that was first in distribution from 2005 to 2010, it is assumed to have been filmed from 2004 to 2009. If this was filmed only in California, then this counts as one TV series in California in those years.

[17] Some productions list more than one region of filming location. For those productions, the production is split equally. I ignore filming locations for pilot episodes since these are not always where the entire season is filmed.

[18] For more background on the industry in California, see Thom (2018 a).

[19] The mean IMDb TV series (feature films) in California is 171.6 (486.6), and 54.2 and 209.0 in New York, respectively. Across the entire sample, California has 43.7% (33.2%) of all IMDb TV series (feature film) filming, and New York has 13.8% and 14.3%, respectively.

[20] I include only TV series that were distributed on a broadcast network or major online medium (e.g., Netflix).

[21] Similar to the IMDb data, the Studio System data does not explicitly list the period of filming for each TV series, so I follow the same process to assign TV series to state-year observations. The years of distribution for the TV series range from two years to 28 years, with a mean of 3.7 and a standard deviation of 3.0. Feature films, however, usually have filming dates (5,868 out of 8,968 have filming dates), allowing me to assign these to state-month observations. When the filming date was unavailable, I assumed a filming date of one year before the release date. Filming the year before distribution is the most common, 55.9% of feature films in the Studio System data are distributed the year after filming (Button, 2018 a).

[22] In California, the means are 95.1 TV series and 8.5 feature films, and in New York, the means are 26.0 TV series and 4.0 feature films. Over the entire sample, California has 58.2% (41.6%) of TV series (feature films), and New York has 15.9% (19.8%).

[23] For some industries, data is not available for years 1976 and 1977.

[24] In the case where either “except TV” or “for TV” does not disclose data for a cell, I code that cell as missing even if data is available for the other sub-industry.

there are 3,299 (611) employees and 289 (91) establishments per state and year. The mean (median) total wages is $18.3 m ($2.30 m) in nominal dollars, and the mean (median) average weekly wage in nominal dollars is $730 ($529). The small number of employees relative to establishments, especially at the median, suggests that most establishments are small, with about a dozen employees per establishment on average. The data again show a concentration of the industry in California and New York.[25]

2.4.1. Issues with QCEW employment data for motion picture production

There are a few problems with the employment estimates in the QCEW that affect the interpretation of the employment estimates.[26] First, because filming is mobile and project-based, some workers may relocate temporarily, and some jobs for these non-residents are counted in the employment estimates. This upward biases the employment counts if job creation for non-residents is not viewed as favorably as job creation for residents, which is likely the case.

Second, the QCEW data does not distinguish between full-time jobs and part-time jobs, or between permanent and temporary jobs. Permanent jobs are more associated with established motion picture production firms and are a better indication of an established film industry. However, it is common for workers in the industry to string together several temporary positions to achieve consistent employment (e.g., Luther, 2010; Christopherson and Rightor, 2010). The more problematic issue is the inability to separate full-time and part-time jobs. Any effects on employment that I estimate are therefore a combination of full-time, part-time, permanent, and temporary jobs.

Because I find few employment effects, these first two issues are less relevant. What is more relevant are issues with the QCEW data that could bias estimated employment effects towards zero. Two issues could do so. First, because the QCEW measures employment at a specific time each month, it may not capture short-term employment that falls between these monthly dates. This partly motivates my use of another dataset, County Business Patterns, which measures employment at a different time.

Second, and most importantly, is that the QCEW data includes employee jobs but not contract jobs. 99.7% of employees (i.e., they get a W-2 tax form) appear in the QCEW employment estimates, but contract workers who do not get a W-2 (they get a 1099 tax form instead) are not included in this data. These contract jobs are more common in motion picture production than in other industries. Not counting these jobs could bias estimated employment effects towards zero. This is a problem given that I find few employment effects, and this merits further discussion and analysis.

While these contract jobs are more common in the motion picture production industry relative to in other industries, they are not too common in the context of the types of jobs that would be created due to filming "on-site" in a state with an SFI. As discussed in detail in Button (2018 a) in case studies of Louisiana and New Mexico, states often discussed as having had "successful" SFIs, there were between 3.8 and 6.7 employee jobs for each contract job in Louisiana and New Mexico in motion picture production, according to data on nonemployer statistics data. In 2008, when those states incentives seemed the most effective during the case study, this was just 788 nonemployer jobs in New Mexico, and 357 nonemployer jobs in Louisiana.

Moreover, contract jobs created from filming are less likely to be created for locals. There are somewhat strict requirements for an individual to be deemed a contractor over an employee, such as having behavioral and financial control, setting their hours and location of work, and often using their equipment (Internal Revenue Service, 2012; Internal Revenue Service, 2018 b; Internal Revenue Service, 2018 a). The vast majority of positions in filming are "below the line," [27] and because management exerts control over these positions, they are seldom able to be contracted. The Internal Revenue Service and others mention this specifically.[28] Contract positions are more relevant for "above the line" positions,[29] but these positions are usually reserved for those who are brought in from out of state.

Thus, the fact that the number of contract jobs is small, and these jobs are less likely to be created for locals during filming suggests that this issue, while not ideal, does not render the QCEW employment data uninformative. To investigate this further, I use three more sets of employment estimates. First, I also examine CBP data, which is generated differently, as discussed below. This data provides another set of employment estimates that are useful to measure the robustness of my estimates using the QCEW employment data. Second, it is possible that some contract jobs could be created for those who are independent artists, and these jobs are not captured in the employment estimates for the motion picture production industry. I use QCEW data for the "Independent artists, writers, and performers" (NAICS 711510)/"Entertainers and entertainment groups" (SIC 7929) industry to quantify effects on this industry as well, as this industry could capture some of these jobs. Third, some contract employment could fall under payroll companies ("Payroll services" (NAICS 541214)/"Services allied to motion picture production" (SIC 7819)) who manage human resources for filming.

2.4.2. Related industries to motion picture production

In additional to quantifying impacts on the "independent artists" and "payroll services" industries, which some employment may fall under, other industries may experience spillover effects from increased filming. These include caterers ("Caterers" (NAICS 722320, no corresponding SIC data)), hotels ("Hotels and motels, except casino hotels" (NAICS 721110)/"Hotels and Motels" (SIC 7011 from 1978 to 1989, SIC 7010 from 1976 to 1977)), costumes ("Formal wear and costume rental" (NAICS 532220, no corresponding SIC data)), building rentals ("Lessors of non-residential buildings" (NAICS 531120, no corresponding SIC data)), and transportation rentals ("Truck, trailer and RV rental and leasing" (NAICS 532120)/"Truck rental and leasing, no drivers" (SIC 7513)). These industries are primarily the ones discussed when advocates argue that SFIs have spillovers effects on other industries.

Table 2 presents summary statistics for employment, establishment, and average weekly wage estimates for these industries. Hotels and motels is by far the largest related industry in terms of employment (26,739 employees on average), followed by caterers (4,027), lessors of non-residential buildings (2,951), payroll services (2,586), truck,

[25] The mean employment (establishments) in California is 87,766 (5,070), and the means for New York are 28,361 and 1,739, respectively. Over the entire sample, California has 52.2% (34.4%) of employment (establishments), and New York has 16.9% (11.8%).

[26] Also see Button (2018 a) for a discussion of this issue.

[27] As noted in Button (2018 a), these positions include assistant director, art director, boom operator, camera operator, character generator, costume designer, dolly grip, drivers, film editor, foley, gaffer, grip, graphic artist, hair stylist, lighting technicians, line producer, location manager, make-up artist, production assistant, property masters, script supervisor, set construction, sound engineer, stage manager, stagehand, stunt performers, technical director (TD), unit production manager, video control broadcast engineering, visual effects editor, and wranglers. See https://entertainment.howstuffworks.com/what-does-below-line-mean-movie-production.htm (accessed 8/7/18) for more information.

[28] See, e.g., http://www.screenlightandgrip.com/html/crew.html, https://abspayroll.com/hiring-independent-contractors/, and http://movieinsure.com/blog/employee-vs-independent-contractor-for-the-entertainment-industry/, all accessed 8/7/18.

[29] E.g., writers, producers, directors, casting directors, and main cast.

Table 2
Summary statistics for related industries, from QCEW data.

Variable	Years	Mean	Median	Std. Dev.	Min	Max	N
(a) Independent artists, writers, and performers							
Employment	1978–2017	896	373	2,118	0	21,753	22,239
Establishments	1978–2017	730	529	934	16	15,051	7,397
Ave. Weekly Wages	1978–2017	$730	$529	$934	$16	$15,051	7,397
(b) Payroll services							
Employment	1978–2017	2,586	791	4,825	0	58,840	20,937
Establishments	1978–2017	113	70	134	0	1,402	6,979
Ave. Weekly Wages	1978–2017	$787	$704	$475	$18	$11,526	6,935
(c) Caterers							
Employment	1990–2017	4,027	2,279	5,071	0	30,510	13,026
Establishments	1990–2017	285	181	333	6	2,450	4,342
Ave. Weekly Wages	1990–2017	$288	$280	$108	$81	$3,049	4,342
(d) Hotels and motels, except casino hotels							
Employment	1976–2017	26,739	17,200	31,189	1,203	215,854	25,038
Establishments	1976–2017	876	646	848	60	5,578	8,346
Ave. Weekly Wages	1976–2017	$291	$263	$154	$63	$1,055	8,346
(e) Formal wear and costume rental							
Employment	1990–2017	326	203	368	4	2,334	14,088
Establishments	1990–2017	48	31	54	3	528	4,696
Ave. Weekly Wages	1990–2017	$344	$324	$127	$53	$1,639	4,696
(f) Lessors of non-residential buildings							
Employment	1990–2017	2,951	1,469	4,455	98	26,701	17,076
Establishments	1990–2017	479	285	673	29	4,451	5,692
Ave. Weekly Wages	1990–2017	$754	$655	$410	$169	$4,892	5,692
(g) Truck, trailer, and RV rental and leasing							
Employment	1978–2017	1,175	708	1,226	6	7,722	22,653
Establishments	1978–2017	99	67	95	3	557	7,551
Ave. Weekly Wages	1978–2017	$591	$576	$218	$115	$1,682	7,551

Notes: The employment data is at a monthly frequency and the establishment and average weekly wage data is at a quarterly frequency. Specific NAICS/SIC codes used are as follows: (a) "Independent artists, writers, and performers" (NAICS 711510)/"Entertainers and entertainment groups" (SIC 7929), (b) "Payroll services" (NAICS 541214)/"Services allied to motion picture production" (SIC 7819), (c) "Caterers" (NAICS 722320, no corresponding SIC data), (d) "Hotels and motels, except casino hotels" (NAICS 721110)/"Hotels and Motels" (SIC 7011 from 1978 to 1989, SIC 7010 from 1976 to 1977), (e) "Formal wear and costume rental" (NAICS 532220, no corresponding SIC data), (f) "Lessors of non-residential buildings" (NAICS 531120, no corresponding SIC data), and (g) "Truck, trailer and RV rental and leasing" (NAICS 532120)/"Truck rental and leasing, no drivers" (SIC 7513).

trailer, and TV rental and leasing (1,175), independent artists, writers, and performers (896), and formal wear and costume rental (326).

2.5. County Business Patterns (CBP) data for motion picture production

I also use employment and establishment counts in the motion picture production industry from County Business Patterns (CBP) from 1986 to 2016 as a robustness check to the QCEW data, similar to Dube et al. (2010). This data is compiled from the Business Register,[30] is annual from to 1998 to 2016, and uses the same industry classifications as the QCEW data.[31] Table 1 panel (e) presents summary statistics for this data. The CBP and QCEW data are similar, although CBP has fewer employees (2,248) and establishments (209) on average compared to the QCEW (3,299 and 289, respectively).

