Tulane Economics Working Paper Series

Funding Stabilization and the Performance of Public Agencies: Evidence from Ohio Libraries

Ali Enami
The University of Akron
aenami@uakron.edu

Kile Byington
Twinsburg Public Library
kbyington@twinsburglibrary.org

James Alm
Tulane University
jalm@tulane.edu

Working Paper 2509
November 2025

Abstract

Do the sources of funding available to public agencies – and shocks to these sources – affect the performance of these agencies? Using data on Ohio public libraries, we exploit the sudden state budget cuts implemented in 2009 following the 2008 recession, along with the bureaucratic delay in approving new local property tax levies to make up for the lost state funding, in order to compare the performance of libraries that had access to property taxes prior to 2008 to those that relied exclusively on state funding. We find that libraries with diversified funding, and so with access to relatively stable property taxes, demonstrated higher service across a wide range of performance indicators in the first year of funding stabilization following the budget cuts relative to libraries without local funding. These effects decrease by about one-half to two-thirds by the fifth year, but they remain statistically significant at the 1 percent level.

Keywords: Property tax, operating funding, funding stabilization, public library, library performance
JEL codes: H41 H71, H76, L86

Funding Stabilization and the Performance of Public Agencies: Evidence from Ohio Libraries

Ali Enami, Kile Byington, and James Alm

Abstract
Do the sources of funding available to public agencies – and shocks to these sources– affect the performance of these agencies? Using data on Ohio public libraries, we exploit the sudden state budget cuts implemented in 2009 following the 2008 recession, along with the bureaucratic delay in approving new local property tax levies to make up for the lost state funding, in order to compare the performance of libraries that had access to property taxes prior to 2008 to those that relied exclusively on state funding. We find that libraries with diversified funding, and so with access to relatively stable property taxes, demonstrated higher service across a wide range of performance indicators in the first year of funding stabilization following the budget cuts relative to libraries without local funding. These effects decrease by about one-half to two-thirds by the fifth year, but they remain statistically significant at the 1 percent level.

JEL Codes: H41 H71, H76, L86.

Keywords: Property tax**,** operating funding, funding stabilization, public library, library performance.

Acknowledgements: We would like to thank Nicholas Glenn and participants in the 2023 Mid-Continent Regional Science Association Conference and seminar series in the Department of Economics at Western Michigan University for their valuable comments on earlier versions of this paper. Affiliations: Ali Enami, Department of Economics, The University of Akron, Akron, OH 44325; email: aenami@uakron.edu; Kile Byington, Twinsburg Public Library, 10050 Ravenna Road, Twinsburg, OH 44087; email: kbyington@twinsburglibrary.org; James Alm, Department of Economics, Tulane University, New Orleans, LA 70118; email: jalm@tulane.edu (corresponding author).

1. INTRODUCTION

Public libraries are community hubs for connecting people, acquiring knowledge, and accessing opportunities by providing free internet, physical and electronic publications, equipment, and learning programs for adults and children (Scott, 2011; Gilpin et al., 2024). Moreover, these public entities have been shown to positively affect various outcomes in the local communities, such as the local labor force participation rate (Ferreira Neto, 2022), the number of patents (Berkes and Nencka, 2024), voter turnout (Preer, 2008),[1] public safety (Ferreira Neto et al., 2023), student test scores (Gilpin et al., 2024), and the future income of students (Karger, 2021). As of 2022, there are 9,019 public libraries with 16,505 stationary outlets and 689 traveling branches (i.e., "bookmobiles") serving people in the 50 states and the District of Columbia.[2]

Most public libraries across the U.S. have traditionally relied mainly on local property taxes to fund their operations. However, this was not the case for Ohio libraries prior to the recession of 2008. While 98 percent of the public libraries in the U.S. received funding from local sources in 2008, as Figure 1 shows, less than 40 percent of the libraries in Ohio had such funding,[3] a percentage that increased rapidly to about 80 percent a few years later to partially make up for the loss of operating revenue due to the state budget cuts following the 2008 recession. The Ohio state budget cuts took effect in 2009, with an 18 percent reduction in the operating budget for libraries followed by another 6 percent cut in 2010. In response, many public libraries searched for other sources of funding, a resulting wave of funding diversification by libraries that did not begin until 2010. The main reason for this delay in diversification was the lengthy process of approving new local tax levies to fund libraries,[4] even though the overall success rate of such proposals was about 66 percent (Fleeter, 2017). Importantly, any revenue *diversification* of libraries also provided a mechanism for the funding *stabilization* of library revenues.

Using the combination of (1) the exogenous shock in the operating budget of Ohio public libraries due to the state budget cuts following the 2008 recession, (2) the significant variation in funding stabilization of these libraries at the time of the shock (i.e., their reliance on local property taxes), and (3) the bureaucratic delay in approving new local tax levies to create more stabilization in response to this fiscal shock, we estimate the causal effect of operating revenue funding stabilization on the performance of public libraries. Our difference-in-differences (DiD) technique compares libraries with access to local funding for their operating expenditure at the onset of the 2008 recession (and so libraries that experienced a smaller budget shock), to those libraries without such funding that were as a result more severely affected by the loss in their operating budget. Moreover, we analyze how the performance of libraries was affected by an increase in the level of funding stabilization (i.e., the percentage of the operating budget that is funded by local taxes). The delay in the approval of new local tax levies for libraries allows us to cleanly identify the effect of funding stabilization on the performance of libraries in 2009 (i.e., the year of the budget cuts). To estimate this effect for later years, we rely on two estimators: a Local Average Treatment Effect (LATE) and a Treatment-On-the-Treated (TOT) estimator that accounts for the “switchers” in the control group (i.e., libraries that secured a local tax levy in 2010 or later). We provide details about these methods in the methodology section.

It is worth noting that, while the 2008 recession affected both types of libraries, we designate libraries without access to local property taxes as the control group for several reasons. First, zero local funding provides a natural baseline for comparison, which is particularly important when analyzing the funding stabilization as a continuous variable. Second, at the onset of the 2008 recession, libraries without local funding constituted nearly 60 percent of all libraries, making them the most suitable benchmark for comparison as opposed to any other potential control group that would have included far fewer libraries and libraries less comparable to others (e.g., libraries with more than 50 percent of funding sourced from property taxes). Third, by 2019 about 80 percent of libraries had secured some level of local funding, underscoring that funding stabilization was a critical policy choice adopted by most libraries. Thus, libraries without access to local funding serve as an appropriate control group in this context.

Our main finding is that funding diversification and the resulting stabilization created by access to local property taxes positively affect the performance of libraries in Ohio. In comparison to our control group (i.e., libraries without local funding), the libraries in the treatment group experienced an economically significant increase in the number of visitors (9.6 percent), circulated materials (9.6 percent), number of programs (26.3 percent), and program attendance (19.5 percent) in the first year of funding stabilization following the 2008 budget cuts. This is expected given that the libraries with diversified and stabilized funding had more open hours (11.2 percent) and full-time equivalent (FTE) employees (12.7 percent) in comparison to the control group, with all variables scaled by the service area population of each library. Within the libraries in the treatment group, a 10 percentage point (i.e., about half a standard deviation) increase in the ratio of the operating budget funded by local taxes lead to an increase in the number of visitors (2.5 percent), circulated materials (2.5 percent), number of programs (6.9 percent), program attendance (5.1 percent), open hours (2.9 percent), and FTE employees (3.3 percent) in the first year following the funding stabilization, according to our preferred TOT model. Based on this model, these effects persist, but their size decreases by about one-half to two-thirds by the fifth year. These positive effects are relative to the libraries in the control group that did not have access to local property taxes; that is, while the 2008 state budget cuts had a negative effect on the performance of all libraries, the libraries with funding stabilization weathered this crisis better than the ones without it.

It is important to note that our estimated coefficients measure the combined effect of funding stabilization for libraries and the resulting additional operating revenue (in relative terms and compared to the libraries that rely solely on state funding) on their performance. In other words, we cannot isolate the former from the latter in our setting. To isolate the effect of funding stabilization, one needs a setting in which libraries replace state funding with local property taxes without any change in the overall operating budget for libraries in the treatment and control groups. While that is an interesting question from the perspective of economic theory, the main value of funding stabilization for public entities such as libraries is at the time of economic crisis when reliance on local property taxes that are much less responsive to these shocks prevents these entities from experiencing a large reduction in their operating budget and allows them to perform better than the entities that lack such funding stabilization. Therefore, our estimated effects are more informative for policy makers because they capture the combined effect of funding stabilization and the resulting additional operating budget following a major economic crisis.

Our study contributes to two strands of the literature. To the best of our knowledge, we are the first to rely on a causal setting to analyze the effect on the performance of libraries of the variation in their operating funding in general and the diversification and the resulting stabilization in the source of this revenue in particular. Despite the existence of an extensive literature on the performance and societal impact of public libraries, there are few studies that employ a reliable causal identification technique in their analysis (Gilpin et al., 2024). Moreover, the few recent papers that employ a strong causal framework are exclusively focused on major capital expenditures stemming from the construction of a new branch because of its associated exogenous and large shock in the provision of library services to a local community.[5] Among the non-causal studies, our paper is closely related to Vitaliano (1997) and Hemmeter (2006), who each find a positive association between local funding for libraries and their efficiency, and to Ferreira Neto and Hall (2019) who find a negative relationship between these two variables.

Additionally, our paper contributes to the existing literature on the effect of funding diversification and stabilization on the performance of local public agencies. Most existing studies focus on municipalities, and find conflicting evidence on the effects of this funding diversification. Several researchers report a negative effect of revenue diversification, especially if it is tax-based diversification, on municipalities in the form of increased fiscal instability and distress (Carroll, 2009; Gorina, 2018; Jimenez and Afonso, 2022). This is mainly attributed to the resulting expansion of the municipalities and the correlated risk of various tax revenues due to their procyclical nature. In contrast, some other studies find evidence in favor of reliance on property taxes as a way of alleviating fiscal shocks (Alm et al., 2011; Mikesell and Liu, 2013; Ihlanfeldt and Willardsen, 2014; Krupa and Kriz, 2021).[6] One explanation for these conflicting results is that property taxes are more stable than other taxes because the assessed taxable value of properties is not automatically adjusted according to their market value and local governments often adjust the millage rates at the time of economic downturns (Alm et al., 2011; Krupa and Kriz, 2021). Our paper contributes to this debate both by analyzing a different type of local public entity (i.e., libraries) and by estimating the effects of funding diversification and the resulting stabilization of revenues via reliance on property taxes on various measures of institutional performance. We also focus our analysis and estimation around the time of a major negative revenue shock, something that has seldom been studied before.[7]

The remainder of this paper is organized as follows. Section 2 provides an overview of our data on Ohio libraries. Section 3 discusses our methodology, identification strategy, and how we address the issue of “switchers” in the control group. Section 4 presents the results for all key models and our robustness checks. Section 5 concludes and offers policy recommendations and suggestions for future research.

