Exploring the Effects of the Small Business Training Program on Firm-Level Economic Outcomes

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October 13, 2025

Abstract

In 2013, the United States government introduced the Small Business Training Program (SBTP) with the goal of providing technical and managerial support to businesses with 100 or fewer employees. A growing body of literature seeks to better understand the effects and implications of large-scale social programs like the SBTP to aid policy makers in improving the efficiency and efficacy of their construction. In this paper, I use panel data from 2010-2019 to explore the program's effects. I estimate the causal effect of SBTP participation on firm productivity with Difference-in-Differences using a Two-Way Fixed-Effects model, with standard errors clustered at the firm level to account for within firm correlation. My findings suggest that firms who chose to adopt the SBTP had, on average, higher productivity gains than those that did not. This amounted to an estimated average revenue per employee that was $1686.43 higher than that of the same firm who had not participated in the program, controlling for firm and date fixed effects.[1][2]

[1]SIEPR Pre-Doc Application Data Task Evaluation

[2]GitHub Repository: https://github.com/KieranCDouglas/metrics/tree/62c76050b787cfe454a68

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Introduction

In 2013, the United States Small Business Administration (SBA) implemented a program with the explicit goal of improving the efficiency and productivity of American firms. The Small Business Training Program (SBTP) had the primary focus of providing technical and managerial support to small businesses, meaning only firms with fewer than 100 concurrent employees could participate. In it's first year, the SBA allocated roughly $170 million to the SBTP. The money was allocated across a broad swath of assistance mechanisms including Small Business Development Centers (SBDC), Women's Business Centers (WBC), and thousands of resource partners around the country [1]. The SBTP was an opt-in program, meaning that eligible firms had the right to choose whether they wanted to participate. If they did partake, they would receive a series of managerial training programs in addition to personalized support with financial planning and counseling.

Initiatives like this can often feel good to hear about, as most of us like the idea of governments pushing legislation that could plausibly improve the economy. However, elected representatives have strong incentive to inform their constituents of their virtue, which can obscure the true consequences of their decisions. For this reason, third-party program evaluation becomes a vital aspect of any functioning society. In this paper, I use U.S. monthly firm-level panel data from 2010–2019 to examine the effects of the Small Business Training Program (SBTP) on economic outcomes. The guiding research question is: What was the causal effect of the SBTP on firm-level economic performance? To answer this question, I estimate Difference-in-Differences using a Two-Way Fixed-Effects model (DiD with TWFE), with standard errors clustered at the firm level to account for within firm correlation. A firm's adoption status is the treatment and the primary outcome of interest is revenue per employee as a general measure of labor productivity. Understanding these relationships can aid in the development of more efficient social policy. In this brief paper, I will first outline the data used to conduct my analysis. Then, I will explain my empirical strategy and theoretical justifications, followed by the empirical results from my analysis. Finally, I will briefly discuss my findings and the limitations I encountered before concluding. All associated figures and resources are included in the appendix.

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Data

The data used in this analysis come from the SBA Open Data Portal[3] and are contained within three separate datasets. They include basic firm information such as firm ID and name, monthly firm sales data, and firm auxiliary data that include monthly reports of employment and earnings statistics. To kick things off, I went through each file and created a data directory[4] in which I documented variable names, units, and provided a brief description. The data cleaning process was moderately involved due to reporting errors that are common with administrative data, but not overly complicated. Four things stood out: coding inconsistencies in dates, missingness, data that exceeded the scope of my analysis, and model assumption

[3] I would assume, it was not actually specified in the instructions...
[4] See the appendix for the complete data directory.

violations.

2.1 Data Cleaning

The most glaring issue was a lack of uniformity in reporting dates which made merging the data frames impossible. To address this, I forced all dates to be in year-month-day format and changed every day to be the first of that month. This is an acceptable move since what day the data were reported does not really matter, we are concerned with months and years and this allows us to effectively merge. To tackle missingness, I first needed to determine whether the NA values present were systematic (thus prime for imputation) or random (in which case they could be dropped). To do this, I created a missingness indicator for each dependent variable and ran a series of logistic regressions to find the probability that a value was missing as a function of all other covariates. My findings suggested that the nature of the missingness was missing completely at random (MCAR) due to a general lack of statistical significance in predictors. This means that the probability of missingness is unrelated to the included observables, providing sufficient justification for dropping missing values. Since portions of the data exceeded the scope of my analysis, I limited my final dataset to firms with less than 100 concurrent employees and omitted all duplicate entries. Finally, estimating DiD with TWFE relies on the assumption of treatment homogeneity. The fact that firms seem to opt in or out of the training program at staggered times is cause for concern. To address this, I limited my analysis to firms that either adopted the program in 2013 (treatment group) or those who never adopted it (as my control group).