3. Methodology

3.1. Basic model - average effects of SFIs

I first conduct a panel regression with two-way fixed effects (a panel difference-in-differences). While I use all states, plus D.C., in my analysis, the effect of SFIs is identified only from states that at some point adopt an SFI. Intuitively, my approach compares states, over time, that adopt SFIs to other states, over the same time period, that have not yet adopted SFIs. This exploits the variation created from states adopting SFIs at different times. This approach calculates the average increase in the outcome variable in the period after SFI adoption.[32] This regression is:

$$IHS(Y_{st}) = \beta SFI_{st} + \delta_s \varphi + \mu_t \tau + X_{st}\Phi + \epsilon_{st} \qquad (1)$$

[30] The Business Register is a database of all known single and multi-establishment employer companies maintained and updated by the U.S. Census Bureau. This Business Register contains up-to-date information on these establishments. See https://www.census.gov/programs-surveys/cbp/about.html (accessed 10/13/18) for more detailed information.

[31] "Motion picture and video production" (NAICS 512110) from 1998 to 2016 and "Motion picture and video production" (SIC 7812) from 1986 to 1997.

[32] One could consider doing this analysis at a more local level, such as for metropolitan areas. There are some benefits to this as one could explore effects within a state and could explore the few city-level incentives that are available. However, this would be very difficult to do as it would require matching filming to metropolitan areas instead of states, making the matching of IMDb and Studio System data more error-prone and resulting in fewer matches. For example, cities are not always listed (or are incorrectly listed) in the data.

Y_{st} is one of the outcome variables (TV series filming, feature film filming, employment, establishments, average weekly wages, total wages), for state s at time t.[33] IHS is the inverse hyperbolic sine function.[34] Following established practice, I use the IHS function instead of a log because there are zeros in the filming data, and these observations would drop. The IHS avoids this while having the same interpretation as a log-linear regression (Burbidge et al., 1988; Mackinnon and Magee, 1990).[35] SFI_{st} is an indicator variable for whether state s has an SFI (cash rebate, grant, refundable tax credit or transferable tax credit) available at t.

δ_s are state fixed effects which control for time-invariant state characteristics such as the average filming, employment, or establishments by state. For example, without state fixed effects, more populous states would be directly compared to less populous states, so the effects of SFIs would get confounded with the fact that more populous states are more likely to have SFIs (Leiser, 2017; Thom and An, 2017), or other sources of endogeneity from time-invariant state characteristics.

μ_t are time fixed effects which control for the national average change in the outcome variable in each period. These control for national trends or shocks in motion picture production that affect all states. Since motion picture production has been increasing over time, excluding time fixed effects would confuse this trend with the adoption of SFIs, which has also been increasing over time.

X_{st} is a set of other control variables that vary by state and time. These include controls for the few SFIs that are neither refundable nor transferable, including a separate control for California's incentive of this type,[36] and a control for states having a repealed SFI, analyzed in Section 7. I also include the state unemployment rate, as Thom and An (2017)'s analysis shows that SFI adoption was correlated with increases in unemployment rates, although Leiser (2017) does not find evidence of this. In Section 5.2, I explore the robustness of my results to the inclusion and exclusion of these and other control variables.[37]

This panel regression model with two-way fixed effects provides an unbiased estimate of the effect of SFIs under three assumptions: (1) the treatment and control states have "Parallel Paths" (discussed in Section 3.2), (2) SFI adoption is not endogenous to the outcomes I study or anything I do not control for that is correlated with these outcomes (this is related to "Parallel Paths" and is discussed in Section 3.4), and (3) the Stable Unit Treatment Value Assumption (SUTVA) (discussed in Section 3.5).

3.2. Time trends and the parallel paths assumption

A fundamental assumption behind the panel regression (difference-in-differences) methodology is the "Parallel Paths" assumption (to use the terminology in Mora and Reggio (2017), also called the parallel trends assumption). This assumption is that if the states that had adopted SFIs (the treatment group), actually did *not* adopt them, then the changes in outcomes would be the same for the treatment group and the control group (states that did not adopt SFIs). Put another way, the control group provides the "business as usual" case for what would have happened in a counterfactual world where states that adopted SFIs chose instead not to adopt them.

It is impossible to test explicitly for if this assumption holds, but some tests are helpful. This parallel paths assumption is likely violated if the treatment and control group have different existing trends or if there is endogeneity whereby trends in outcomes predict SFI adoption, a point discussed in Section 3.4. To otherwise control for any differential trends in outcomes that could be correlated with SFI adoption, I include, in one set of my main regressions, controls for state-specific linear time trends. These linear trends controls for any linear trend difference whereby states that adopted SFIs had rising (falling) filming or a growing (contracting) film industry, relative to states that did not adopt. If this occurred, then the parallel paths assumption is violated, and my estimates of the effects of SFIs are biased. I follow a more modern approach of fitting my linear trends to the pre-treatment period only rather than over the entire span of the data. This is to avoid possible attenuation of the estimates, relative to estimating the trend over the entire span of the data.[38]

The process of including this trend control, estimated off the pre-treatment period data, is not as straightforward as the more traditional approach of just including linear trends by state. First, I estimate the state-specific linear trends off the pre-treatment data only, using a regression similar to Eq. (1) (except without the SFI_{st} variable). Then I run the main regression in Eq. (1) but with the regression coefficients for each state-specific linear time trend constrained to be the estimates from the earlier regression off the pre-treatment period data only.

Since this process requires running a regression based upon the results of a first regression (which estimates the pre-trends), the process has to be bootstrapped to allow the error from the first regression to be carried forward. I conduct a state-clustered bootstrap, with 10,000 replications, to estimate a bias-corrected percentile-based 95% confidence interval.[39] Because I estimate confidence intervals, my tables present confidence intervals in all cases to allow for easy comparisons. For regressions without this linear trend, I cluster my standard errors at the state level (Bertrand et al., 2004) and report 95% confidence intervals based on these standard errors.

In Section 5.1, I discuss and estimate results for a broader set of different trends to see how robust my estimates are to these trends. These include trends at the Census Region, Census Division, or state level, with these trends either based of the pre-treatment data only (as in the main estimates) or based on the entire span of the data (the more classical approach). This robustness check is crucial since Mora and Reggio (2017) shows that difference-in-differences estimates are often sensitive to the inclusion or exclusion of these trends.

3.3. Event study - effects over time

I next conduct an event study to estimate effects separately by each year relative to SFI adoption, following Mora and Reggio (2017) and Reber (2005). This fully relaxes any parallel path assumptions (Mora and Reggio, 2017), going beyond the inclusion of state-specific linear time trends to identify all changes in time non-parametrically, both

[33] The data frequency is annual for IMDb and Studio System TV series, IMDb feature films, CBP employment and establishments, quarterly for QCEW establishments, average weekly wages, and total wages, and monthly for Studio System feature films and QCEW employment.

[34] $IHS(Y_{st}) = log(Y_{st} + (Y_{st}{}^2 + 1)^{0.5})$.

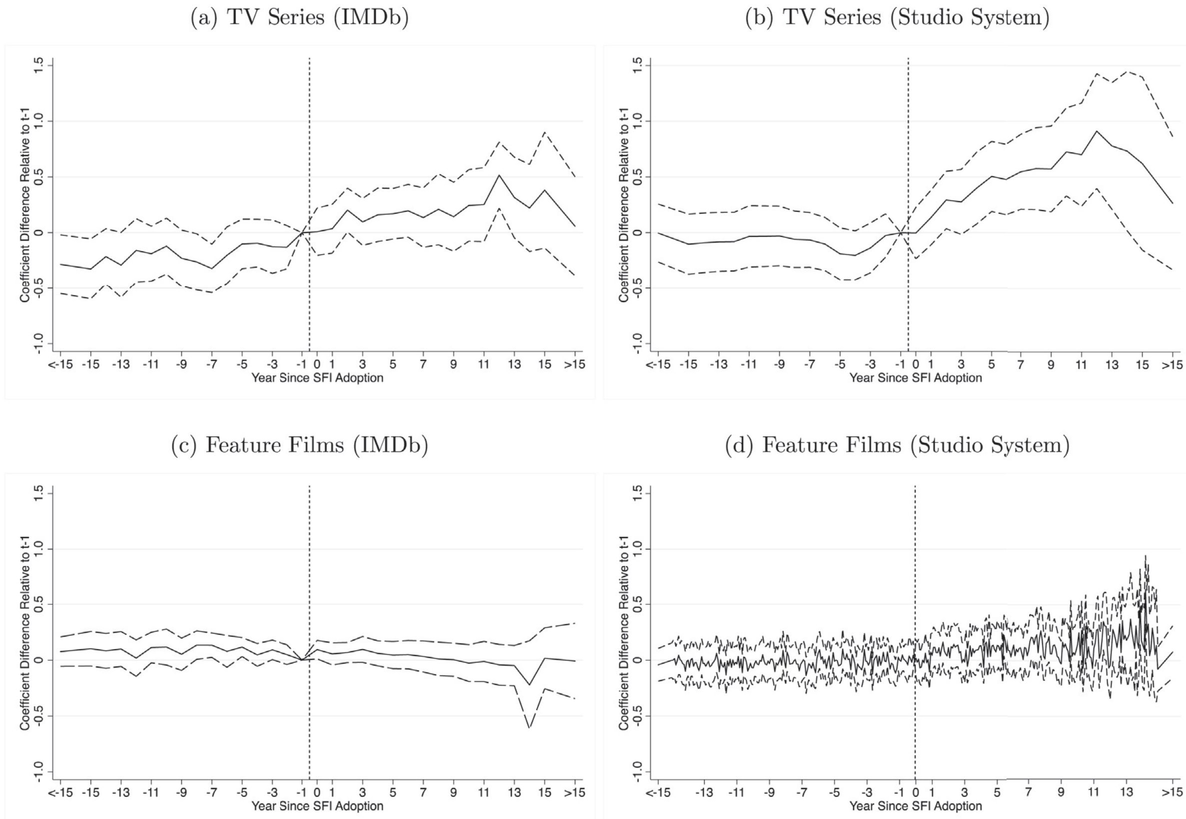
[35] That said, I explore how my results differ for the QCEW variables, where the zeros are not an issue. My results are similar for log-linear regressions instead. These estimates are available upon request.

[36] See Thom (2018 b) for an analysis of California's incentives.

[37] One possible control variable is state sales tax rates, although including this variable is complicated by local tax rates. However, this control variable is unlikely to matter for a few reasons. First, state fixed effects already control for average sales tax rates. Second, changes in sales tax rates would need to be correlated with SFI adoption for the estimates on *SFI* to be biased. Third, prior work suggests that excluding this variable leads to little omitted variable bias (Rohlin and Thompson, 2018). Another possible control variable is incentives at the local level, although these are neither as common nor are as aggressive as SFIs. By not including these, my estimates could be slightly biased towards finding no effect, as local incentives appear positively correlated with SFIs.

[38] When treatment effects are dynamic, that is, where treatment effects occur in part as an increase in the growth rate (slope change) rather than just an immediate jump in levels, then trends identified off both the pre- and post-treatment period pick up some of this growth effect, attenuating estimates (Meer and West, 2016).

[39] As is recommended practice, I bootstrap a confidence interval rather than bootstrapping a standard error, given that a percentile-based confidence interval is a pivotal statistic, unlike a standard error, which is a function of unknown parameters (Horowitz, 2001; MacKinnon, 2002).



Notes: See the notes to Table 1. These regressions are based on 2,142 state-year observations (IMDb) from 1976 to 2017, 1,734 state-year observations (Studio System TV series) from 1984 to 2017, and 20,808 state-month observations (Studio System feature films) from 1984 to 2017. These series are the 95% confidence intervals for the β_t estimates from Equation 2. The effect at time $t = -1$ is normalized to zero so that all other points in time are relative to $t = -1$. Positive values indicate that filming was higher in states with SFIs than in states without them, relative to at time $t = -1$. All sub-figures use the same y-axis range to allow for an easier comparison across outcomes. This estimation does not include any parametric time trend controls, instead it presents the results for each point in time non-parametrically so that any possible pre-trends and dynamic treatment effects can be clearly seen.