2. DATA

Ohio libraries annually collect and report their financial, employment, and usage data to Institute of Museum and Library Service (IMLS) in response to its Public Libraries Survey. For this paper, we focus on the following performance indicators for libraries extracted from IMLS data: annual visits, circulated materials, number of programs, and program attendance. Additionally, given the service-nature of public libraries, we look at the number of open hours and full-time equivalent (FTE) employees as key determinants of the performance of libraries. Our panel includes 250 libraries for which we have data as early as 1998 (data are not available for all variables in all years). We limit our panel to 2019 to avoid the effect of the COVID-19 pandemic and its significant impact on the ability of the libraries to be open and to serve the public.

Table 1 provides summary statistics for the main variables of interest. Of note, there is a significant variation in the sizes of the libraries, the services they provide to their communities, and their operating revenues. For example, some libraries are limited to only one physical building (branch), while the biggest library system in the sample has 42 branches. This is also reflected in the populations they serve, which range from less than 200 to over 86,000. Consequently, all performance indicators have a high coefficient of variation, measured as the ratio of standard deviation to mean, ranging from 2.2 for program attendance to 2.7 for the number of circulated materials. The average operating revenue for a library in our sample is about $3 million, but this also varies significantly from slightly below $50 thousand to over $170 million. Lastly, the extent of funding stabilization among the libraries in the sample is measured by the percent of operating revenue funded locally, and this measure is also quite variable, ranging from 0 percent (i.e., libraries that do not receive any property taxes) to 78 percent.

[Table 1 about here]

As discussed in the methodology section, we rely on the sudden cuts in the state budget for libraries beginning in 2009 to identify the effect of funding stabilization, measured by library reliance on local property taxes, on the performance of libraries. Therefore, it is important to look at the role of local revenue in the overall funding of Ohio libraries and its evolution over time. We use IMLS data to determine the existence and amount of local tax revenue for a library. We reviewed the raw data for the local operating revenue to remove any incorrect entry that should have been classified as “other operating revenue” as opposed to “local operating revenue”. An example of such an incorrect entry is a one-time value that would indicate a grant or a gift, rather than a voter approved tax levy (which often lasts for at least 5 years). The Ohio Library Council (2024) maintains a record of library local operating levy ballot outcomes from 2010 to the present. If we had a question as to the history of a local operating revenue before 2010, we contacted the library directly to inquire about the history of operating levies for that entity.

Figure 1 shows that prior to 2009 less than 40 percent of the libraries in Ohio received any funding through local property taxes. By 2019, this number had doubled, and almost 80 percent of the libraries relied on local funding. Figure 2 provides an intuitive rationale for this major shift of revenue diversification and the resulting stabilization of revenues across Ohio libraries. Libraries without local funding experienced a drastic reduction in their operating revenue per service area population following the state budget cuts, as much as about 20 percent on average. In contrast, libraries that had access to the local taxes in those years only lost about 2.5 percent of their operating budget on average. It is worth noting that in 2008 (i.e., the year before the budget cuts) libraries with local funding are on average larger and located in more rural areas compared to the libraries without local funding, but the counties in which they are located have a relatively similar median income and poverty rate. As Table 2 shows, on average, libraries with access to local property taxes have 4 branches (as opposed to 2 branches that libraries with no local funding have), have an operating budget that is about 4.3 times larger, serve 3.6 times visitors, and about 7 percent of them are located in areas designated as rural (as opposed to the 4 percent of libraries with no local funding).

[Figure 1 about here]

[Figure 2 about here]

[Table 2 about here]

3. METHODOLOGY

The decision of a library in Ohio to diversify its funding sources in order to stabilize its revenues by using a local tax levy is not a random choice. This means one cannot simply measure the effect of this stabilization on the performance of libraries using a difference-in-differences (DiD) model, in which one compares the libraries that create such a levy to those that do not. For example, it is possible that a library proposes such a tax levy and successfully secures the necessary vote for it because of a new leadership that is both skilled at convincing the local community to vote for such a levy and that has an effective plan to improve the performance of the library regardless of whether the requested local funding is approved or not. In such a scenario, the correlation between funding stabilization and higher performance of a library is spurious because both variables are caused by a third variable (i.e., the quality of the leadership).

The sudden state budget cuts in 2009 due to the Great Recession create a unique opportunity to causally identify the effect of funding stabilization on the performance of libraries in Ohio. As Figure 1 shows, the percent of libraries with local taxes is relatively stable prior to 2009. This means that libraries did not have any foresight about the upcoming state budget cuts in 2009 due to the Great Recession, and so they did not preemptively react to it by securing extra funding using local taxes. In fact, given the time-consuming process of proposing and passing a local tax levy referendum to fund a library, the percent of libraries with a local tax is virtually unchanged from 2008 to 2009 (see Figure 1).[8] The fact that the percent of libraries with local funding increased from about 40 percent in 2009 to 80 percent in 2019 suggests strongly that most libraries that did not have a local tax levy in 2009 simply did not have enough time to create one, even though they no doubt saw a need for a local tax levy.

Now if our goal was to cleanly identify the effect of funding stabilization on the performance of libraries in the year of the budget cuts (i.e., in 2009), then we could rely on a two-way fixed effects difference-in-differences (TWFE DiD) model, as specified in equation (1).

This model compares the change in the performance of the libraries with a local tax to those without it before and after the budget cuts in year 2009:

$$Y_{L\tau} = \alpha + I(\tau = 1) + \delta_1\big[I(\tau = 1) * LocalFund_{L,-1}\big] + Library_L + \varepsilon_{L\tau}\ ;\ \tau = 0,1 \tag{1}$$

where $Y_{L\tau}$ is a library performance indicator (e.g., log of the total number of circulated materials per service area population)[9] for library L, τ years after the last year prior to the budget cuts (i.e., last year prior to the treatment assignment). Specifically, $\tau = 0$ corresponds to 2008, the last year before the budget cuts (pre-treatment) and $\tau = 1$ corresponds to 2009, the first year of the budget cut (post-treatment). $I(\tau = 1)$ is an indicator variable equal to 1 if year is 2009 (0 otherwise). $LocalFund_{L,-1}$ is either an indicator or a continuous variable related to the local funding status of a library in the year before the budget cuts (i.e., 2008 or $\tau = 0$). In our initial models we use an indicator variable for *LocalFund*, which is equal to 1 if a library has a local tax levy in 2008 to fund its operating expenditure (0 otherwise). In our later models we use the "local operating revenue ratio"[10] as our *LocalFund* variable to allow for the model to account for the continuous treatment. The models that use this continuous variable have an advantage of distinguishing between the level of funding stabilization for each library in the treatment group. *Library* is library fixed effects, α is the intercept, and ε is white noise. Our main coefficient of interest is δ_1, which represents the effect of funding stabilization (or a one percentage point increase in the level of stabilization in the continuous treatment models) on the performance of the libraries in the treatment group in the year of budget cuts (i.e., $\tau = 1$ or 2009).

However, we are not just interested in estimating the effect of funding stabilization on the performance of libraries in the first year of the budget cuts. Further, estimating the effect of funding stabilization beyond the first year of budget cuts (i.e., for $\tau > 1$) is not as clean as the estimation in the first year of budget cuts. As Figure 1 shows, a significant portion of the libraries react to the budget cuts by successfully securing funding through local taxes. This means that we have a large number of "switchers" in our control group, which would bias our estimated effects toward zero.[11] We must consider the effects of these switchers in our estimation methods, as we discuss next.

Regardless of the complications created by the switchers, the starting point is to estimate these intent-to-treat (ITT) effects in order to give a lower bound for the true effect of funding stabilization on the performance of libraries in years beyond the year of the budget cuts. Equation (2) presents the model that we use to estimate the ITT effects, and it is an extended version of equation (1). We limit our analysis to 5 years after the budget cuts (i.e., 2014):

$$Y_{L\tau} = \alpha + \sum_{h=1}^{5}\left\{B_h I(\tau = h) + \delta_h\left[I(\tau = h) * LocalFund_{L,-1}\right]\right\} + Library_L + \varepsilon_{L\tau}\ ;\ \tau = 0, \dots, 5 \qquad (2)$$

One approach to account for the switchers in the control group is to estimate local average treatment effects (LATE) using the initial treatment assignment of the libraries as an instrumental variable (IV) for their actual treatment assignment τ years later (Angrist and Pischke, 2009). Specifically, we estimate equation (3), or

$$Y_{L\tau} = \alpha + \sum_{h=1}^{5}\left\{B_h I(\tau = h) + \delta_h \widehat{LocalFund}_{Lh}\right\} + Library_L + \varepsilon_{L\tau}\ ;\ \tau = 0, \dots, 5 \qquad (3)$$

where $\widehat{LocalFund}_{Lh}$ is the "predicted value" of $LocalFund_{Lh}$, or the local funding status of library L in year h as calculated from the regression model in equation (4):

$$LocalFund_{Lh} = \alpha + LocalFund_{L,0} + \varepsilon_{Lh}\ ; estimated\ separately\ for\ h = 1, \dots, 5 \qquad (4)$$

Another method to account for the switchers is to approach our setting as a case of a staggered treatment in which the members of the treatment group receive the treatment in different calendar years. In this case, we are able to employ an event study DiD method to identify the causal effect of interest in different relative years (τ). These relative years continue to have the same meaning as previous models; that is, the DiD effect estimated for $\tau = 1$ represents the effect of funding stabilization on the performance of the libraries in the first year that a library has access to local property taxes post-2008.[12] The inclusion of pre-treatment relative years (i.e., $\tau \leq 0$) allows us to test if the treated and control libraries experience a similar trend in their performance prior to funding stabilization. Equation (5) captures this event-study DiD model:

$$Y_{Lt} = \alpha + \sum_{\substack{\tau=-5 \\ \tau \neq 0}}^{5} \delta_\tau LocalFund_{L\tau} + Library_L + Year_t + \varepsilon_{Lt} \tag{5}$$

This model regresses the outcome of interest for library L in calendar year t (i.e., Y_{Lt}) on the library and calendar year fixed effects as well as a set of variables ($LocalFund_{L,\tau}$) that capture when a library gained access to the local funding (post-2008) relative to the point in time that the outcome of interest is measured. For example, if a library gained access to local funding in 2012 and the outcome of interest is measured in 2010, only $LocalFund_{L,-2}$ has a positive value (equal to $LocalFund_{L,2012}$) and the rest of the $LocalFund_{L,\tau}$ variables are zero. As model 5 shows, we use the year before stabilization (i.e., $\tau = 0$) as the reference point, and we include a 5-year window around it in our event study. The choice of $\tau = 0$ as the reference point ensures that our main parameter of interest δ_τ has a DiD interpretation comparable to our ITT and LATE estimators.