2.2 Variable Generation

The primary dependent variable of interest, revenue per employee, was generated by taking the quotient of monthly revenue and number of people employed. I created several other derived variables that seemed theoretically meaningful. This included a wage-revenue ratio which indicates the portion of firms revenue being spent on labor, sales growth rate which uses lagged values to generate a rate of change per month, revenue growth rate, and monthly change in revenue per employee. Finally, I developed a performance index (despite having qualms with their interpretability) for sake of exploration and additional robustness. Composed of change variables, the index normalizes by z-score, showing the number of standard deviations in performance the firm is from the mean as the result of a treatment. The resulting dataset contains 25,012 observations and two tables of summary statistics are included in the Summary Tables section of the Appendix.

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Empirical Strategy

I employ a Difference-in-Differences approach using Two-Way-Fixed-Effects to estimate the effect of the Small Business Training Program on firm performance. This approach is optimal since I am dealing with panel data that involves multi-firm statistics over time. The treatment variable in this analysis is a binary indicator for whether a firm opted into the SBTP in 2013 and the primary outcome of interest is a derived variable representing the revenue per employee in a given month. This endogenous variable is theoretically meaningful, since it has both intuitively and empirically been demonstrated to act as a good measure of productivity. Since the SBTP is largely concerned with managerial training with the explicit goal of productivity gains, revenue per employee is a reasonable outcome to observe for this analysis. The model allows me to effectively control for unobserved time-invariant characteristics like base level productivity, location, or industry, all of which are factors that could otherwise create meaningful discrepancies in the programs effect across different firms. Additionally, the model controls for exogenous factors such as drought or local policy change that could impact one firm but not others, closing many of the back doors that would otherwise prevent valid causal inference.

3.1 Assumption Checks

In the interest of strengthening the validity of the model, I run several pre-checks to ensure that assumptions are met. The first, which was discussed in section 2.1, is the assumption of treatment homogeneity. This essentially states that the effect of the treatment does not vary by group or over time. To ensure this assumption was met, I limit analysis to firms that either started the program at the same time (in the treatment group) and those who never adopted it (the control group). I also omit firms that failed to participate consistently in the program, leaving only complete cases for analysis. Another vital assumption for DiD is the parallel trends assumption. This states that absent some treatment, the difference in outcomes between the two groups would have remained constant. Since we cannot prove this counterfactual, we need to assume based on prior trends that it would have held true. My evidence in favor of this assumption being met stems from two techniques. The first is rather old-school, and involved plotting pre-trend firm data leading up to the treatment, with separate lines for firms that eventually opted into the treatment and those that did not. By comparing these trend lines, it will generally become obvious if they were not parallel leading up to the intervention date, in the case of this analysis, they were[5]. In the interest of employing a more empirical technique, I run a pre-trend linear regression for each of the dependent variables of interest. Using a pre-2013 subset of the cleaned data, I regressed each potential outcome of interest on an interaction term between date and adoption status. A general lack of statistically significant coefficients indicate that the parallel trends assumption holds across these data.

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Empirical Results

I regress revenue per employee on an indicator for SBTP adoption with firm and date fixed effects, using clustered standard errors at the firm level to account for any potential within-firm correlation that could bias output. I find that, on average, SBTP adoption increases revenue per employee by about $1,686 relative to the same firm absent adoption, controlling for firm and date fixed effects. This finding is highly statistically significant at the $p < 0.001$ level. To further validate this finding, I use OLS to regress revenue per employee on adoption status, firm, sector, and date, yielding results that were very similar. In the interest of exploring these data and perhaps strengthening my case, I (separately) regress the derived performance index, firm employment, and cost of labor on SBTP adoption, also controlling for fixed effects via firm ID and date and using clustered standard errors at the firm level. I find a small but statistically significant increase in firm performance index equating to a roughly 0.03 standard deviation effect of SBTP adoption ($p < 0.01$), no real change in employment numbers ($p = 0.2$), and an