Fig. 4. Event study estimates of the effects of SFIs on the filming of TV series and feature films.

pre- and post-treatment. This approach allows any pre-trends to be seen visually, providing evidence of if the parallel paths assumption (or less restrictive assumptions like "Parallel Growth," see Mora and Reggio, 2017) is violated. It also estimates dynamic treatment effects, which is important because the effects of SFIs may not have been immediate or long term.

For the annual data,[40] the event study regression is:

$$IHS(Y_{st}) = \beta_{t<15} SFI_{s,t<15} + \sum_{t=-15}^{-2} \beta_t SFI_{st} + \sum_{t=0}^{15} \beta_t SFI_{st} + \beta_{t>15} SFI_{s,t>15} + X_{st}\Phi + \delta_s \varphi + \mu_t \tau + \epsilon_{st}. \quad (2)$$

Time, t, here refers to time relative to SFI adoption, where $t = -1$ is the period before SFI adoption. In the equation, the first summation includes periods from 15 years before adoption to the period just before adoption; the second summation includes the period of adoption ($t = 0$) until 15 years after adoption. Also included is a variable for all periods before 15 years before adoption, $SFI_{s,t<15}$, and all periods after 15 years of adoption, $SFI_{s,t<15}$. I exclude $SFI_{s,t=-1}$ from the regression so that the remaining β_t coefficients measure effects relative to the period before SFI adoption ($t = -1$). The coefficients β_t are interpreted as a year-by-year difference-in-difference: the difference between states with SFIs and states that have not yet adopted SFIs in time t relative to this difference at time $t = -1$.[41]

In Fig. 4 to B4, I plot the 95% confidence intervals of β_t. This provides visual evidence of whether a pre-trend exists in the SFI-adopting states before they adopt (discussed further below) relative to non-adopting states, and illustrates how the treatment effects evolve over time.

3.4. Possible SFI endogeneity

A fundamental assumption of a difference-in-differences (panel fixed effects) empirical strategy is that policy adoption is exogenous, otherwise, estimates could be biased Besley and Case (2000). Two studies, Leiser (2017) and Thom and An (2017), study the diffusion of SFIs. Leiser (2017) finds that SFI adoption was positively related to the size of the state's existing film industry and how many other states had adopted (which explains the bandwagon effect seen in the mid-2000s in Fig. 1). Leiser (2017) finds that having neighboring states

[40] For the variables that are quarterly or monthly, the equation is similar but includes SFI_{st} variable for each quarter or month.

[41] For states that never adopt SFIs, all the SFI variables in Eq. (2) are set to zero. Since $SFI_{s,t=-1}$ is excluded from Eq. (2), this sets the "relative time" variable to be $t = -1$ for these states. However, these states that never adopt SFIs provide no identification to the SFI variables, as is the case for all other analysis.

with SFIs did not affect SFI adoption, nor did the Democrat/Republican balance of power in the state. Thom and An (2017) confirm Leiser (2017)'s result that bordering states do not drive adoption of SFIs. The fact that regional tax mimicking does not drive SFI adoption is in contrast to many studies that find this to be important in policy diffusion (e.g., Walker, 1969; Ladd, 1992; Heyndels and Vuchelen, 1998; and Shipan and Volden, 2008 in some cases). However, there are also many studies that find that this is not important or less important than thought (e.g., Fletcher and Murray, 2006; Volden et al., 2008; Shipan and Volden, 2012). Thom and An (2017) do not find that the existing concentration of the film industry matters, but, unlike Leiser (2017), do find that state unemployment rates predict adoption.

The fact that SFI adoption is possibly endogenous to the size of the existing film industry (Leiser, 2017) is not too surprising, as larger industries were better at lobbying for these incentives. Since my regressions include state fixed effects, I control for the existing size of the film industry already and any other time-invariant factors. Similarly, the "bandwagon effect" of adoption is not a concern, in terms of endogeneity, since if states are reacting to national trends in adoption, then this is controlled for with the time fixed effects.

However, endogeneity could occur from factors correlated with SFI adoption that vary *within* states over time, and are not controlled for in X_{st}. More specific to SFIs, one could be concerned that *growth* in the film industry, rather than economic conditions in general, predicts adoption.

I attempt to control for this possible endogeneity bias in two ways. First, I include state-specific linear time trends in half my main specifications to control for existing trend differences between states that adopt and do not adopt SFIs. I discuss these trends in detail in Section 5.1, and I explore robustness to alternative trends. Second, in Section 5.2 I explore how my results change when I include other control variables (from Leiser (2017) and Thom and An (2017)) that may predict SFI adoption.

3.5. State competition and the stable unit treatment value assumption

The "Stable Unit Treatment Value Assumption" (SUTVA) (Rubin, 1980) is another fundamental assumption behind the difference-in-differences (two way fixed effects) empirical strategy. This assumption is that the treatment status of one unit (state) does not affect outcomes for other units (states). Given that states may compete with each other for filming, or there could be regional spillovers, this assumption may not hold, and this could have implications for my estimates.

A violation of SUTVA could create either a positive or negative bias to my estimated effects of SFIs. The bias is positive if states with SFIs take productions from states without SFIs.[42,43] Previous studies (e.g., Wilson, 2009, and somewhat in Moretti and Wilson, 2014) found these "beggar thy neighbor" effects and these could occur in this context as well. On the other hand, this bias could be negative if there are positive spillovers, which could occur if a state with an SFI gets filming and some of this filming happens in nearby states.

I explore SUTVA and the state competition issue in several ways. First, I estimate if the effects of SFIs were moderated by SFIs in nearby states, following the approach of (Wilson, 2009). I test both if there are spillovers or regional state competition, by adding a variable for if nearby states have SFIs. I also test if the effects of SFIs differ when nearby states also have SFIs, by adding an interaction between nearby states' SFIs and own state's SFI. I detail this approach and the results in Section 5.3.

Second, I test the sensitivity of my results to the inclusion of Census Division-by-time fixed effects (Section 5.2). This further allows me to explore if there is regional competition or spillovers by identifying the effects of SFIs only from the within-Census Division variation in SFIs. This forces the control group to be states within the same Census Division rather than states anywhere in the nation. If the estimated effects change from this different control group, then it is suggestive of spillovers or state competition affecting the result. For example, if state competition were fierce, then the estimated impact of SFIs would be larger when Census Division-by-time fixed effects are included.

Third, I estimate if my results are sensitive to the exclusion of California and New York (Section 5.2). Instead of states competing regionally for filming, states with SFIs may instead take filming from California or New York, where most filming occurs.[44] If the results are smaller with California and New York excluded, then this could suggest that my main estimates were positively biased because filming was taken from California and New York, and these two states formed some part of the control group for a period of time.

4. Results

4.1. TV series

Table 3 panel (a) presents estimates of the effect of SFIs on the number of TV series. Columns (1) and (2) use the IMDb data while columns (3) and (4) use the Studio System data. Even columns include state-specific linear time trends estimated off the pre-treatment period only, while odd columns do not include any trends. Starting with column (1), the coefficient on the SFI_{st} variable, β, is 0.292. This is an average increase in IMDb TV series filming after SFI adoption of 33.9% ($e^{0.292} - 1$), statistically significant at the 1% level. However, after adding a linear control for pre-trends (column [2]), this estimate loses statistical significance and decreases in magnitude to 6.4%. The Studio System TV series filming estimates show more substantial and robust effects: a 55.4% increase (without a trend control, column [3]) or a 37.7% increase (with a trend control, column [4]), both statistically significant at the 1% level.

Fig. 4a and b presents the event study of the effects on the filming of TV series over time, with IMDb and Studio System data, respectively. These figures show the difference in filming between states with and without SFIs relative to this difference the year before SFI adoption ($t = -1$), which is normalized to be zero. In Fig. 4a there is an existing pre-trend, whereby filming of IMDb TV series was already rising faster in SFI-adopting states, relative to state that had not adopted. This confirms that controlling for pre-trends is crucial in this case and that the estimate with these trends (column [2]) is likely more reliable. While Fig. 4a shows that filming is higher in the post-period, much of this could be attributed to the continuation of the existing trend. While one estimate in the post period ($t = 12$, 12 years after the year of adoption) is statistically-significantly different from the estimate the year before adoption ($t = -1$), this effect goes away in the following years and there is a corresponding negatively statistically-significant estimate at

[42] In this case the effect of SFIs is identified off the increase in states with SFIs plus the decrease in states without SFIs. This overstates the effects of SFIs by including the decrease for states without SFIs. This bias could also be interpreted more like a relative substitution effect, where the treatment causes a substitution of a benefit towards treated groups and away from the control group (see, e.g., the effects of discrimination laws, where employment increases for the protected minority group relative to the control group (Button, 2018 b).)

[43] This bias could still exist even though earlier analysis suggests that states do not adopt SFIs in response to nearby states adopting SFIs (Thom and An, 2017; Leiser, 2017).

[44] California has between 33.2% (IMDb feature films) and 58.2% (Studio System TV series) of filming in the entire sample. For New York, this is 13.8% (IMDb TV series) to 19.8% (Studio System feature films).

Table 3
Effects of SFIs on filming.

	IMDb		Studio System	
	(1)	(2)	(3)	(4)
(a) TV Series				
SFI	0.292***	0.062	0.441***	0.320***
	(0.102, 0.483)	(-0.071, 0.189)	(0.225, 0.658)	(0.178, 0.486)
(b) Feature Films				
SFI	−0.028	−0.027	0.076***	0.053*
	(-0.123, 0.067)	(-0.209, 0.104)	(0.026, 0.127)	(-0.013, 0.121)
State-SpecificLinear Pre-Trends:	No	Yes	No	Yes

Notes: See the notes to Table 1. These regressions are based on 2,142 state-year observations (IMDb) from 1976 to 2017, 1,734 state-year observations (Studio System TV series) from 1984 to 2017, and 20,808 state-month observations (Studio System feature films) from 1984 to 2017. Estimates come from Eq. (1). 95% confidence intervals are presented in parentheses. Odd columns do not include state-specific trends and are estimated using standard errors that are clustered on state. State-specific linear time trends are included in even columns and are estimated off of pre-trends only. This requires a state-clustered bootstrap of bias-corrected confidence intervals, hence presenting confidence intervals instead of standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

$t = -7$. Thus, the event study shows little evidence of effects on IMDb TV series filming.

Fig. 4b shows little evidence of any pre-trend in Studio System TV series filming, but shows clear evidence of a meaningful increase in filming. The increase starts at about the year after adoption, and peaks at 149.0% higher filming (relative to the difference at $t = -1$) at 12 years after the year of adoption. No estimates in the pre-period are statistically significant, while the estimates in the range $[3 \leq t \leq 13]$ are significant at the 5% level or more.

In sum, there appears to be evidence of a large effect on TV series filming, although the evidence is not entirely robust. To put the range of estimates in perspective, the lower bound of a 6.4% increase in IMDb TV series corresponds to 0.67 additional IMDb TV series, and the upper bound of a 55.4% increase in Studio System TV series corresponds to 1.50 additional Studio System TV series.[45]

4.2. Feature films

Table 3 panel (b), columns [1] and [2] and Fig. 4c presents estimates of the effect of SFIs on the number of IMDb feature films. There is no evidence of a change in either the table or in the event study figure. In the table, the estimate is insignificant and small (either −0.028 or −0.027).

Table 3 panel (b), columns [3] and [4] presents estimates of the effect of SFIs on the number of Studio System feature films. The Studio System data, however, does show some evidence of effects on feature films. In the regression without trends (column [3]), the estimate is 0.076 (an increase of 7.9%), significant at the 1% level. However, the coefficient decreases to 0.053 (5.4%) and becomes statistically significant only at the 10% level when adding in the pre-trend control (column [4]).

The coefficients in the event study figure, Fig. 4d, are noisy given that the feature film data is monthly. No estimates are statistically significant relative to the year before adoption ($t = -1$).[46] Nevertheless, the coefficient estimates show little change over time, at best a slight upward trend. Given this, there is less reason to be concerned about pre-trends in the estimates in this case.