Under the assumptions of the parallel trend in outcome variables, no anticipation, and the homogeneity of the treatment effects, the estimation of this model using a simple OLS technique would identify the casual effect of interest without any bias. However, as recent developments in the DiD literature show, if the treatment effects are heterogenous across the treated libraries, then the estimated δ_τs from this regression are potentially biased (de Chaisemartin and D'Haultfoeuille, 2024). We use the Jakiela (2021) diagnostic test, as discussed in Appendix A, to determine if our library-specific effects are heterogenous, and this test confirms our suspicion. We therefore rely on an estimation technique developed by de Chaisemartin and D'Haultfoeuille (2024) to estimate δ_τs, which accounts for the heterogenous treatment effect assumption.

At its core, the de Chaisemartin and D'Haultfoeuille (2024) approach to estimating the parameters of an event study model of the kind displayed in equation (5) is based on first identifying library-specific effects for each relative year (τ) and then averaging these effects to calculate δ_τ to ensure all weights are positive and proportional to the importance of each library-specific effect. In the first step, the library-specific effect for each τ is estimated using a DiD model, and the control group is limited to libraries that are not yet treated. These library-specific effects are scaled using the size of treatment each library receives (i.e., when *LocalFund* is continuous) so that they are comparable across libraries before they are averaged to calculate δ_τ in the second step. This feature of the de Chaisemartin and D'Haultfoeuille (2024) event study technique is ideal for our context given that the degree of stabilization varies across libraries in our treatment group.[13]

The library-specific estimation of the effect of funding stabilization allows for the production of auxiliary statistics that can be used to determine the appropriateness of the application of the de Chaisemartin and D'Haultfoeuille (2024) method, in addition to the Jakiela (2021) diagnostic test discussed in Appendix A. Appendix B presents two statistics developed by de Chaisemartin and D'Haultfoeuille (2020). The first one is the minimum necessary standard deviation for the entity-specific (i.e., library-specific) treatment effects that are needed for the TWFE DiD estimator to potentially produce a zero average treatment effect. The second one is a similar threshold that is needed for the TWFE DiD estimation to have a potentially incorrect sign. If the value of both thresholds is low and it is plausible that the actual standard deviation of the library-specific treatment effects exceeds either threshold, then the TWFE DiD estimation is potentially biased. As Appendix Table B1 shows, the values of these thresholds are indeed relatively low for almost all outcome variables.

The Jakiela (2021) and de Chaisemartin and D'Haultfoeuille (2020) diagnostic tests, discussed respectively in Appendices A and B, all point to potential shortcomings of the traditional TWFE DiD model and the advantage of the most recent DiD event study techniques such as those proposed by de Chaisemartin and D'Haultfoeuille (2024). Therefore, in what follows we use the latter as our preferred estimation technique, and we refer to its results as treatment on the treated (TOT) effects because they measure the effect of funding stabilization on the treated libraries. We also present the results of our ITT and LATE models for comparison.

4. RESULTS AND DISCUSSION

We begin by presenting the results of our event study (the TOT effects) with an indicator treatment variable (i.e., *LocalFund* is equal to 1 if a library has access to local property taxes, 0 otherwise). This allows us to examine both the effect of funding stabilization on operating revenue of treated libraries and various performance indicators, and also whether there is any effect on these outcome variables prior to the funding stabilization taking effect. The latter is effectively a parallel trend test that ensures these variables follow a similar trend in libraries of the treatment and control group prior to the treatment assignment. As Figure 3 shows, almost all pre-treatment DiD coefficients (i.e., when $\tau < 0$) are not statistically different from zero, which increases our confidence in our ability to identify the causal effect of funding stabilization on the performance of libraries.

Figure 3 shows that funding stabilization following the 2008 state budget shock had immediate and positive effects on the operating revenue of libraries and almost all outcome variables, that these effects remain relatively stable over time, and that these effects are all statistically significant at the 1 percent level. The only exceptions are for some of the coefficients for the number of visitors and open hours that are nonetheless still statistically significant at the 5 percent level (see Panel C in Table 3). It is important to recognize that these positive effects are relative to the libraries without funding stabilization. In other words, the post-2008 budget cuts had a negative effect on all outcome variables, but libraries with access to local property taxes weathered this shock better than libraries without these local property taxes.

[Figure 3 about here]

To better analyze the TOT effects and to compare them to the results of our ITT and LATE models, we present these coefficients in Table 3. The first takeaway is that all three models produce relatively similar effects for the first year following the funding stabilization (i.e., $\tau = 1$). The only exceptions are operating revenue, number of programs, and open hours, where the TOT effects are noticeably higher. Some of the LATE effects in the second year continue to be close to the TOT effects, but overall the TOT effects remain larger than the ITT and LATE effects in the second through the fifth years. Additionally, almost none of the ITT and LATE effects remain statistically significant beyond the second year. A priori, we expect the positive effect of funding stabilization to remain statistically significant throughout all post-treatment years given that funding stabilization is accompanied by a higher operating revenue for treated libraries. Our TOT effects are consistent with this expectation.

Focusing on Panel C of Table 3, we find that, in the first year following the 2008 crisis and resulting state budget cuts, libraries with funding stabilization experienced a 30 percent higher operating revenue per service area population compared to libraries that solely rely on state funding. This effect increases to about 40 percent by the fifth year. Importantly, this extra funding resulted in better performance across all indicators. For example, in the first year of funding stabilization libraries in the treatment group experienced 9.6 percent more visitors and circulated materials, 26.3 percent more programs, and 19.5 percent more attendance in these programs compared to the libraries in the control group. This can be explained by the fact that the number of open hours and full-time equivalent (FTE) employees for the treated libraries were 11.2 percent and 12.7 percent higher, respectively. Similar to the estimated effects of funding stabilization on the operating revenue, parameter estimates related to all indicators of library performance increase over time. Remember that all variables are scaled by the service area population of each library.

[Table 3 about here]

One potential concern about the parameter estimates in Table 3 is that all libraries are assumed to have received the same level of treatment (e.g., funding stabilization) because all three models use an indicator variable for the local funding status of a library. To produce more reliable estimates that have better policy relevance, one should use a continuous treatment variable (i.e., the ratio of the operating revenue that is funded by local property taxes). The estimation results using this treatment variable are reported in Table 4 for our three models.

Similar to results in Table 3, the coefficients in Table 4 for the effect of funding stabilization on various outcome variables in the first year are relatively similar across the three models.

Moreover, similar to Table 3 only the TOT effects are statistically significant beyond the second year. However, unlike Table 3, the TOT estimates in Table 4 decrease over time.

Focusing on Panel C of Table 4, a 10 percentage point (i.e., about half of the standard deviation per Table 1) increase in the percent of operating revenue funded locally leads to 7.9 percent higher operating revenue per service area population in the first year of funding stabilization, but this effect is reduced to about 2 percent by the fifth year. Similarly, a 10 percentage point increase in the ratio of the operating budget funded by local taxes leads to an increase in the per service area population of the number of visitors (2.5 percent), circulated materials (2.5 percent), number of programs (6.9 percent), program attendance (5.1 percent), open hours (2.9 percent) and FTE employees (3.3 percent) in the first year. These effects decrease by about one-half to two-thirds by the fifth year.

[Table 4 about here]

There are several potential explanations for the decrease in the estimated TOT effects over time that are reported in Table 4. First, libraries in the control group may do more to secure other types of funding such as grants and donations. As the revenue gap between the libraries in the treatment and control groups decreases, the difference in their performance decreases too. Second, the initial fiscal shock may be accompanied by other shocks, such as an initial psychological shock to library managers, and the latter may alleviate or disappear over time. Lastly, libraries without access to any source of funding to make up for the lost state budget may be forced to become more efficient over time, and as a result their higher efficiency in later years may reduce the difference in the performance of libraries in the treatment and control groups.

5. CONCLUDING REMARKS

How does funding diversification and the resulting stabilization of revenues affect the performance of public institutions at the time of fiscal shocks? In this paper we analyze the effect of operating funding diversification via local property taxes and the resulting revenue stabilization on the performance of public libraries in Ohio following the state budget cuts that resulted from the 2008 recession. We rely on the exogenous Ohio state government budget cuts in 2009 (and later) to compare the performance of libraries that already had access to local funding before the recession to those that exclusively relied on the state funding. Given the lengthy process of proposing and approving a local tax levy by voters, libraries in the latter group did not have time to react to their budget cuts in 2009 by stabilizing their sources of funding and so seem likely to be more affected by the budget cuts. This setting allows us to cleanly identify the effect of budget stabilization on the performance of libraries in 2009, or the first year of the budget cuts. We use LATE and TOT models to account for the libraries in the control group that secure local property taxes in later years.