[5] These charts are under the Assumption and Robustness Checks section of the Appendix

increase of about \$5938 per period in firm labor cost ($p < 0.001$) indicating either increases to worker compensation or hours worked (all relative to the same firm who has not adopted, controlling for firm and date fixed effects). Among the statistically significant coefficients, the within-firm R^2 values are all between $4 - 9\%$ indicating that a small but existent portion of the observed variance in the outcomes can be explained by a firms choice to adopt the program. A link to the GitHub repository containing all of the code for this analysis is in the Regression Outputs section of the Appendix, alongside the main regression tables.

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Discussion & Limitations

The empirical results highlight increases to labor productivity among participating firms, and the absence of an employment effect indicates that firms may be getting more bang for their buck. The economically significant increase in labor expenditures is particularly interesting, and its mechanism should be further explored in future work. There are several limitations that exist to this analysis. Despite my assumption checks, it is still plausible that there could be unaccounted for parallel trends violations. Additionally, beyond the context of the United States, these findings should be taken with a high degree of skepticism. Different political and economic environments breed heterogeneous responses to stimulus, and my findings in this paper are not suggestive of trends outside of of the U.S. Finally, whether the results are adequate for making strong causal claims remains an open question. Each individual's threshold may vary, and I would like for readers to arrive at their own conclusions.

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Conclusion

In this paper, I explored the effects of the U.S Small Business Training Program on firm-level economic outcomes. Using panel data from 2010-2019, I estimated Difference-in-Differences using a Two-Way Fixed-Effects model, with standard errors clustered at the firm level to account for within firm correlation. My findings suggest that firms who chose to adopt the SBTP in 2013 had, on average, higher productivity gains than those that did not. This amounted to an estimated average revenue per employee that was \$1686.43 higher than that of the same firm who had not participated in the program, controlling for firm and date fixed effects. This makes a reasonable case in favor of funding programs that aid small businesses in improving productivity and efficiency. These findings add to the literature surrounding government funded training programs, and will ideally aid policy makers in the construction of more efficient social policy.

Appendix

Data Directory

firm_data: Firm Characteristics

- firm_id: Unique firm identifier (character), consistent across datasets.
- firm_name: Registered firm name (character) associated with each firm_id.
- firm_sector: Industry or sector classification for each firm (character).

ag_sales: Monthly Agricultural Sales

- firm_id: Unique firm identifier (character), consistent across datasets.
- date: Date of sales report; formatted as YYYY/MM/DD.
- sales_t: Quantity of sales per firm, in units per month (numeric).

monthly_data: Monthly Firm Statistics (Merged)

- date: Reporting date for firm statistics, formatted as YYYY/MM/DD.
- firm_id: Unique firm identifier (character), consistent across datasets.
- employment_t: Number of employees per firm per month (numeric).
- wage_bill_t: Total wage payments ($) by firm for the month (numeric).
- revenue_t: Total revenue ($) generated by a firm during the reporting month (numeric).
- adopt_t: Indicator for program adoption (0 = No, 1 = Yes); binary (numeric).

MERGED NEW: Derived Performance Metrics

- rev_per_employee: Revenue per employee in dollars (revenue_t/employment_t).
- wagerev_ratio: Ratio of wage bill to revenue (wage_bill_t/revenue_t); higher values indicate larger labor cost share.
- salesgrowth: Monthly growth rate in units sold (numeric).
- revgrowth: Monthly growth rate in revenue ($; numeric).
- ever_adopted: Whether or not a firm has at any point opted into the SBTP (factor).
- performance_index: Composite index based on normalized variables; 0 is average, positive above-average, negative below-average performance.