In sum, there is some non-robust evidence on a small effect on feature films, but even if this small effect exists it is not of a meaningful magnitude. To put this in perspective, if we assumed that the increase in Studio System feature films was 13.5% (the upper bound of the 95% confidence interval for the statistically significant estimate in column (3) of 7.9%), this would only be 0.032 additional Studio System feature films relative to the mean number of Studio System feature films in the month before SFI adoption (0.24 feature films).

4.3. Employment in motion picture production

Table 4 panel (a) present estimates of the effect of SFIs on employment in motion picture production using the QCEW data (columns [1] and [2]) and the CBP data (columns [3] and [4]). The QCEW data shows no effect when excluding pre-trend controls, but an effect of 0.081, an 8.4% increase, statistically significant at the 5% level, when including pre-trends controls. On the other hand, both estimates using the CBP data are negative, either −0.034 or −0.041, and the estimate without a pre-trend control (−0.034) is statistically significant at the 10% level.

Fig. 5a and b presents the estimated effects over time for employment using the QCEW data and the CBP data, respectively. Fig. 5a shows an existing negative pre-trend that persists into the treatment period, suggesting that the earlier positive estimate with trends is preferred (column [2]) over the estimate without trends (column [1]). Despite this existing negative trend, employment rises from about 6 to 9 years after adoption, after which point it appears that the existing negative trend returns. This increase in employment is of a magnitude of about ten percentage points net of the pre-trend. If this is taken as causal, this would be only a modest increase in employment with a rather late onset. On the other hand, the CBP data again does not show any effect. In sum, the evidence for small employment effects exists but is not robust. Any possible employment effects are not at a meaningful magnitude: an 8.4% increase in employment is only 146 jobs for the average SFI-adopting state, or 314 jobs using the upper bound of the 95% confidence interval (an 18.2% increase).[47]

4.4. Establishments in motion picture production

Table 4 panel (b) presents estimates of the effect of SFIs on the number of business establishments in the motion picture production industry. The QCEW estimates are negative without a trend control (−0.029) and positive with one (0.051) but are not statistically significant in

[45] This calculation again uses the means from the period before SFI adoption: 10.4 (2.7) for IMDb (Studio System) TV series, 39.7 (0.24) for IMDb (Studio System) feature films.

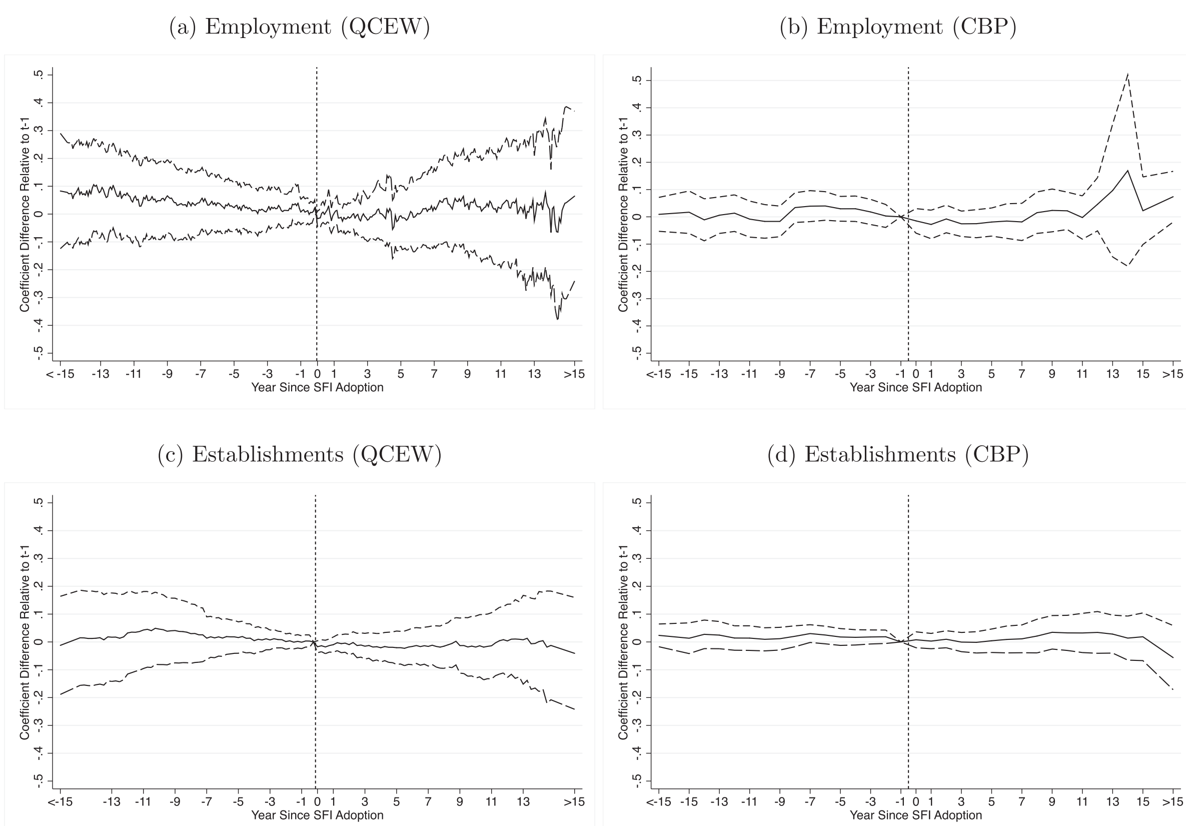
[46] This may not necessarily be the case if months were combined into quarters or years, matching the other outcome variables. Power would increase if the testing were between years or quarters, rather than months.

[47] I calculate this using the mean employment for SFI adopting states at time $t = -1$, the month before SFI adoption, which is 1,725 jobs.

Table 4
Effects of SFIs on employment, establishments and wages in the motion picture production industry.

	QCEW		CBP	
	(1)	(2)	(3)	(4)
(a) Employment				
SFI	−0.017	0.081**	−0.034*	−0.041
	(-0.113, 0.078)	(0.005, 0.167)	(-0.072, 0.005)	(-0.103, 0.033)
(b) Establishments				
SFI	−0.029	0.051	−0.010	−0.012
	(-0.085, 0.027)	(-0.033, 0.173)	(-0.047, 0.028)	(-0.060, 0.034)
(c) Average Weekly Wages				
SFI	−0.048*	0.027	…	…
	(-0.098, 0.001)	(-0.037, 0.141)		
(d) Total Wages				
SFI	−0.085**	0.083	…	…
	(-0.151, −0.019)	(-0.011, 0.267)		
State-SpecificLinear Pre-Trends:	No	Yes	No	Yes

Notes: See the notes to Tables 1 and 3. These regressions using QCEW data are based on 20,508 state-month observations for employment, or 7,413 state-quarter observations for establishments (7,397 for average weekly wages and total wages), all from 1978 to 2017. For the CBP data, this is 1,523 state-year observations from 1986 to 2016. There is no wage data in the CBP. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.



Notes: See the notes to Figure 4 and Table 1. These regressions using QCEW data are based on 20,508 state-month observations for employment, or 7,413 state-quarter observations for establishments, both from 1978 to 2017. For the CBP data, this is 1,523 state-year observations from 1986 to 2016. All sub-figures in the figures using QCEW and CBP data (Figures 5 to B4 use the same y-axis range (except for Figures B1a and B1b) to allow for an easier comparison across variables, data sources, and industries.

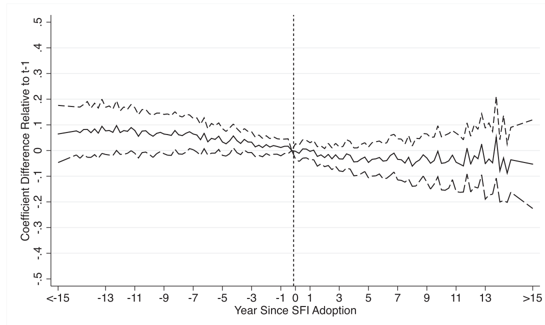
Fig. 5. Event study estimates of the effects of SFIs on employment and establishments in the motion picture production industry.

either case. The CBP data also shows no effect, with coefficient estimates closer to zero (−0.010, −0.012). The event study estimates in Fig. 5c and d also show no changes over time, either before or after SFI adoption.

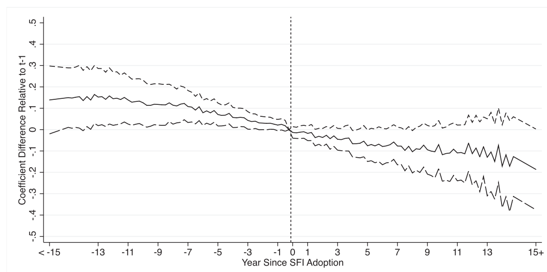
4.5. Wages in motion picture production

While there are no effects on employment, there could still be an effect on wages. If, for example, the supply of labor is relatively fixed,

(a) Average Weekly Wages



(b) Total Wages



Notes: See the notes to Figures 4 and 5 and Table 1. This wage data comes from the QCEW as there no wage data in the CBP. These regressions are based on 7,397 state-quarter observations from 1978 to 2017.

Fig. 6. Event study estimates of the effects of SFIs on average weekly wages and total wages in the motion picture production industry.

then an increase in demand would materialize as an increase in wages rather than as an increase in employment, which would be captured in the average weekly wages variable from the QCEW. Similarly, if there is an increase in hours only (e.g., part-time workers move closer to full-time work), this would not be picked up in employment variable either but would be captured in the total wages variable in the QCEW.

Table 4 presents the estimates of the effect of SFIs on average weekly wages (panel [c]) and total wages (panel [d]) in motion picture production. These estimates use the QCEW data only, as there is no wage information in the CBP data. The estimates for average weekly wages are −0.048 without trends, statistically significant at the 10% level, and an insignificant 0.027 with trends. These estimates are more pronounced for total wages: 0.085 without a trend control, statistically significant at the 5% level, or an insignificant 0.083 with a trend control.

Fig. 6a and b presents the results of the event study of average weekly wages and total wages, respectively. Mirroring the estimates in the table, there appears to be a decrease in average weekly wages and especially total wages, but it is due to the pre-existing negative trend. Net of this existing trend there does not appear to be any effect on wages. In sum, the evidence suggests no effects on average weekly wages and total wages.

4.6. Effects on related industries

While there are few, if any, effects on the motion picture production industry, this could be because the QCEW estimates do not capture all of this employment, as some of the employment may fall under “Independent artists, writers, and performers” or under “Payroll services.” There could also be effects on other, related, industries, although this is unlikely given the lack of impacts on the targeted industry itself. Table 5 presents estimates of the effects of SFIs on employment, establishments, and average weekly wages in these industries, and Online Appendix Figs. B1–B4 present the event study figures. Across all these related industries there is little evidence of impacts.

Table 5 panel (a) present the effects on the “Independent artists, writers, and performers” industry. For employment, the estimate is either statistically significant at the 10% level and negative (−0.082, an 8.5% decrease), without a pre-trend control, or statistically significant, at the 5% level, and positive (0.082), with a pre-trend control. The event study figure shows clear evidence of a negative pre-trend, so the positive estimate with trends is preferred. However, the event study figure shows no employment effect at all. So, the evidence of a positive employment effect is not robust. Despite there possibly being a small positive employment effect, there is no evidence effects on establishments or wages.

Table 5 panel (b) and (c) presents the effects on the “Payroll services” and “Caterers” industries, respectively. The regressions without pre-trend controls show negative effects on employment and wages, but the regressions with pre-trend controls show no effect. There are no effects on establishments. Panels (d), (e), and (f) show no statistically significant or economically meaningful positive effects for hotels and motels, costume rental, or lessors of non-residential buildings, respectively, regardless of if pre-trend controls are included. For “Truck, trailer and RV rental and leasing” (panel [g]), the employment estimate without a pre-trend control is an insignificant 0.008 and with a trend control is a positive 0.032, statistically significant at the 5% level. However, the event study figure does not show evidence of any positive effect on employment, even net of the slightly negative existing pre-trend. Thus, the evidence for employment effects is weak. There is no evidence of any effects on establishments or wages.