Based on our preferred TOT models, we find that libraries with access to local property taxes experienced an increase in the number of open hours (11.2 percent) and FTE employees (12.7 percent) in the first year of funding stabilization, resulting in an increase in the number of visitors (9.6 percent), circulated materials (9.6 percent), number of programs (26.3 percent), and program attendance (19.5 percent). Our continuous treatment TOT model, which accounts for the variation in the level of funding stabilization among the libraries, shows that a 10 percentage point increase in the ratio of the operating budget funded by local taxes leads to an increase in the per service area population of the number of visitors (2.5 percent), circulated materials (2.5 percent), number of programs (6.9 percent), program attendance (5.1 percent), open hours (2.9

percent) and FTE employees (3.3 percent) in the first year of funding stabilization. These effects decrease by about one-half to two-thirds by the fifth year, but they remain statistically significant at the 1 percent level. It is important to note that these positive effects are all relative to the libraries in the control group that do not have access to the local property taxes. In other words, libraries in both treatment and control groups were negatively affected by the state budget cuts following the 2008 recession, but the libraries with access to local property taxes had a higher performance compared to those that did not.

Our findings are consistent with prior work that finds positive effects of reliance on property taxes for municipalities and their ability to deal with negative fiscal shocks (Alm et al., 2011; Mikesell and Liu, 2013; Ihlanfeldt and Willardsen, 2014; Krupa and Kriz, 2021). Importantly, we show that these positive effects are observed in public libraries as well. Additionally, to the best of our knowledge, we are the first to provide causal evidence for the role of locally funded operating budget for libraries. Despite the existence of an extensive literature on the performance and societal impact of public libraries, very few studies employ a reliable causal identification technique and they are exclusively focused on the role of major capital expenditures (Berkes and Nencka, 2024; Gilpin et al., 2024). Among the non-causal studies, our results are similar to Vitaliano (1997) and Hemmeter (2006), who find a positive association between the efficiency of libraries and the share of local taxes in funding their operation. Moreover, our empirical results are consistent with theoretical models, such as the seminal work by Hoxby (1999), which show that local property tax finance is superior to centralized finance in enhancing the efficiency of local public goods provision.

While an increase in reliance on local property taxes may result in libraries operating more efficiently, it may also increase inequality across communities for several reasons. Libraries in low-income and rural areas are relatively less funded throughout the U.S. (Sin, 2011). Further, low-income areas are less likely to support higher property taxes[14] necessary to make-up for lost state funding. Lastly, high-income households are less reliant on the free services provided by public libraries given that they have the necessary disposable income to purchase them in the marketplace (Ebdon et al., 2019). This trade-off between efficiency and equity is a key consideration in determining the optimal share of the public libraries operating revenue that should be funded locally.

Our findings have a clear policy recommendation for local public agencies that have the option to diversify and stabilize their funding sources by relying on local property taxes. The existing literature on municipalities, along with our analysis of public libraries, both indicate that property taxes are a stable source of revenue for public entities at the time of economic crisis and/or budget cuts at the state or federal levels. We believe that it would be beneficial for future studies to continue to provide additional causal evidence for the effect of funding stabilization on the performance of public agencies. In the context of public libraries, our identification strategy can be adopted by other researchers to examine the societal impacts of operating revenue funding stabilization on such important variables as student test scores or crime rates.

REFERENCES

Alm, J., Buschman, R. D., & Sjoquist, D. L. (2011). Rethinking local government reliance on the property tax. *Regional Science and Urban Economics*, *41* (4), 320-331.

Angrist, J. D., & Pischke, J. S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Berkes, E., & Nencka, P. (2024). Knowledge access: The effects of Carnegie libraries on innovation. *Review of Economics and Statistics*, 1-45.

Cain, B. E., Cooper, E., Ferejohn, S., & Potter, C. (1997). California library referenda: the determinants of success and failure. *The Bottom Line*, *10* (2), 44-57.

Carroll, D. A. (2009). Diversifying municipal government revenue structures: Fiscal illusion or instability? *Public Budgeting & Finance*, *29* (1), 27-48.

de Chaisemartin, C., & D'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *The American Economic Review*, *110* (9), 2964-2996.

de Chaisemartin, C., & D'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, 1-45.

Ebdon, C., Park, J. H., Franklin, A. L., & Moore, J. (2019). Institutional arrangements for public library funding and spending. *The American Review of Public Administration*, *49* (5), 532-544.

Ferreira Neto, A. B., & Hall, J. C. (2019). Economies of scale and governance of library systems: evidence from West Virginia. *Economics of Governance*, *20* (3), 237-253.

Ferreira Neto, A. B. (2022). Do public libraries impact local labour markets? Evidence from Appalachia. *Spatial Economic Analysis*, *18* (2), 216-238.

Ferreira Neto, A. B., Nowicki, J., & Shakya, S. (2023). Do public libraries help mitigate crime? Evidence from Kansas City, MO. *Journal of Cultural Economics*, *49* (1), 1-21.

Fleeter, H. (2017). *Analysis of Property Tax Levies for Library Purposes*. Ohio Library Council Technical report. Available at: https://olc.org/wp-content/uploads/2021/07/Library-Levy-Report-Dec-2017.pdf (last accessed on 28 January 2023).

Fleeter, H. (2021). *Ohio's Public Libraries ROI Report*. Ohio Library Council Technical Report. Available at: https://olc.org/resources/ohios-public-libraries-roi-report/ (last accessed on 20 January 2023).

Gentry, W. M., & Ladd, H. F. (1994). State tax structure and multiple policy objectives. *National Tax Journal*, *47* (4), 747-772.

Gilpin, G., Karger, E., & Nencka, P. (2024). The returns to public library investment. *American Economic Journal: Economic Policy*, *16* (2), 78-109.

Gorina, E., Maher, C., & Joffe, M. (2018). Local fiscal distress: Measurement and prediction. *Public Budgeting & Finance*, *38* (1), 72-94.

Harden, J. W., & Hoyt, W. H. (2003). Do states choose their mix of taxes to minimize employment losses? *National Tax Journal*, *56* (1), 7-26.

Helm I. & Stuhler J. (2024). The dynamic response of municipal budgets to revenue shocks. *American Economic Journal: Applied Economics*, *16* (4), 484-527.

Hemmeter, J. A. (2006). Estimating public library efficiency using stochastic frontiers. *Public Finance Review*, *34* (3), 328-348.

Hoxby, C. M. (1999). The productivity of schools and other local public goods producers. *Journal of Public Economics*, *74* (1), 1-30.

Ihlanfeldt, K. R., & Willardsen, K. (2014). The millage rate offset and property tax revenue stability. *Regional Science and Urban Economics*, *46* (1), 167-176.

IMLS: Institute of Museum and Library Services (2024). *Public Libraries Survey.* Available at: https://www.imls.gov/research-evaluation/data-collection/public-libraries-survey (data retrieved on 15 June 2024).

Jackson, C. K., Wigger, C., & Xiong, H. (2021). Do school spending cuts matter? Evidence from the Great Recession. *American Economic Journal: Economic Policy*, *13* (2), 304-335.

Jacobson, E. (2021). Who votes for library bonds? A principal component exploration. *arXiv preprint arXiv:2107.01095*.

Jakiela, P. (2021). Simple diagnostics for two-way fixed effects. *arXiv preprint arXiv:2103.13229*.

Jimenez, B. S., & Afonso, W. B. (2022). Revisiting the theory of revenue diversification: Insights from an empirical analysis of municipal budgetary solvency. *Public Budgeting & Finance*, *42* (2), 196-220.

Karger, E. (2021). The long-run effect of public libraries on children: Evidence from the early 1900s. *SocArXiv Working Paper (No e8k7p)*. Available at: https://econpapers.repec.org/paper/osfsocarx/e8k7p.htm.

Kevane, M. J. and Sundstrom, W. A. (2016). Public libraries and political participation, 1870-1940. *Scholar Commons Working Paper (Economics)*, Paper 55. Available at: http://scholarcommons.scu.edu/econ/55.

Krupa, O., & Kriz, K. A. (2021). Property tax assessments, collections, and revenue performance in economic downturns: an examination of large American cities. *Journal of Property Tax Assessment & Administration*, *18* (1), 1357-1419.

Mikesell, J. L., & Liu, C. (2013). Property tax stability: A tax system model of base and revenue dynamics through the great recession and beyond. *Public Finance and Management*, *13* (4), 310-334.

Misiolek, W. S., & Perdue, D. G. (1987). The portfolio approach to state and local tax structures. *National Tax Journal*, *40* (1), 111-114.

Ohio Library Council (2024). Public Library Levies. Available at: https://olc.org/levies/ (last accessed on 1 July 2024).

Ohio Revised Code (2021). *Section 5705.23: Special levy for public library – resolution – submission to electors*. Available at: https://codes.ohio.gov/ohio-revised-code/section-5705.23 (last accessed on 3 February 2023)

Preer, J. (2008). Promoting citizenship: How librarians helped get out the vote in the 1952 presidential election. *Libraries & the Cultural Record*, *43* (1), 1-28.

Sin, S. C. J. (2011). Neighborhood disparities in access to information resources: Measuring and mapping US public libraries' funding and service landscapes. *Library & Information Science Research*, *33* (1), 41-53.

Scott, R. (2011). The role of public libraries in community building. *Public Library Quarterly*, *30* (3), 191-227.

U.S. Census (2008). State and County Estimates for 2008. Available at: https://www.census.gov/data/datasets/2008/demo/saipe/2008-state-and-county.html (data retrieved on July 8, 2025).

Vitaliano, D. F. (1997). X-inefficiency in the public sector: the case of libraries. *Public Finance Review*, *25* (6), 629-643.