Summary Tables

Pre-2013 Firm-Level Summary Statistics		
Characteristic	**Not Adopted** N = 2,732[1]	**Adopted** N = 4,839[1]
Number Employed	72 (21)	60 (21)
Labor Cost	19,829 (8,093)	15,682 (7,459)
Revenue per Employee	3,876 (2,019)	3,053 (1,852)

[1] Mean (SD)

Figure 1: Pre-2013 Firm-Level Summary Statistics

Post-2013 Firm-Level Summary Statistics		
Characteristic	**Not Adopted** N = 6,257[1]	**Adopted** N = 10,978[1]
Number Employed	72 (20)	60 (21)
Labor Cost	20,851 (9,977)	22,729 (12,050)
Revenue per Employee	4,043 (2,517)	4,892 (3,726)

[1] Mean (SD)

Figure 2: Post-2013 Firm-Level Summary Statistics

Assumption and Robustness Checks

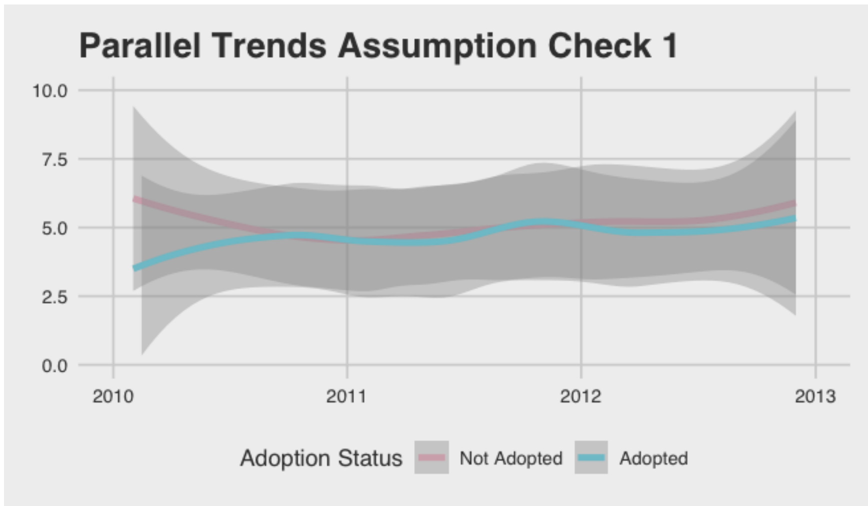

Figure 3: Parallel Trends Assumption Check 1

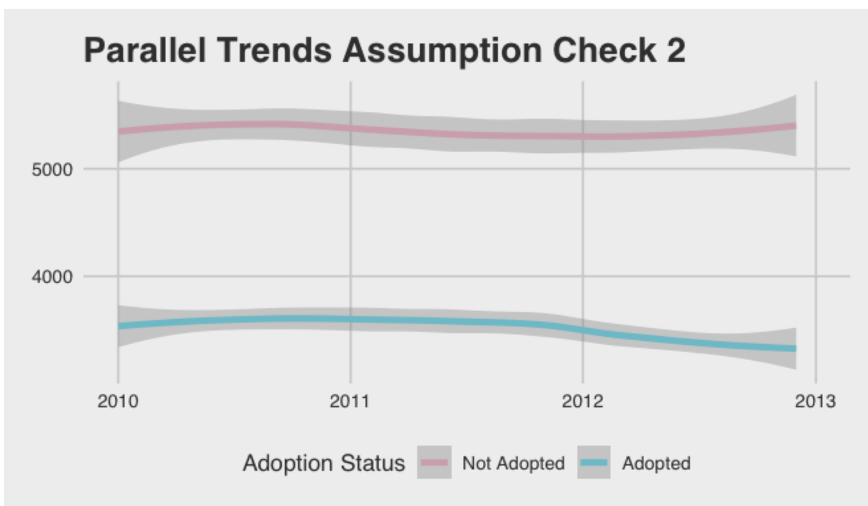

Figure 4: Parallel Trends Assumption Check 2

Regression Output

GitHub Repository: https://github.com/KieranCDouglas/metrics/tree/62c76050b787cfe454a68

	model_revperemp
Dependent Var.:	rev_per_employee
adopt_t	1,686.4*** (196.6)
Fixed-Effects:	------------------
firm_id	Yes
date	Yes
_______________	__________________
S.E.: Clustered	by: firm_id
Observations	24,999
R2	0.72171
Within R2	0.04909

Figure 5:

	model_performan..
Dependent Var.:	performance_index
adopt_t	0.0310** (0.0099)
Fixed-Effects:	-----------------
firm_id	Yes
date	Yes
_______________	_________________
S.E.: Clustered	by: firm_id
Observations	24,676
R2	0.01153
Within R2	4.85e-5