Thus, across all related industries, most of the evidence points towards no effects. The only evidence of positive effects, albeit weak and non-robust, is evidence of small increases in employment in the independent artists and transportation rental industries. However,

Table 5
Effects of SFIs on related industries.

	Employment		Establishments		Average Weekly Wages	
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Independent artists, writers, and performers						
SFI	−0.082*	0.082**	−0.029	0.051	−0.036	−0.010
	(-0.169, 0.004)	(0.003, 0.214)	(-0.085, 0.027)	(-0.033, 0.173)	(-0.084, 0.011)	(-0.043, 0.023)
(b) Payroll services						
SFI	−0.124**	0.027	−0.051	0.039	−0.091**	0.072
	(-0.230, −0.018)	(-0.073, 0.152)	(-0.134, 0.031)	(-0.052, 0.161)	(-0.175, −0.007)	(-0.043, 0.247)
(c) Caterers						
SFI	−0.028**	−0.076	−0.016	−0.001	−0.022***	0.002
	(-0.053, −0.003)	(-0.423, 0.124)	(-0.043, 0.011)	(-0.033, 0.053)	(-0.038, −0.006)	(-0.025, 0.061)
(d) Hotels and motels, except casino hotels						
SFI	0.009	−0.005	0.013	−0.001	0.004	−0.008*
	(-0.018, 0.036)	(-0.020, 0.006)	(-0.010, 0.036)	(-0.012, 0.011)	(-0.003, 0.011)	(-0.020, 0.001)
(e) Formal wear and costume rental						
SFI	−0.003	−0.001	−0.015	−0.024	0.013	0.010
	(-0.067, 0.061)	(-0.057, 0.040)	(-0.090, 0.061)	(-0.096, 0.046)	(-0.003, 0.030)	(-0.009, 0.029)
(f) Lessors of non-residential buildings						
SFI	0.005	−0.006	−0.005	−0.005	0.001	−0.013
	(-0.016, 0.027)	(-0.023, 0.009)	(-0.024, 0.015)	(-0.020, 0.010)	(-0.016, 0.018)	(-0.033, 0.004)
(g) Truck, trailer, and RV rental and leasing						
SFI	0.008	0.032**	0.007	0.006	0.002	−0.007
	(-0.042, 0.057)	(0.002, 0.070)	(-0.028, 0.043)	(-0.022, 0.032)	(-0.013, 0.017)	(-0.025, 0.007)
State-SpecificLinear Pre-Trends:	No	Yes	No	Yes	No	Yes

Notes. See the notes to Table 2 for information on the years of each data source and Fig. 3 for details on the methodology. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

across all the variables and industries (3×7), it is not surprising to have one or two estimates be significant at the 5% level even without effects. Even if these positive effects are taken as given, most estimates are statistically insignificant, and there is are even negative and statistically significant estimates, suggesting that the broader evidence points towards no effects on related industries.

5. Robustness checks

I conduct numerous robustness checks of my main estimates. These include incorporating alternative time trend controls (Section 5.1), adding control variables and sample restrictions (Section 5.2), and exploring SUTVA and possible bias from state competition and regional spillovers (Section 5.3). These robustness checks help explore if my results are biased due to endogeneity, due to a violation of the parallel trends assumption, or due to a violation of SUTVA.

5.1. Alternative time trends

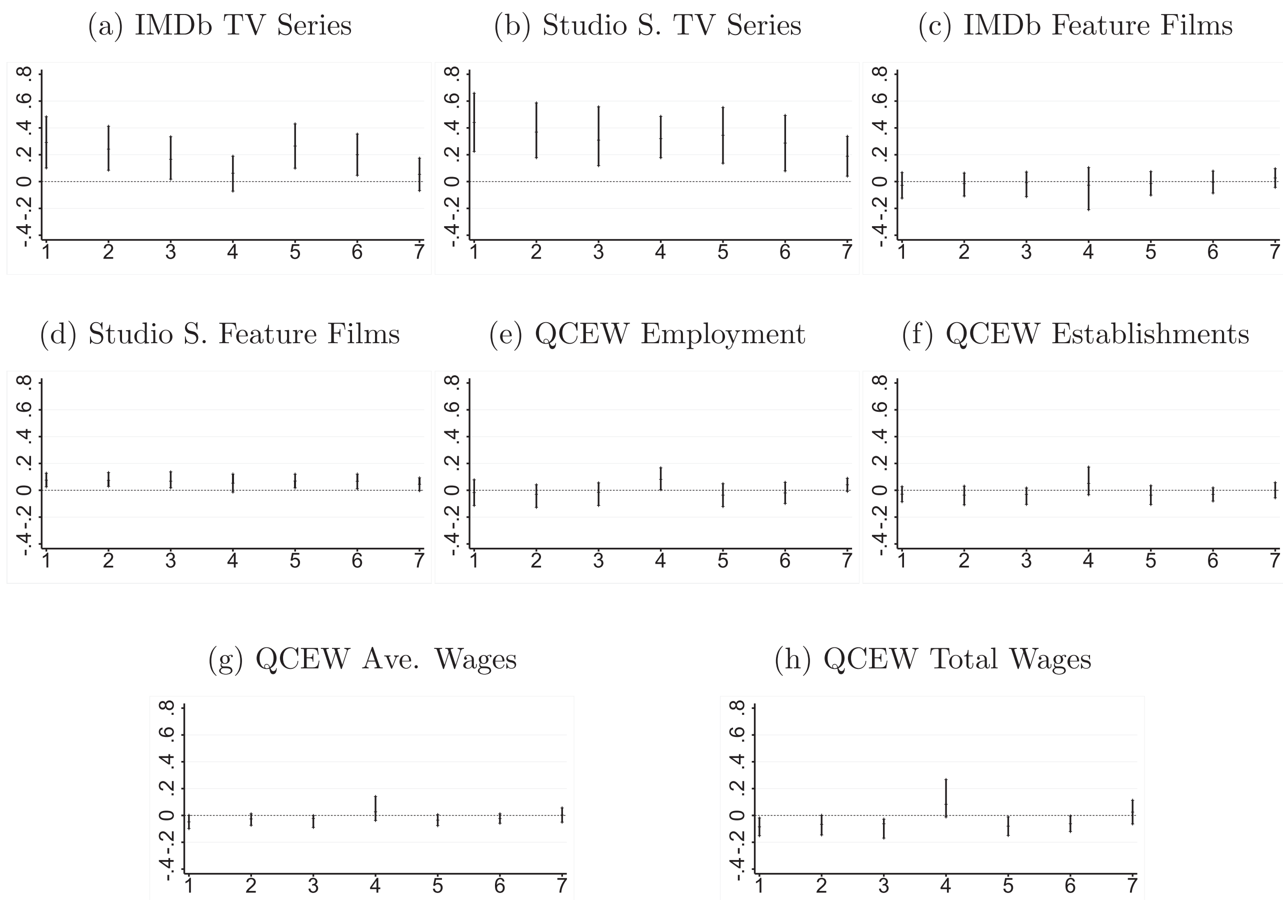
My results could be sensitive to the inclusion or exclusion of state-specific or group-specific time trends, and to the type of these trends or how they are estimated. This concern is by no means unique to this study, as Mora and Reggio (2017) find that many studies using a similar methodology had results that were sensitive to time trends.

In the main tables (Tables 3–5), I present results without trend controls and with state-specific linear time trends that are identified off of the pre-trend only. To further explore the robustness of my results to the specific type of trend used, I also consider some less restrictive trends by Census Region and Census Division in addition to state-specific trends. I estimate regressions with these three possible trends both where the trends are identified off the pre-period data only (a more modern approach, and the approach I take in my main estimates) and where the trends are identified off the entire span of the data (a more traditional approach).

Fig. 7 presents 95% confidence intervals of my estimates under all six types of linear trends, plus no trends. From these figures, we learn to what extent the main estimates are robust to different types of trends. We also learn how different types of trends tend to affect the results, which is informative more broadly as it is never entirely clear to researchers which trends to use, especially as identifying trends off the pre-treatment period data only is growing in popularity but is not yet considered standard practice.

Across these seven confidence intervals, the confidence intervals without trends (#1 in each figure) are nearly identical to the intervals with Census Region and Census Division trends (#2, #3, #5, #6). This suggests that the trends do not differ much between Census Regions and Divisions. The confidence intervals with state-specific linear time trends identified off the pre-period only (#4) are also nearly identical to those identified off the entire span of the data (#7). So generally the choice between identifying linear trends off the pre-period versus the entire span of the data does not matter much in this application.

However, including state-specific trends does affect the estimates when there is evidence, from the event study figures, of existing trends. For IMDb TV Series (Fig. 7a), the estimates go from positive and statistically significant with no trend (#1) or with Census Region or Division trends (#2, #3, #5, #6) to insignificant when including state-specific linear time trends (#4 and #7). For all other filming variables (Fig. 7b–d) the confidence intervals do not change much across specifications. For all four QCEW variables (Fig. 7e–h) the estimates are generally small and negative (sometimes statistically significant) until state-specific linear trends are added (#4 and #7). These make the estimates positive but usually not statistically significant, except for employment and total wages with the preferred state trends identified off the pre-period (#4).



(i) Legend

	1	2	3	4	5	6	7
Geographical Basis for Trends:							
Census Region		x			x		
Census Division			x			x	
State				x			x
Trends Estimated Over:							
Pre-Treatment Period Only		x	x	x			
Entire Span of Data					x	x	x

Notes: See the notes to Table 1. Estimates #1 and #4 are from the main tables. Estimates #2 to #4 include state-specific linear time trends that are estimated over the pre-period only, as in the main tables. Estimates #5 to #7 include state-specific linear time trends that are estimated over the entire span of the data. All figures use the same y-axis range to allow for easy comparisons across variables.

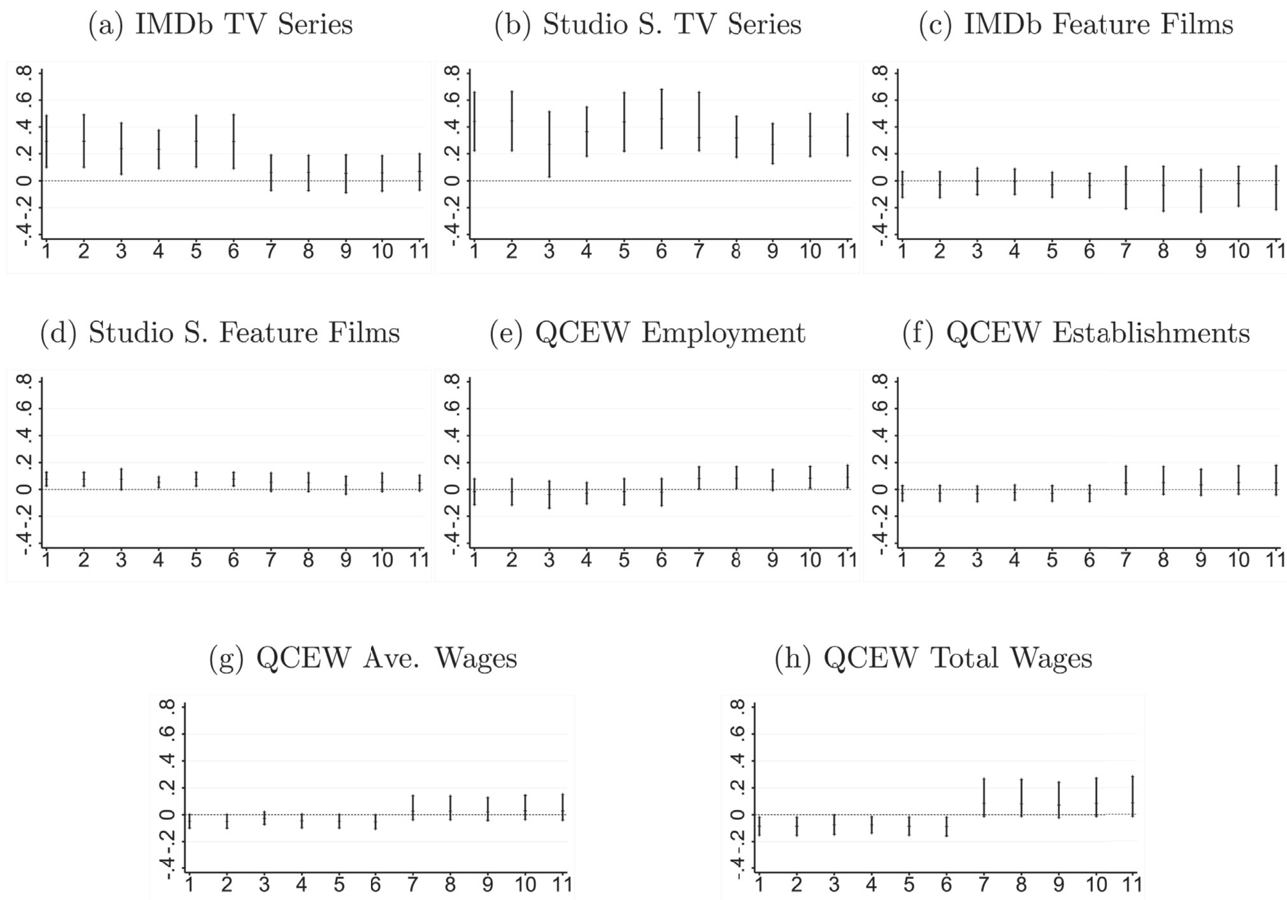
Fig. 7. 95% confidence intervals testing robustness to different linear trends.