ENDNOTES

---

[1] It is worth noting that Kevane and Sundstrom (2016) do not find a consistent short run effect of libraries on the voter turnout following the construction of a library in the pre-1940 period.
[2] Unless otherwise cited, all statistics related to public libraries in this section are from our own calculations using data from the Institute of Museum and Library Service (IMLS) (2024), as discussed later.
[3] This is probably because Ohio's state-level per capita operating expenditure on libraries is one of the highest in the nation. In fact, despite the post-2008 budget cuts, Ohio is ranked second in the nation as of 2019 (Fleeter, 2021).
[4] All library systems in Ohio have the power to take funding measures to the ballot box in their districts (Ohio Revised Code, 2012).
[5] For example, see Berkes and Nencka (2024) and Gilpin et al. (2024).
[6] These findings are also consistent with earlier research that finds a positive relationship between a diversified "portfolio" of tax instruments and the revenue stability of state and local governments (Misiolek and Perdue, 1987; Gentry and Ladd, 1994; Harden and Hoyt, 2003).
[7] Note that there has been some limited work on the impact of revenue shocks on institutional performance. For example, Helm and Stuhler (2024) examine local governments' reactions to small revenue changes, such as the ones caused by census counts. In work more closely related to our work here, Jackson et al. (2021) analyze the effect of the 2008 recession on the performance of public schools, and find that schools that relied more on local property taxes as opposed to state funding were less affected by the resulting negative budget shock.
[8] Only three libraries have local funding in 2009 that did not have it in 2008. We removed these 3 libraries from the sample for the rest of the analysis.
[9] Given the significant variation in the size of libraries as shown in Table 1, all outcome variables are scaled using the service area population of libraries to ensure their comparability. Service area population is a better variable than the number of branches to scale outcome variables, because the latter is more probable to be affected by the fiscal shock to the libraries. Service area population of libraries is also used to weight observations in all of our regression models.
[10] This variable is between 0 and 1, and it is created by dividing "operating revenue provided by local taxes" by "total operating revenue."
[11] In the extreme case, if all members of the control group secure a local tax levy and if the effect of access to local funding is limited to the year in which a library secures it, then the difference between the treatment and control group becomes equal to zero. Note that in this example there is no difference between the members of these two groups because they all have access to local taxes and because we assume that local funding only has a contemporaneous effect on the performance of the libraries.
[12] To be able to rely on the 2008 shock as the natural experiment that identifies the causal effect of interest, we only allow for the treatment to "switch on" in 2009 or later.
[13] See de Chaisemartin and D'Haultfoeuille (2024) for a more technical discussion of their event study estimators.
[14] For example, see Cain et al. (1997). However, some evidence to the contrary exists. For example, Jacobson (2021) finds that low socio-economic status is positively associated with support for library bonds.

TABLES

Table 1. Summary statistics for key variables

Variable	Coverage	Observations	Mean	Standard Deviation	Min	Max
Visitors	1998-2019	5,500	315,796	791,601	1,196	8,775,052
Circulated Materials	1998-2019	5,499	697,130	1,913,594	1,885	21,226,498
Programs	2004-2019	3,972	1,002	2,319	0	27,328
Program Attendance	2004-2019	3,990	22,763	50,029	5	510,238
Operating Revenue	1998-2019	5,500	2,936,965	8,427,277	47,075	173,503,070
Percent of Operating Revenues Funded Locally	1998-2019	5,500	17%	20%	0%	78%
Branches	1998-2019	5,500	3	5	1	42
Open Hours	1998-2019	5,500	8,270	14,404	752	159,432
FTE Employees	1998-2019	5,500	37	88	1	860
Service Area Population	1998-2019	5,500	45,826	99,801	197	861,147

Source: IMLS (2024) and own calculations

Notes: The sample includes 250 unique libraries. The unit of observation is library-by-year. Some libraries have multiple branches, but the data for all branches are aggregated and reported as part of the same entity. The observations are limited to the libraries that were accessible to the public in a given year (defined as having non-zero visitors for that year). Values are rounded to the closest integer.

Table 2: Summary statistics by local funding status in 2008

	Library Type		
Variable	**No Local Funding**	**Some Local Funding**	**All**
Number of Libraries	156	94	250
Visitors	186,246	672,320	369,010
Circulated Materials	394,200	1,390,660	768,869
Programs	501	1,709	955
Program Attendance	11,510	41,189	22,669
Operating Revenue	$1,307,899	$5,597,325	2,920,723
Percent of Operating Revenues Funded Locally	0%	30%	11%
Branches	2	4	3
Open Hours	5,835	11,417	7,934
FTE Employees	21	69	39
Service Area Population	30,538	71,777	46,044
Percent Rural	4%	7%	5%
County-Level Variables:			
Median Income	$47,476	$49,427	$48,209
Poverty Rate	12%	12%	12%

Source: IMLS (2024), U.S. Census (2008), and own calculations

Notes: The sample is limited to the libraries in 2008. The unit of observation is library. Some libraries have multiple branches, but the data for all branches are aggregated and reported as part of the same entity. The observations are limited to the libraries that were accessible to the public in a given year (defined as having non-zero visitors for that year). For the summary statistics related to county variables, a county is represented more than once if it has more than one library located in it. Values are rounded to the closest integer.

Table 3. The effect of funding stabilization on the main outcomes of interest: Models with a binary treatment variable

Relative Year (τ)	Dependent Variable (in log form)						
	Operating Revenue	Visitors	Circulated Materials	Programs	Program Attendance	Open Hours	FTE Employees
Panel A: ITT Estimates							
$\tau = 1$	0.172*** (0.026)	0.096** (0.039)	0.092*** (0.022)	0.265*** (0.082)	0.117** (0.052)	0.077 (0.064)	0.129*** (0.043)
$\tau = 2$	0.047 (0.059)	0.044 (0.054)	0.113*** (0.039)	0.258** (0.113)	0.232** (0.114)	0.044 (0.070)	0.084** (0.036)
$\tau = 3$	-0.034 (0.070)	-0.005 (0.092)	0.084 (0.052)	0.110 (0.102)	0.061 (0.100)	-0.019 (0.070)	0.037 (0.048)
$\tau = 4$	0.068 (0.154)	-0.049 (0.075)	0.065 (0.050)	0.063 (0.108)	0.028 (0.105)	-0.048 (0.066)	0.026 (0.053)
$\tau = 5$	-0.059 (0.065)	-0.104 (0.074)	0.025 (0.058)	0.095 (0.118)	0.023 (0.107)	-0.022 (0.063)	-0.014 (0.042)
Panel B: LATE Estimates							
$\tau = 1$	0.172*** (0.026)	0.096** (0.038)	0.092*** (0.022)	0.265*** (0.078)	0.117** (0.053)	0.077 (0.066)	0.129*** (0.041)
$\tau = 2$	0.069 (0.076)	0.065 (0.074)	0.168*** (0.049)	0.382** (0.155)	0.344** (0.147)	0.065 (0.100)	0.124*** (0.041)
$\tau = 3$	-0.095 (0.217)	-0.013 (0.254)	0.236* (0.123)	0.307 (0.274)	0.169 (0.277)	-0.053 (0.212)	0.104 (0.128)
$\tau = 4$	0.216 (0.481)	-0.154 (0.257)	0.206 (0.137)	0.201 (0.336)	0.089 (0.342)	-0.153 (0.238)	0.083 (0.171)
$\tau = 5$	-0.206 (0.270)	-0.364 (0.317)	0.089 (0.191)	0.333 (0.386)	0.081 (0.384)	-0.078 (0.25)	-0.049 (0.162)
Panel C: TOT Estimates (de Chaisemartin and D'Haultfoeuille, 2024)							
$\tau = 1$	0.303*** (0.022)	0.096** (0.040)	0.096*** (0.018)	0.263*** (0.068)	0.195*** (0.059)	0.112** (0.047)	0.127*** (0.031)
$\tau = 2$	0.339*** (0.026)	0.172*** (0.052)	0.178*** (0.029)	0.353*** (0.101)	0.387*** (0.103)	0.159** (0.066)	0.173*** (0.027)
$\tau = 3$	0.399*** (0.047)	0.172*** (0.049)	0.225*** (0.043)	0.319*** (0.072)	0.336*** (0.067)	0.218*** (0.048)	0.210*** (0.037)
$\tau = 4$	0.493*** (0.100)	0.196*** (0.051)	0.252*** (0.043)	0.359*** (0.074)	0.378*** (0.072)	0.216*** (0.050)	0.216*** (0.040)
$\tau = 5$	0.411*** (0.045)	0.202*** (0.057)	0.286*** (0.049)	0.431*** (0.090)	0.439*** (0.083)	0.252*** (0.053)	0.207*** (0.039)

Source: IMLS (2024) and own calculations

Notes: Each panel shows the effect of the treatment (i.e., funding stabilization post-2008) on an outcome variable related to libraries. All outcome variables are scaled using the service area population of libraries to ensure their comparability before they are used in the log form. Relative years (τ) are with respect to the last year before the treatment group receives the treatment. ITT, LATE, and TOT effects are estimated using models in equations (2), (3), and (5), respectively and the models all have library and year fixed effects. The TOT effects are estimated using the DiD technique developed by de Chaisemartin and D'Haultfoeuille (2024). See the methodology section and the appendices for more details. Standard errors are in parentheses and clustered at the library level in the ITT and TOT panels. In the LATE panel, cluster bootstrapped standard errors (with 1000 replications) are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

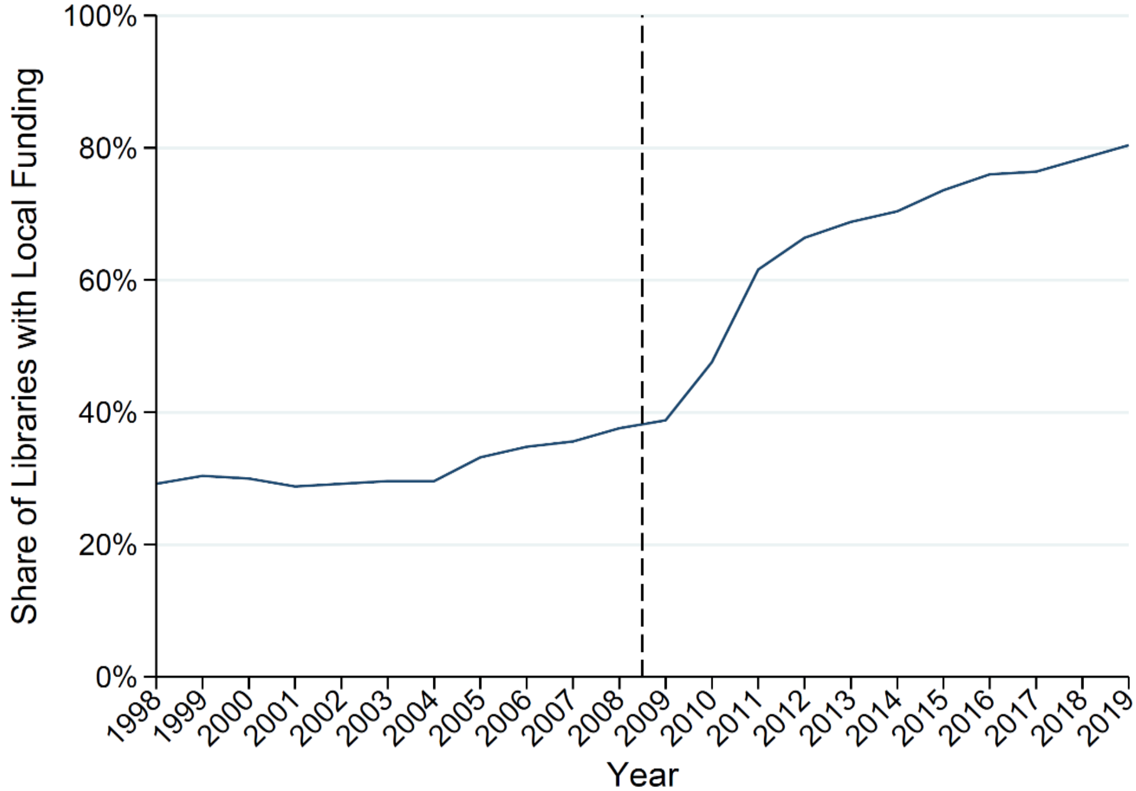
Table 4. The effect of funding stabilization on the main outcomes of interest: Models with a continuous treatment variable (Local Operating Revenue Ratio)