Figure 6:

```
                      model_employ
Dependent Var.:       employment_t

adopt_t          -0.1608 (0.1247)
Fixed-Effects:   ----------------
firm_id                       Yes
date                          Yes
_______________  ________________
S.E.: Clustered       by: firm_id
Observations               24,999
R2                        0.96798
Within R2                 8.13e-5
---
```

Figure 7:

```
                          model_wage
Dependent Var.:          wage_bill_t

adopt_t          5,938.3*** (641.1)
Fixed-Effects:   ------------------
firm_id                         Yes
date                            Yes
_______________  __________________
S.E.: Clustered         by: firm_id
Observations                 24,999
R2                          0.83613
Within R2                   0.08163
---
```

Figure 8:

Figures

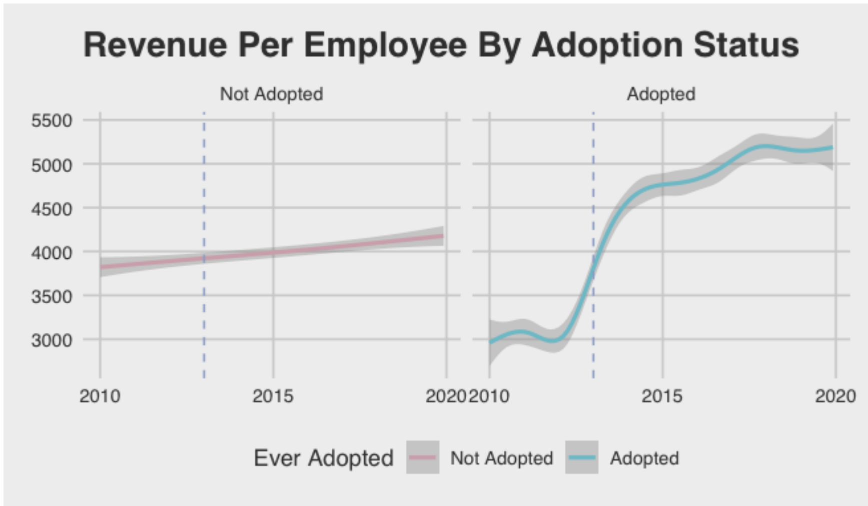

Figure 9: Revenue Per Employee By Adoption Status

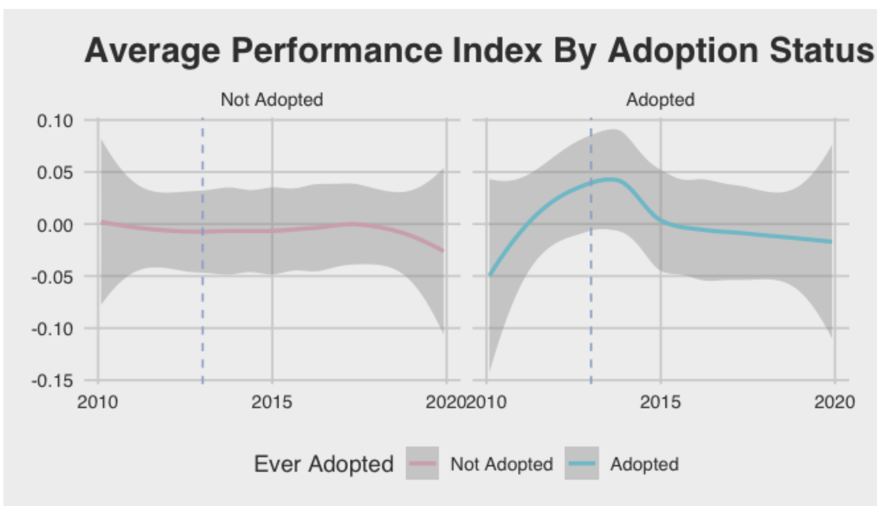

Figure 10: Average Performance Index By Adoption Status

References

[1] Robert Jay Dilger. *Small Business Management and Technical Assistance Training Programs*. Congressional Research Service Report R41352, 2013. https://www2.law.umaryland.edu/marshall/crsreports/crsdocuments/R41352_02272013.pdf