In sum, the earlier conclusions are generally unaffected when considering alternative time trends. The only changes are that these estimates with alternative trends are more suggestive of positive effects on IMDb TV series and no effect on QCEW employment and total wages. This strengthens the earlier observation of there only being an effect on TV series filming.

5.2. Control variables and sample composition

Since SFI adoption could be endogenous to time-variant state characteristics, I consider how robust my estimates are to the inclusion of other control variables from Leiser (2017) and Thom and An (2017) that may predict SFI adoption.[48] I also explore

[48] Leiser (2017) finds that the following predict SFI adoption: per capita gross state product (GSP), per capita GSP in motion picture production, the age of the state film commission, and if a state that borders Canada. State and time fixed effects control for the last two. Thom and An (2017) finds that SFI adoption was driven by a national bandwagon effect (but not the adoption of neighbors) and by state unemployment rates. Time fixed effects control for the former, and I control for state unemployment rates directly by including them in my main analysis.



(i) Legend

	1	2	3	4	5	6	7	8	9	10	11
Unemployment Rate	x		x	x	x	x	x		x	x	x
Census Division by Time Fixed Effects			x								
Per Capita Gross State Product (GSP)				x					x		
GSP in Motion Picture Production				x					x		
Legislative Professionalism					x					x	
Excludes California and New York						x					x
State-Specific Linear Pre-Trends							x	x	x	x	x

Notes: See the notes to Table 1. Estimates #1 and #7 are from the main tables. State-specific linear time trends are estimated over the pre-period only, as in the main tables. All figures use the same y-axis range to allow for easy comparisons across variables.

Fig. 8. 95% confidence intervals testing robustness to controls and sample restrictions.

how my results change if I exclude the state unemployment rate control, exclude California and New York, and if I add Census Division-by-time fixed effects as another way to control for regional trends that could be correlated with outcomes and SFI adoption.

Fig. 8 presents 95% confidence intervals of estimates with these changes in controls or sample composition. Mirroring the main estimates, I estimate all of these both without state-specific linear time trends (confidence intervals #1 to #6) and with state-specific linear time trends, estimated over the pre-period only (#7 to #11). Confidence intervals #1 and #7 are the main specifications from preceding tables, which include unemployment rates as a control variable and include New York and California.[49] Relative to confidence intervals #1

[49] The other possible control variables that could predict selection in SFIs are not included in my default specifications because they do not have data over the entire period. The GSP data is only available at an annual frequency, from 1997 to 2016. The legislative professionalism data from Squire (1992), Squire (2007), Squire (2012), and Squire (2017) is only available for the years 1979, 1986, 1996, 2003, 2009, and 2015. I follow Leiser (2017) and use a linear interpolation of this data so that no periods of my data drop when I include these controls.

Table 6
Effects of SFIs on filming, by nearby state SFIs.

	IMDb		Studio System	
	(1)	(2)	(3)	(4)
(a) TV Series				
SFI	0.183**	−0.014	0.208	0.004
	(0.032, 0.334)	(-0.349, 0.191)	(-0.194, 0.610)	(-0.236, 0.196)
Nearby SFI	0.694**	0.206	0.696	0.708
	(0.028, 1.361)	(-0.620, 1.258)	(-0.468, 1.860)	(-0.331, 1.980)
SFI x Nearby SFI	0.146	0.089	0.484	0.618***
	(-0.140, 0.431)	(-0.271, 0.577)	(-0.214, 1.181)	(0.171, 1.056)
(b) Feature Films				
SFI	−0.028	0.013	0.005	−0.041
	(-0.155, 0.099)	(-0.174, 0.136)	(-0.071, 0.080)	(-0.130, 0.028)
Nearby SFI	0.156	−0.340	−0.018	0.044
	(-0.361, 0.674)	(-0.785, 0.181)	(-0.396, 0.359)	(-0.367, 0.512)
SFI x Nearby SFI	−0.011	0.090	0.150**	0.184**
	(-0.270, 0.248)	(-0.165, 0.400)	(0.013, 0.288)	(0.010, 0.385)
State-SpecificLinear Pre-Trends:	No	Yes	No	Yes

Notes: See the notes to Tables 1 and 3. Estimates come from Eq. (3). *NearbySFI* is a variable ranging from 0 to 1 that captures the proportion of nearby states, weighted by distance, that have SFIs. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

and #7, the other columns make the following changes (see the legend, Fig. 8i):

1. Removes state unemployment rates (#2 and #8).
2. Adds Census Division-by-time fixed effects (#3).[50]
3. Adds per capita Gross State Product (GSP) and GSP in motion picture production (#4 and #9).
4. Adds the legislative professionalism measure from Squire (1992), Squire (2007), Squire (2012), and Squire (2017) (#5 and #10).
5. Excludes California and New York (#6 and #11).

Fig. 8 shows that the results do not change much when these other controls are added or the unemployment rate control is removed. The other robustness checks (adding Census Division-by-time fixed effects, excluding California and New York) also do not affect the results. Thus, this is further evidence that my results are unlikely to be biased from the plausibly endogenous adoption of SFIs.

5.3. SUTVA, state competition, and spatial spillovers

My analysis thus far has not incorporated the issue of competition between states which could violate SUTVA, leading to biased estimates, as discussed in Section 3.5. It is the case that states could compete with each other, perhaps on a regional basis, for filming, leading to positively-biased estimates. On the other hand, the estimates could be negatively biased if there are positive spillovers to nearby states when a state attracts filming.

To explore this, I first explore whether SFIs in nearby states moderate the effect of SFIs and if nearby SFIs affect filming. I extend the main regression, Eq. (1), as follows:

$$IHS(Y_{st}) = \beta_1 SFI_{st} + \beta_2 NearbySFI_{st} + \beta_3 SFI_{st} \times NearbySFI_{st} + \delta_s \varphi + \mu_t \tau + X_{st}\Phi + \epsilon_{st} \tag{3}$$

where SFI_{st} is the indicator variable for having an SFI, and $NearbySFI_{st}$ is a variable capturing the proportion of nearby states that have SFIs. I follow the approach of Wilson (2009) and construct this variable by creating a weighted combination of the *SFI* variable for other states, where the weights are equal to the inverse distance between each pair of states.[51] The coefficient on SFI_{st}, β_1, captures the effect of a state's own SFI on its own outcome. The coefficient on $NearbySFI_{st}$, β_2, captures if the outcome in state *s* is different when nearby states have SFIs. If β_2 is positive (negative), then there are positive (negative) spillovers. The coefficient on $SFI_{st} \times NearbySFI_{st}$, β_3, captures if SFIs are less effective ($\beta_3 < 0$) or more effective ($\beta_3 > 0$) when nearby states also have SFIs.

Tables 6 and 7 present the estimates from Eq. (3). For TV series filming (Table 6 panel [a]) where there were effects in the main results, there are some effects of interactions with nearby SFIs. For IMDb TV series, where there were positive effects without trend controls, we again see positive effects of SFIs when trends are not included (column [1]), with a coefficient of 0.183 on *SFI*, statistically significant at the 5% level. However, the coefficient is significantly larger for *NearbySFI*, 0.694, and is also significant at the 5% level. The coefficient on *SFI* × *NearbySFI* is positive, 0.146, but is not statistically significant. These results suggest that SFIs again increase IMDb TV series filming but states also get a significant boost in filming just be being nearby other states with SFIs. This is suggestive of positive spillovers rather than negative spillovers. However, as in the main results, none of these estimates are significant once trends are controlled (column [2]), and the event study figure shows an existing trend. The results are similar, but are less precise, for Studio System TV series. All three coefficients are positive, regardless of trend controls. However, none of the estimates are statistically significant except for one at the 1% level (*SFI*×*NearbySFI*). The magnitudes of the coefficients on *NearbySFI* and *SFI*×*NearbySFI* are large, ranging from 0.484 to 0.708, again suggesting positive spillovers.

For feature films (Table 6 panel [b]), the IMDb estimates again show no clear effects. For Studio System feature films, the coefficients on SFI_{st} and $NeighborSFI_{st}$ are never statistically significant and are not of a particularly large magnitude. However, the estimate on the interaction is either 0.150 or 0.184, both significant at the 5% level, suggesting that the small, non-robust increase in Studio System feature films we

[50] I was unable to include state-specific linear pre-trends along with census division-by-time fixed effects. Adding these numerous fixed effects requires the “absorb” command in STATA, which cannot be used in conjunction with a constrained regression.

[51] More specifically, I measure the distance between two states by using population centroids, calculated from 2000 Census data. I thank Daniel Wilson for providing this data.

Table 7
Effects of SFIs on QCEW employment, establishments, and wages, by nearby state SFIs.

	(1)	(2)
(a) Employment		
SFI	0.000	0.093
	(-0.064, 0.064)	(-0.064, 0.308)
Nearby SFI	0.105	−0.125
	(-0.293, 0.503)	(-0.793, 0.361)
SFI x Nearby SFI	−0.037	−0.024
	(-0.230, 0.156)	(-0.418, 0.262)
(b) Establishments		
SFI	−0.033	−0.024
	(-0.128, 0.063)	(-0.113, 0.037)
Nearby SFI	−0.141	0.050
	(-0.462, 0.180)	(-0.488, 0.588)
SFI x Nearby SFI	0.006	0.160
	(-0.144, 0.156)	(-0.083, 0.521)
(c) Average Weekly Wages		
SFI	−0.027*	−0.094**
	(-0.056, 0.003)	(-0.322, −0.005)
Nearby SFI	0.062	−0.014
	(-0.180, 0.305)	(-0.473, 0.392)
SFI x Nearby SFI	−0.046	0.262**
	(-0.165, 0.072)	(0.023, 0.813)
(d) Total Wages		
SFI	−0.051	−0.058
	(-0.136, 0.035)	(-0.326, 0.012)
Nearby SFI	0.045	0.003
	(-0.250, 0.341)	(-0.723, 0.594)
SFI x Nearby SFI	−0.076	0.305
	(-0.234, 0.083)	(-0.021, 1.012)
State-Specific Linear Pre-Trends:	No	Yes

Notes: See the notes to Tables 1, 3 and 6. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

saw in the main results occurs only when neighboring states also have SFIs. For the QCEW variables (Table 7), there continue to generally be no effects.[52]

While this analysis is not a conclusive test of regional competition and spillovers between states, the results suggest that the main results do not change in a way that affects my conclusions. This analysis shows some evidence of positive spillovers for TV series and Studio System feature films, but no effects of spillovers otherwise. Positive spillovers suggest that my earlier TV series and Studio System feature film estimates that did not consider spillovers could have been negatively biased. For TV series, where the effects were large, this suggests even larger effects. For Studio System feature films, this increases the likelihood of there being some small effects, but does not change the conclusion that even if these effects existed, they would be of a small magnitude.[53]

As a second investigation of SUTVA, I test how my estimates change from adding Census Division-by-time fixed effects. By adding these fixed effects, the control group changes from any state without SFIs to only states within the same Census Division that did not have SFIs, forcing the control group to be nearby states. If there is regional competition or spillovers, we could see the estimates be sensitive to the inclusion of these fixed effects as SUTVA would be more violated when comparing nearby states. Fig. 8 presents how my main estimates (#1 and #7) change when these fixed effects are included (#3). None of the estimates change in any meaningful way.