Relative Year (τ)	Dependent variable (in log form)						
	Operating Revenue	Visitors	Circulated Materials	Programs	Program Attendance	Open Hours	FTE Employees
Panel A: ITT Estimates							
$\tau = 1$	0.430*** (0.078)	0.245*** (0.093)	0.210*** (0.060)	0.593** (0.245)	0.310** (0.120)	0.212 (0.174)	0.394*** (0.100)
$\tau = 2$	0.106 (0.143)	0.175 (0.135)	0.288** (0.115)	0.677** (0.301)	0.552** (0.256)	0.160 (0.187)	0.238*** (0.088)
$\tau = 3$	-0.085 (0.204)	0.016 (0.210)	0.208 (0.138)	0.238 (0.291)	0.048 (0.208)	0.016 (0.179)	0.097 (0.128)
$\tau = 4$	0.274 (0.483)	-0.058 (0.173)	0.170 (0.128)	0.192 (0.295)	0.025 (0.228)	-0.018 (0.169)	0.107 (0.147)
$\tau = 5$	-0.139 (0.187)	-0.188 (0.184)	0.078 (0.146)	0.330 (0.320)	0.078 (0.239)	0.051 (0.147)	-0.003 (0.102)
Panel B: LATE Estimates							
$\tau = 1$	0.41*** (0.054)	0.234*** (0.087)	0.201*** (0.050)	0.566** (0.251)	0.296** (0.124)	0.203 (0.168)	0.376*** (0.103)
$\tau = 2$	0.134 (0.163)	0.222 (0.152)	0.364*** (0.118)	0.856** (0.394)	0.698** (0.303)	0.203 (0.226)	0.3*** (0.097)
$\tau = 3$	-0.131 (0.342)	0.025 (0.310)	0.319 (0.213)	0.366 (0.432)	0.074 (0.340)	0.025 (0.298)	0.149 (0.192)
$\tau = 4$	0.546 (1.201)	-0.115 (0.358)	0.338 (0.221)	0.383 (0.690)	0.050 (0.479)	-0.036 (0.364)	0.214 (0.349)
$\tau = 5$	-0.210 (0.316)	-0.286 (0.277)	0.118 (0.215)	0.501 (0.457)	0.119 (0.379)	0.078 (0.243)	-0.004 (0.169)
Panel C: TOT Estimates (de Chaisemartin and D'Haultfoeuille, 2024)							
$\tau = 1$	0.794*** (0.029)	0.252*** (0.061)	0.253*** (0.036)	0.691*** (0.088)	0.512*** (0.090)	0.293*** (0.095)	0.333*** (0.068)
$\tau = 2$	0.438*** (0.019)	0.222*** (0.041)	0.230*** (0.026)	0.456*** (0.092)	0.500*** (0.102)	0.205*** (0.069)	0.224*** (0.026)
$\tau = 3$	0.334*** (0.020)	0.143*** (0.034)	0.188*** (0.031)	0.267*** (0.041)	0.281*** (0.040)	0.183*** (0.032)	0.176*** (0.025)
$\tau = 4$	0.310*** (0.014)	0.123*** (0.028)	0.159*** (0.024)	0.226*** (0.032)	0.238*** (0.035)	0.136*** (0.026)	0.136*** (0.018)
$\tau = 5$	0.204*** (0.012)	0.100*** (0.025)	0.142*** (0.021)	0.214*** (0.033)	0.218*** (0.033)	0.125*** (0.023)	0.103*** (0.017)

Source: IMLS (2024) and own calculations

Notes: Each panel shows the effect of the treatment (i.e., funding stabilization post-2008) on an outcome variable related to libraries. All outcome variables are scaled using the service area population of libraries to ensure their comparability before they are used in the log form. Relative years (τ) are with respect to the last year before the treatment group receives the treatment. ITT, LATE, and TOT effects are estimated using models in equations (2), (3), and (5), respectively and the models all have library and year fixed effects. The TOT effects are estimated using the DiD technique developed by de Chaisemartin and D'Haultfoeuille (2024). See the methodology section and the appendices for more details. Standard errors are in parentheses and clustered at the library level in the ITT and TOT panels. In the LATE panel, cluster bootstrapped standard errors (with 1000 replications) are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Figure 1. The percent of libraries with local funding for operating revenue



Source: IMLS (2024) and own calculations

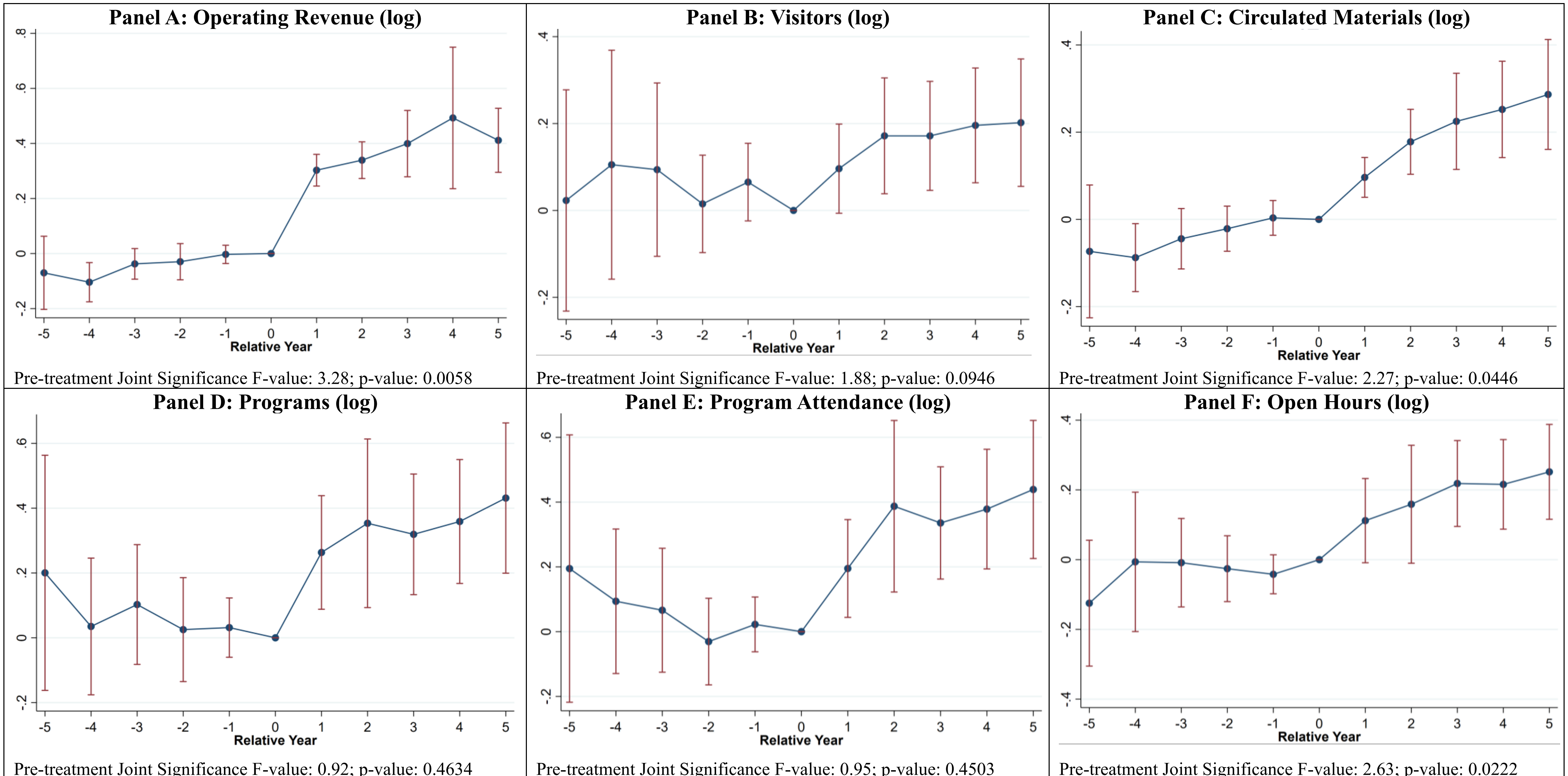
Notes: The sample includes 250 unique libraries. The unit of observation is library-by-year. Some libraries have multiple branches, but the data for all branches are aggregated and reported as part of the same entity. The observations are limited to the libraries that were accessible to the public in a given year (defined as having non-zero visitors for that year). The vertical dash line separates the years before and after the state budget cuts.

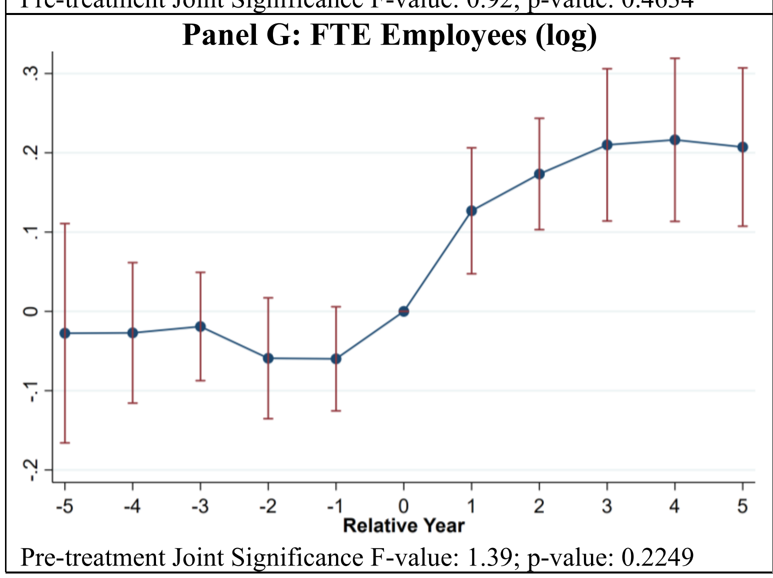
Figure 2. The change in operating revenue per service area population for libraries with versus without local funding

Source: IMLS (2024) and own calculations

Notes: The sample includes 250 unique libraries. The unit of observation is library-by-year. Some libraries have multiple branches, but the data for all branches are aggregated and reported as part of the same entity. The observations are limited to the libraries that were accessible to the public in a given year (defined as having non-zero visitors for that year). The vertical dash line separates the years before and after the state budget cuts.

Figure 3. The effect of funding stabilization on the operating revenue and performance of public libraries: Event study





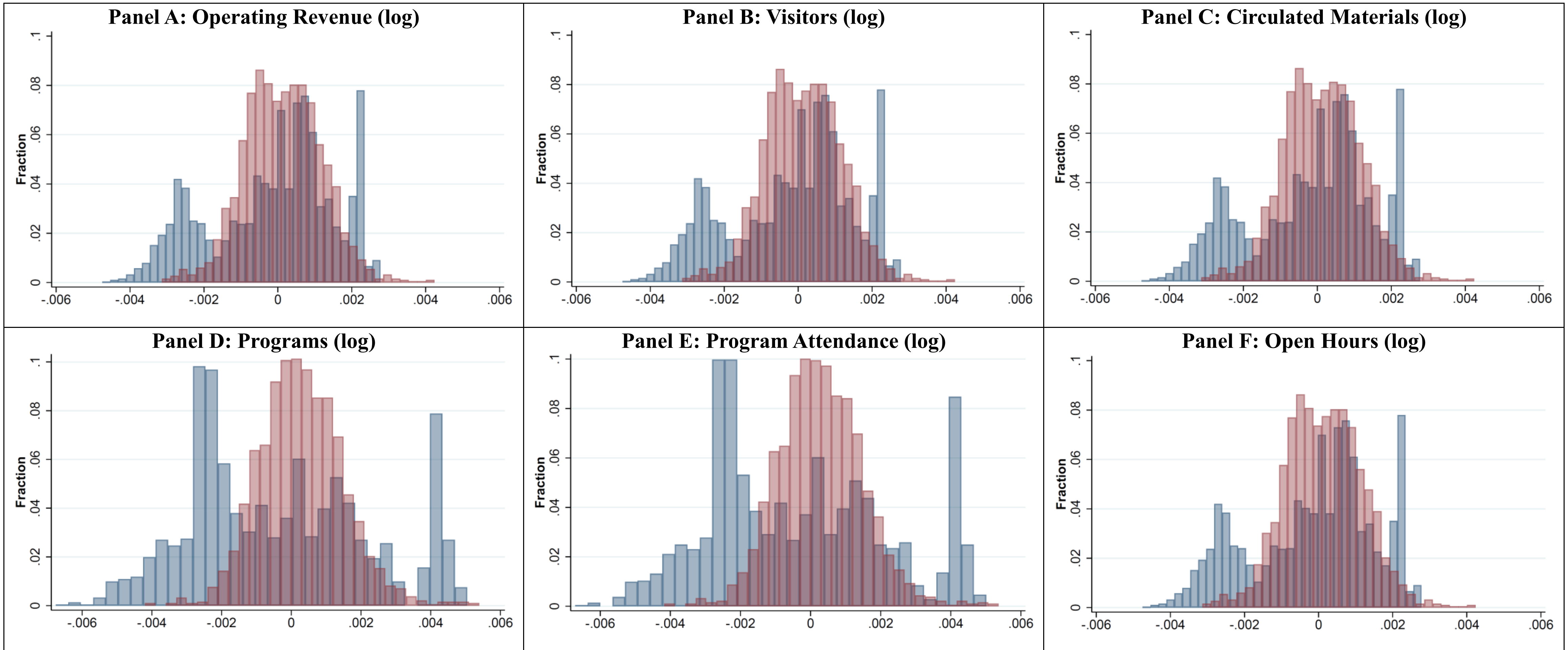
Source: IMLS (2024) and own calculations

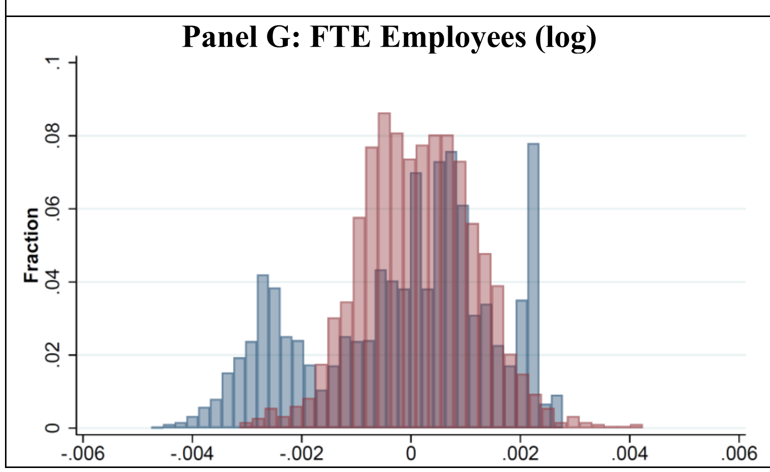
Notes: Each panel shows the effect of the treatment, i.e., funding stabilization post-2008, on an outcome variable related to libraries. All outcome variables are scaled using the service area population of libraries to ensure their comparability before they are used in the log form. The vertical red lines represent 99% confidence interval. Relative years (τ) are with respect to the last year before the treatment group receives the treatment, so $\tau \leq 0$ is the pre-treatment period. The parameter estimates are based on equation (5) in the methodology section, but are estimated using the DiD technique developed by de Chaisemartin and D'Haultfoeuille (2024). See the methodology section and the appendices for more details.

Appendix A:
Jakiela (2021) heterogenous treatment effects diagnostic test

Jakiela (2021) shows that the estimation techniques that allow for the heterogeneous treatment effect assumption produce larger standard errors, and she proposes a diagnostic test to determine if one should use them. The Jakiela (2021) diagnostic test has two parts. The first part relies on the residuals from the regression of the treatment (i.e., $LocalFund_{Lt}$) on library and time fixed effects ($Library_L$ and $Year_t$, respectively). Jakiela (2021) shows that the weight assigned to each observation when a TWFE DiD model is estimated using the OLS technique is equal to the value of residualized treatment for that observation scaled by the sum of the squared residuals across all observations. Appendix Figure A1 shows the distribution of these weights for the observations related to the libraries in the treatment and control groups. The reason we have one panel for each outcome variable is because our panel is not fully balanced for all outcome variables and two of the variables (i.e., the number of programs and program attendance) are only available for a limited number of years (see Table 1). So, to ensure that we include relevant observations in this diagnostic test, we repeated the treatment residualization process, each time focusing on the observations that would be actually used in the estimation of equation (5) for a given outcome variable. The prevalence of a negative weight in all panels of Appendix Figure A1 is a major point of concern in terms of the ability of equation (5) to produce unbiased estimates if an OLS technique is used.

Appendix Figure A1. Jakiela (2021) heterogenous treatment effect diagnostic test (first part): Distribution of TWFE weights assigned to observations