In my third test of SUTVA, I estimate if my results are sensitive to excluding California and New York. Instead of competition occurring between nearby states, it could be states taking filming from California and New York, who have the bulk of filming. If the results are smaller with California and New York excluded, then this could suggest that my estimates were positively biased because productions were taken from California and New York, which were in the control group for a period of time because they adopted SFIs later. Fig. 8 presents how my main estimates (#1 and #7) change when excluding California and New York from the sample (#6 and #11). None of the estimates change in any meaningful way.

[52] One exception is for average weekly wages (Table 7 panel [c]). For the regression with a trend control (column [2]), the coefficient on *SFI* is −0.094 and is statistically significant at the 5% level, suggesting that SFIs decrease average weekly wages. This mirrors some of the estimates earlier that found some negative effects. The coefficient on the interaction *SFI* × *NearbySFI*, however, is 0.262 and is statistically significant at the 5% level. This suggests that SFIs had a more negative effect on average weekly wages when few nearby states had SFIs, but as the proportion of states that had SFIs increased, the effect moved more towards zero and may have become positive. However, there is a limited range under which the sum of *SFI*, *NearbySFI*, and *SFI* × *NearbySFI* is positive and statistically significant. The mean for *NearbySFI* when *SFI* = 1 is 0.69. At this mean the sum of all three coefficients is not statistically significant. This sum reaches statistical significance at around the 80th percentile of *NearbySFI* when *SFI* = 1. Thus the evidence still generally points toward either a negative effect or no effect on average weekly wages.

[53] More specifically, if we take the larger coefficient on $SFI_{st} \times NeighborSFI_{st}$ for Studio System feature films, and then take the upper bound of its 95% confidence interval (so a 47.0% increase in filming), this suggests only 0.113 additional feature films, on average.

Table 8
Effects of SFIs on filming, by existing industry size.

	IMDb		Studio System	
	(1)	(2)	(3)	(4)
(a) TV Series				
SFI × Small	0.139	0.308***	0.005	0.169
	(-0.094, 0.372)	(0.046, 0.551)	(-0.341, 0.350)	(-0.119, 0.515)
SFI × Medium	0.331***	0.045	0.433***	0.467***
	(0.141, 0.521)	(-0.112, 0.242)	(0.126, 0.739)	(0.204, 0.760)
SFI × Large	0.236**	−0.116	0.675***	0.254**
	(0.042, 0.430)	(-0.329, 0.112)	(0.358, 0.991)	(0.020, 0.549)
(b) Feature Films				
SFI × Small	0.078	−0.010	−0.010	0.026
	(-0.064, 0.221)	(-0.161, 0.147)	(-0.073, 0.053)	(-0.069, 0.108)
SFI × Medium	−0.040	0.132**	0.109*	0.069*
	(-0.160, 0.081)	(0.002, 0.259)	(-0.007, 0.225)	(-0.004, 0.153)
SFI × Large	−0.085	0.024	0.090*	0.032
	(-0.219, 0.049)	(-0.073, 0.138)	(-0.003, 0.183)	(-0.050, 0.119)
State-SpecificLinear Pre-Trends:	No	Yes	No	Yes

Notes: See the notes to Tables 1 and 3. The 17 states in *Small*, in increasing order of size, are: WV, ND, SD, DE, ID, WY, AK, RI, NH, VT, ME, AL, MT, AR, NE, SC, MS. The 17 states in *Medium*, in increasing order of size, are: OK, IA, KS, KY, LA, NM, OR, NV, WI, NC, CT, HI, WA, AZ, CO, IN, and UT. The 17 states in *Large*, in increasing order of size, are: MD, VA, NJ, DC, MN, MI, GA, MO, OH, TN, MA, PA, FL, TX, IL, NY, and CA. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

6. Heterogeneous effects

Next, I explore what moderates my main results and if there are perhaps effects that do not appear on average but appear in other circumstances. I test if there are agglomeration economies whereby the effects of SFIs vary by the existing size of the film industry (Section 6.1), if my main estimates vary by the strength and characteristics of SFIs (Appendix A), and if the effects of SFIs differed based on the timing of their adoption, where there could be an early-mover advantage (Appendix B).

6.1. Agglomeration economies

A large prior literature tests for agglomeration effects (e.g., Kline and Moretti 2014; Glaeser and Ward 2009; Greenstone et al. 2010; Storper and Christopherson 1987; He and Romanos 2015; Rosenthal and Strange 2003; Feldman 1999; Ellison and Glaeser 1999; Combes et al., 2010) which are often found to be significant factors in business location or productivity. I take Eq. (1) and replace the SFI_{st} indicator variable with three separate, mutually-exclusive, SFI_{st} indicator variables that split states into three equal groups (small, medium, large) based on the existing size of their motion picture production industry.[54] This estimates the effects of SFIs separately for these three size groups.

Tables 8 and 9 present the results of these regressions with the three size groups. The results do not show a clear trend of how the existing size of the film industry moderates the effects of SFIs, except perhaps for TV series. For IMDb TV series, the positive effect seen earlier for the main results without a trend control comes from states with medium or larger industries (Table 8 panel [a], column [1]). However, in the main results there is no effect after adding a trend control, but this analysis shows that there are positive effects on small states only (column [2]). For Studio System TV series, the effects by industry size are the same regardless of if trends are included (Table 8 panel [a], columns [3] and [4]): no effects for small states but large statistically significant effects for medium and large states. For feature films, there is some evidence that the small increases in feature films occur in medium states only.

For the QCEW variables, the effects do not seem to vary much by existing industry size. More specifically, there is some evidence of decreases in employment, establishments, average weekly wages, and total wages for states with large existing industries, but only when trends are not included (Table 9 column [1]). These estimates without trend controls are less reliable since there is some evidence of pre-trends. The magnitude of the estimates with trend controls do point towards some modest effects for states with a medium or large industry (and no effects or a negative effect for states with a small industry), but none of these estimates are statistically significant.

Generally, this analysis suggests that when there are effects of SFIs, these are concentrated in states with existing industries that are medium or large. Put another way, it seems that states with existing industries that are small are not able to attract many positive benefits.

6.2. Effects by SFI characteristics

All the analysis thus far estimates the average effects of SFIs. However. SFIs differ in their strength, namely by the subsidy rates for three categories of spending: the payroll of state residents, the payroll of non-state residents, and non-labor expenditure (e.g., catering, transportation, costumes). This analysis is also useful since it could speak to if specific characteristics of SFIs drive the earlier results, or if there are only effects of SFIs in certain circumstances. For example, some states subsidize the payroll of state residents over other expenditures, and this could incentivize employment.

Appendix Tables A2 and A3 present the effects of SFIs by their characteristics. Generally, there is no clear relationship between specific subsidy rates and outcomes, even for TV series filming. In the few cases where there are statistically-significant estimates, there is no clear trend

[54] To group states I calculate their average employment in motion picture production using the QCEW over 1978 to 1985, which was before almost all states had incentives. The 17 states with the smallest industries, in increasing order of size, are: WV, ND, SD, DE, ID, WY, AK, RI, NH, VT, ME, AL, MT, AR, NE, SC, MS. The 17 states with the middle group, in increasing order of size, are: OK, IA, KS, KY, LA, NM, OR, NV, WI, NC, CT, HI, WA, AZ, CO, IN, and UT, and the large group has the remaining 17 states, in increasing order of size: MD, VA, NJ, DC, MN, MI, GA, MO, OH, TN, MA, PA, FL, TX, IL, NY, and CA.

Table 9
Effects of SFIs on QCEW employment, establishments, and wages, by existing industry size.

	(1)	(2)
(a) Employment		
SFI × Small	0.052	−0.113
	(-0.104, 0.208)	(-0.415, 0.038)
SFI × Medium	0.039	0.115
	(-0.074, 0.151)	(-0.013, 0.255)
SFI × Large	−0.104**	0.141
	(-0.205, −0.004)	(0.048, 0.258)
(b) Establishments		
SFI × Small	0.040	−0.001
	(-0.067, 0.148)	(-0.164, 0.188)
SFI × Medium	−0.024	0.083
	(-0.109, 0.061)	(-0.075, 0.277)
SFI × Large	−0.064*	0.042
	(-0.130, 0.002)	(-0.053, 0.169)
(c) Average Weekly Wages		
SFI × Small	−0.034	0.010
	(-0.112, 0.043)	(-0.149, 0.209)
SFI × Medium	−0.031	0.061
	(-0.089, 0.026)	(-0.038, 0.196)
SFI × Large	−0.071**	0.000
	(-0.126, −0.016)	(-0.080, 0.120)
(d) Total Wages		
SFI × Small	−0.012	−0.004
	(-0.101, 0.078)	(-0.272, 0.301)
SFI × Medium	−0.092**	0.130
	(-0.175, −0.008)	(-0.007, 0.357)
SFI × Large	−0.111***	0.075
	(-0.180, −0.043)	(-0.031, 0.269)
State-Specific Linear Pre-Trends:	No	Yes

Notes: See the notes to Tables 1, 3 and 8. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

as to which subsidy rates matter.[55] Interestingly, no subsidy rates are strongly linked to changes in employment. There is a significant positive effect of the resident labor subsidy on employment in the regression without trends, but only at the 10% level (Appendix Table A3 panel [a], column [1]), but this regression is less reliable since there appear to be pre-trends for employment. This effect decreases significantly and becomes insignificant when trends are added (column [2]).

6.3. Effects by SFI timing

In Appendix Tables B1 and B2, I explore if the effect of SFIs was stronger if they were adopted earlier when fewer states had SFIs. I take Eq. (1) and add an interaction between the SFI_{st} indicator variable and the year of SFI adoption (minus 2005). In most cases, this interaction variable is not statistically significant. It is significant, however, for Studio System TV series, but only when trends are included (Appendix Table B1 panel [a], column [4]). The coefficient is negative and statistically significant at the 1% level, suggesting that the effects on Studio System TV series are concentrated to the early 2000s and earlier when fewer states had SFIs. For average weekly wages only when trends are included (Appendix Table B2 panel [c], column [2]), there is a positive, statistically significant, interaction, suggesting that SFIs increased average weekly wages for SFIs adopted in the later years. Outside of these results, there generally is no effect of SFI timing.

7. A preliminary analysis of repealed SFIs

Given the effects of SFIs on TV series filming, there is a question of if filming would remain after SFIs are repealed. This speaks to cluster theory, whereby once the benefits of agglomeration have set in, agglomeration economies create a natural incentive for economic activity to occur there, regardless of the incentives offered.

As of the end of 2017, 14 states repealed their SFIs.[56] The first repeal occurred in 2009 (Kansas), so there is a shorter time frame over which to estimate how states that have repealed their SFIs have faired, hence why I deem these estimates to be preliminary. Table 10 presents the coefficients on *Repealed*, from Eq. (1). These coefficients present the effect relative to states without SFIs, controlling of course for states that still have SFIs.