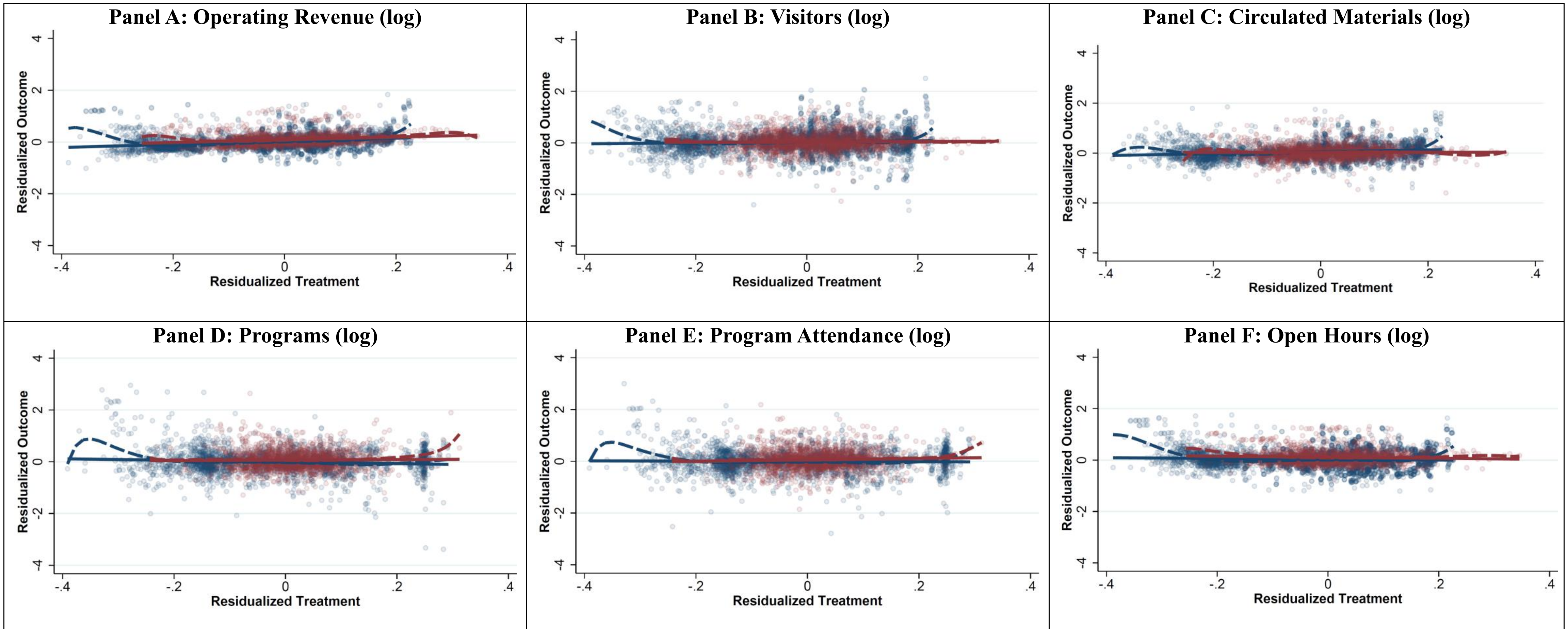


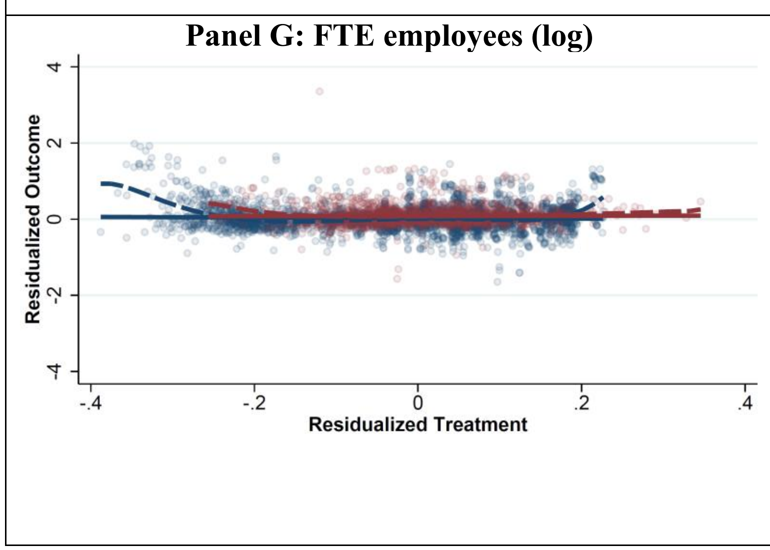
Source: IMLS (2024) and own calculations

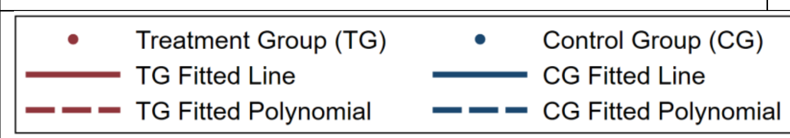
Notes: Each panel displays the distribution of weights used by a two-way fixed effects (TWFE) DiD model to calculate the impact of funding stabilization (through local property taxes) on a particular outcome variable related to libraries. Jakiela (2021) shows that the weights are equal to residuals from the regression of the treatment variable (i.e., *LocalFund*, or the ratio of operating revenue funded locally) on library and year fixed effects, scaled by the sum of the squared residuals across all observations.

Jakiela (2021) shows that the negative weights are not problematic if there is enough evidence to justify the homogenous treatment assumption. The second part of her diagnostic test concerns this assumption. She shows that, if this assumption is valid, the relationship between the residualized outcome variable (calculated by regressing the outcome of interest on the library and year fixed effects) and the residualized treatment is linear and similar across the observations related to the treatment and control group. Appendix Figure A2 shows that for most outcome variables, when we allow for a polynomial of order 3, the fitted curve deviates from the linear line, indicating that the relationship between the two residualized variables is non-linear. Moreover, as Appendix Table A1 shows, the lines fitted to the observations related to the treatment and control groups generally do not have the same slope, as demonstrated by the coefficient of the interaction term in Appendix Table A1. Therefore, the second part of Jakiela (2021) diagnostic test also indicates that more recent techniques such as the one proposed by de Chaisemartin and D'Haultfoeuille (2024) should be used to estimate δ_τs in equation (5).

Appendix Figure A2. Jakiela (2021) heterogenous treatment effect diagnostic test (second part): Residualized outcome variables versus residualized *LocalFund*







Source: IMLS (2024) and own calculations

Notes: Each panel displays the relationship between a specific residualized outcome variable and residualized treatment (i.e., *LocalFund*, or the ratio of operating revenue funded locally). The residualized outcome (treatment) is from the regressions of this variable on library and year fixed effects. All outcome variables are scaled using the service area population of libraries to ensure their comparability before they are used in the log form. Jakiela (2021) shows that, if the homogenous treatment effect is a valid assumption, then the relationship between the two residualized variables is linear and the line has the same slope for the observations related to the treatment and control groups. We fit a separate line (solid blue and red) for each group and use a polynomial of order 3 (dashed blue and red) to assess if it can better capture the relationship between the two residualized variables. The deviation of the fitted polynomial from the fitted line indicates the non-linearity of the relationship between the two residualized variables for a portion of the observations.

Appendix Table A1. Jakiela (2021) heterogenous treatment effect diagnostic test (second part): The relationship between residualized outcome variables and *LocalFund*

Regressors	Dependent Variables (Residualized Log)						
	Operating Revenue	**Visitors**	**Circulated Materials**	**Programs**	**Program Attendance**	**Open Hours**	**FTE Employees**
LocalFund (Residualized)	0.906*** (0.030)	0.269*** (0.058)	0.563*** (0.033)	0.499*** (0.065)	0.470*** (0.064)	0.509*** (0.039)	0.383*** (0.029)
Treatment Group (TG)	0.022*** (0.005)	0.034*** (0.010)	0.017*** (0.006)	0.040*** (0.011)	0.039*** (0.011)	0.007 (0.007)	0.012** (0.005)
TG × *LocalFund* (Res.)	-0.377*** (0.055)	-0.620*** (0.108)	-0.470*** (0.060)	-0.802*** (0.120)	-0.769*** (0.119)	-0.150** (0.073)	-0.197*** (0.054)
Observations	5,434	5,434	5,433	3,922	3,942	5,434	5,434

Source: IMLS (2024) and own calculations

Notes: The table shows whether the slope of the lines fitted for the observations related to the treatment and control groups in Appendix Figure A2 have the same slope or not. A statistically significant interaction term (last regressor) indicates that the lines have different slopes and, per Jakiela (2021), that there is evidence to support the heterogenous treatment effect assumption. The dependent variable in each column is the residuals from the regression of that variable (in log form) on the library and year fixed effects. All outcome variables are scaled using the service area population of libraries to ensure their comparability before they are used in the log form. *LocalFund* (Residualized) is from the regression of this variable (i.e., the ratio of operating revenue funded locally) on library and year fixed effects. Treatment Group is an indicator variable equal to 1 if the observations belong to the treatment group, 0 otherwise. Standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Appendix B:
de Chaisemartin and D'Haultfoeuille (2020) heterogenous treatment effects diagnostic statistics

This appendix presents two statistics developed by de Chaisemartin and D'Haultfoeuille (2020) that help determine the importance of employing DiD estimation techniques that account for heterogenous treatment effects. The first one is the minimum necessary standard deviation for the entity-specific (i.e., library-specific) treatment effects that is needed for the TWFE DiD estimator to potentially produce a zero average treatment effect. The second one is a similar threshold that is needed for the TWFE DiD estimation to have a potentially incorrect sign. If the value of both thresholds is low and it is reasonably plausible that the actual standard deviation of the library-specific treatment effects would be more than them, then the TWFE DiD estimation is potentially significantly biased and is not reliable.

These two and several other statistics are presented in Appendix Table B1. First, the table shows an average treatment effect if one relies on a traditional two-way fixed effects (TWFE) DiD model to estimate it. (This is an instantaneous effect of funding stabilization and therefore comparable to δ_0 in the event study model. To be specific, the traditional TWFE DiD model regresses an outcome of interest in library *L* in year *t* on the *LocalFund* variable (related to that library in that year) and library and year fixed effects.) In the next rows, Appendix Table B1 shows the underlying number of library-specific effects that are effectively aggregated by a traditional TWFE DiD estimator and the number of library-specific effects that receive a positive versus negative weight (as well as the sum of weights in each of these two categories). As Appendix Table B1 shows, about half of the library-specific effects effectively receive a negative weight regardless of the outcome of interest. This is concerning because it can result in the traditional TWFE DiD model producing biased estimations. Specifically, if the treatment effect is heterogenous, then the existence of these negative weights can result in the TWFE estimation becoming zero or having a sign that is the opposite of the true effect. The last two rows of the table present the main statistics, or thresholds, introduced above. As Appendix Table B1 shows, the values of these thresholds are indeed relatively low for almost all outcome variables.

Appendix Table B1. de Chaisemartin and D'Haultfoeuille (2020) heterogenous treatment effect diagnostic statistics

Statistics	Dependent Variables (in log form)						
	Operatin g Revenue	**Visitors**	**Circulate d Materials**	**Program s**	**Program Attendanc e**	**Open Hours**	**FTE Employee s**
β^{TWFE} (Average Treatment Effect Estimated Using a TWFE DiD Model)	0.8205	0.1236	0.4390	0.3184	0.2984	0.4724	0.3386
Total Library-Specific Effects	1818	1818	1817	1816	1818	1818	1818
Total Library-Specific Effects with Positive Weight [Sum of Weights]	977 [1.20]	977 [1.20]	977 [1.20]	1058 [1.24]	1057 [1.24]	977 [1.20]	977 [1.20]
Total Library-Specific Effects with Negative Weight [Sum of Weights]	841 [-0.20]	841 [-0.20]	840 [-0.20]	758 [-0.24]	761 [-0.24]	841 [-0.20]	841 [-0.20]
Minimum Treatment Effect Standard Division Necessary for $\beta^{TWFE} = 0$	0.5915	0.0891	0.3165	0.1972	0.1855	0.3406	0.2441
Minimum Treatment Effect Standard Division Necessary for β^{TWFE} with an Incorrect Sign	1.4690	0.2214	0.7862	0.4501	0.4240	0.8459	0.6063

Source: IMLS (2024) and own calculations

Notes: The table shows the heterogenous treatment effect diagnostic statistics proposed by de Chaisemartin and D'Haultfoeuille (2020). See the methodology section for more details. All outcome variables are scaled using the service area population of libraries to ensure their comparability before they are used in the log form.