For Studio System TV series, where there were meaningful and robust effects on filming, the coefficient on *Repealed* is near zero and is statistically insignificant, regardless of if trends are controlled. This suggests that the boost in Studio System TV series filming goes away

[55] For Studio System feature films, there is a statistically significant effect, at the 5% level, for the subsidy for state residents in the regression with trends (Appendix Table A2 panel [b], column [4]). A one percentage point increase in the resident subsidy rate is linked to about a one percent increase in Studio System feature films. This suggests that the small and non-robust effect on Studio System feature films is concentrated in states that subsidized resident labor more, especially relative to non-residents or non-labor expenditures (which have negative estimates in the table). For QCEW establishments and total wages, the more reliable regressions with trend controls (Appendix Table A3 panels [b] and [d], column [2]) show that higher subsidy rates for the payroll of non-state residents are linked to increases in establishments and total wages.

[56] See footnote 11 for the list.

Table 10
Effects of repealed SFIs, relative to states without SFIs.

	(1)	(2)
IMDb TV Series	0.242*	0.261*
	(-0.005, 0.489)	(-0.004, 0.509)
Studio System TV Series	−0.008	−0.008
	(-0.318, 0.303)	(-0.287, 0.258)
IMDb Feature Films	−0.036	−0.127
	(-0.196, 0.123)	(-0.561, 0.137)
Studio System Feature Films	−0.017	−0.015
	(-0.112, 0.079)	(-0.154, 0.078)
QCEW Employment	−0.128**	0.038
	(-0.252, −0.004)	(-0.100, 0.188)
QCEW Establishments	−0.039	−0.070
	(-0.133, 0.058)	(-0.248, 0.091)
QCEW Average Weekly Wages	−0.058	−0.099**
	(-0.145, 0.029)	(-0.162, −0.046)
QCEW Total Wages	−0.118**	−0.118
	(-0.227, −0.008)	(-0.294, 0.092)
State-Specific Linear Pre-Trends:	No	Yes

Notes: See the notes to Tables 1 and 3. These are the estimates for *Repealed* from Eq. (1). Positive (negative) estimates show a positive (negative) effect relative to states that have not adopted SFIs, controlling for states that already have SFIs. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

after the removal of SFIs. On the other hand, the IMDb TV series results may show that the filming increase persists. There are positive estimates (0.242, 0.261), both statistically significant at the 10% level. This matches the positive effect, without trends, in the main results (0.292, Table 3 panel (a), column [1]). As for the other outcomes variables - feature films and the QCEW variables - the estimates are all negative except one (but it is insignificant).[57]

In sum, there is some non-robust evidence that TV series continue to film in states that have since repealed their SFIs, but this is hard to interpret given that it comes from IMDb TV series, where there may not have been an effect of SFIs, but not for Studio System TV series, where there definitely was an effect. Outside of this possible effect on TV series filming, there are no lingering benefits for other outcomes. Revisiting this analysis when more data becomes available would be a useful exercise.

8. Discussion and conclusion

Tax incentives for the film industry became wildly popular at the U.S. state level since about the early 2000s. Studying them can tell us a great deal about how tax incentives affect business location decisions and economic development for two main reasons. First, there is a large amount of variation across time, states, and in the intensity of these incentives. Second, filming is relatively insensitive to locational characteristics, so the film industry provides a useful case study (a "most likely" "crucial case" case study, Gerring, 2012) for where incentives should especially matter.

To estimate the impacts of SFIs on filming location, establishments, employment, and wages, I first combine a database I created on state film incentives (SFIs) from 1976 to 2017 with data on filming locations from the Internet Movie Database (IMDb.com) and Studio System. I also use employment, establishment, and wage data for the motion picture production industry, and other related industries, from the Quarterly Census of Employment and Wages (QCEW), and employment and establishment data for the motion picture production industry from County Business Patterns (CBP).

I use panel regression (two-way fixed effects) to compare states before and after they adopted SFIs to similar states over the same period who did not or have not yet adopted SFIs (a panel difference-in-differences). I start by measuring the average effects of SFIs on filming, employment, establishments, and wages, then I estimate effects over time (an event study). I then explore the robustness of my results to the three assumptions behind this empirical strategy: parallel paths, exogenous adoption of SFIs, and the Stable Unit Treatment Value Assumption (SUTVA). I then explore if other factors moderate the effects of SFIs, such as state competition, the size of the existing film industry (to capture agglomeration economies), the strength and characteristics of SFIs, and the relative timing of SFI adoption.

Overall, I find that SFIs affect the location of TV series filming, with my preferred estimates ranging between a 6.4% and 55.4% increase on average (corresponding to no more than an additional 1.5 TV series). This effect on TV series filming is robust to all checks except that the effect becomes insignificant using the IMDb data only when including state-specific trends.

Additional analysis suggests that this increase in TV series filming occurs gradually over time, and is strongest about 12 years after SFI adoption. The increase in TV series is concentrated in SFI adopting states which had a medium or large existing film industry size (on the scale of Oklahoma or Iowa and larger), suggesting some agglomeration economies even for "footloose" filming. The effect of SFIs on TV series filming is also higher when nearby states also have SFIs, suggesting some positive regional spillovers rather than negative regional spillovers, as might be assumed. There is some preliminary, non-robust, evidence that the increase in TV series filming may persist after SFI repeal.

There is, however, little evidence that SFIs meaningfully affect the filming location of feature films. There is no effect on IMDb feature films. In some cases, there is a small, statistically significant effect on Studio System feature films of no more than a 7.9% increase, but this estimate is not robust. If taken as causal, and using the upper end of the 95% confidence interval (a 13.5% increase), this would only be 0.032 additional Studio System feature films.

Why do SFIs affect the filming location of TV series but do not meaningfully affect the filming location of feature films? It may be because TV series are longer and more expensive, so the cost reduction from SFIs is more considerable. Also, if a filmmaker is deciding to film in an unfamiliar state, there is a significant fixed cost required to gather the required information on the available SFIs and their restrictions

[57] Two estimates are negative and statistically significant, at the 5% level: QCEW employment and total wages, both without trends (column [1]), mirroring similar negative, statistically-significant estimates for the effects of SFIs. However, these negative effects likely represent a continuation of the existing pre-trend.

and requirements, filming locations, local input firms, and local crew. This high fixed cost is more justifiable when the aggregate savings are more substantial, and the filming duration is longer, as they are for TV series.

I find that SFIs have almost no effects on employment, establishments, average wages, or total wages in motion picture production, using either the QCEW data or the CBP data. At best there is a possible small increase in employment in motion picture production (an 8.4% increase, or about 146 jobs on average, or 18.2%, 314 jobs, using the upper end of the 95% percentile) but this estimate is very much not robust. This lack of effects on the motion picture production industry mirrors the conclusions of Adkisson (2013), Thom (2018 a), Thom (2018 b), Button (2018 a) and Swenson (2017) who find no or minimal effects on the motion picture production industry for SFI adopters in general.[58] There could be spillover effects onto related industries, such as independent artists, caterers, hotels and motels, and the rentals of costumes, transportation, and non-residential buildings. However, using QCEW data I do not find meaningful effects on employment, establishments, or average wages in these industries.

Thus, while SFIs relocate TV series filming this increase in filming leads neither to the development of a local film industry nor to any meaningful spillovers to related industries.[59] This means that SFIs do not achieve two of their primary goals: establishing a local film industry or creating economic development in general.

There are, however, some possible benefits of SFIs, or reasons behind why policymakers adopted SFIs, that I did not evaluate. First, there is increased press or notoriety for the states that adopt SFIs, especially when filming brings in major actors and actresses or filming features the state prominently. While it is hard to quantify the impacts of this, they are unlikely to be large and do not materialize into an increase in tourism, at least in terms of effects on the hotels industry. Second, SFIs are sometimes justified to bolster local culture and local filmmakers. However, most SFIs target nationally or internationally-distributed productions, which often are not written or produced by local filmmakers or do not feature the location of filming prominently.[60]

These low possible benefits of SFIs that I can quantify are in contrast to their high costs.[61] So even taking the perspective of a typical state, ignoring the externalities imposed on other states by having an SFI, the costs of SFIs could likely exceed the benefits.[62] The small benefits I quantify here should be considered in a broader cost-benefit calculation. Policymakers should consider these limited positive impacts of SFIs as they use scarce tax revenue to balance multiple policy goals.

We also learn more broadly that even in cases where business location decisions are relatively insensitive to locational characteristics, and incentives are lucrative, incentives can still have little impact on business location and economic activity. These results mirror other studies of incentives that find few effects or even adverse effects on economic development (e.g., Schmenner, 1982; Plaut and Pluta, 1983; Carlton, 1983; Schmenner et al., 1987; Blair and Premus, 1987; Dabney, 1991; Bondonio and Engberg, 2000; Dye and Merriman, 2000; Lee, 2008; Hanson, 2009; Neumark and Kolko, 2010; Hanson and Rohlin, 2013; Freedman, 2015) but are in contrast to studies that do find meaningful effects (e.g., Bartik, 1985; Bartik, 1989; Walker and Greenstreet, 1991; Papke, 1991; Wu, 2008; Krupka and Noonan, 2009; Freedman, 2013; Strauss-Kahn and Vives, 2009; Rogers and Wu, 2012; Moretti and Wilson, 2014; Weinstein, 2018). Given that this case study of state film incentives is one where one would expect large effects, the conclusions of this study tip the non-consensus (Wasylenko, 1999; Buss, 2001; Arauzo-Carod et al., 2010) in the literature more towards a conclusion that incentives are generally ineffective at creating industry clusters or inspiring economic development.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.regsciurbeco.2019.06.002.

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[58] However, Swenson (2017) does conclude that incentives in New York and California were effective at increasing employment and establishments, despite a more detail analysis by Thom (2018 b) finding no effects for California. However, it is difficult to put much weight on studies of New York and California only since these states are unique and it is much less likely that the parallel paths assumption and SUTVA hold for these states. Also, when analyzing a single state, the preferred approach is a synthetic control case study (Abadie et al., 2010) or a panel difference-in-differences that employs Conley and Taber (2011) confidence intervals (otherwise the precision of the estimates is overstated).

[59] Another way to measure spillovers is through a general multiplier, but the multiplier for the film industry is pretty average, suggesting that the film industry does not create large spillovers compared to other industries. As an example, economist Bruce Seaman estimates that the multiplier for the film industry is 1.83 in Georgia, a relatively average multiplier. This means that for each $1 spent by the film industry, $1.83 of economic activity is created. This contradicts the much larger multipliers that industry lobbyists, or their hired consultants, claim. See http://www.politifact.com/georgia/statements/2015/aug/07/georgia-department-economic-development/film-industrys-impact-georgia-economy-overstated/ (accessed 5/9/18).

[60] Some SFIs do specifically attempt to target local filmmakers or encourage local content. For example, there is the Indigenous Oregon Production Investment Fund. See https://secure.sos.state.or.us/oard/displayDivisionRules.action?selectedDivision=4221 (accessed 2/21/19).

[61] Nationally, SFIs cost $1.5 billion in the fiscal year 2010 (Tannenwald, 2010), exceeding spending in many other state programs such as R&D tax credits (Tannenwald, 2010) and arts programs (Christopherson and Rightor, 2010). As discussed by Button (2018 a), SFIs of early, aggressive adopters in Louisiana and New Mexico cost $446.9 million and $152.6 million, respectively over fiscal years 2004–2009.

[62] One way to quantify the benefits of SFIs relative to costs is to estimate a cost per job created. Some independent studies of specific SFIs estimated the cost per job created. These show high costs, such as Zin (2010) which estimates that "The cost to taxpayers of employment associated with the tax credit ranged from $186,519 per job to $42,991 per job, depending on whether only direct jobs or total employment impacts are examined." Button (2018 a) estimates a cost per motion picture production job for the Louisiana (New Mexico) incentive from 2002 to 2008 to be $67,757 ($48,002) under unrealistically optimistic assumptions (notably that these employment effects are causal, when there are not statistically significant effects on employment). There are also several independent reports that estimate the return-on-investment of SFIs, showing that SFIs generate only some tax revenue for the state, such as 16–18¢ p̃er dollar spent in Louisiana (Albrecht, 2005) and 14.4¢ in New Mexico (Popp and Peach, 2008).

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