Social Media and Labor Market outcomes An analysis of Facebook effect on college graduates earnings

May 2025

Abstract

We provide quasi-experimental estimates of the impact of social media on earnings one, five, and ten years after graduation by leveraging a unique natural experiment: the staggered introduction of Facebook across US colleges. Our difference-in-difference estimates suggest that the rollout of Facebook at a college had a negative impact on student wages up to five years after graduation, along the whole income distribution. In the year after graduation, wages reduced by about 4% in comparison to pre-Facebook graduates. Heterogeneity analysis suggests the effect might be mainly driven by workers who graduated in Humanities subjects.

1 Introduction and Motivation

Social media have fundamentally transformed how individuals interact, communicate, and spend time. This paper examines the causal impact of exposure to social media during university studies on post-graduation earnings. Specifically, we investigate how access to Facebook during college years affected labor market outcomes up to ten years after graduation.

Our identification strategy exploits a unique natural experiment: the staggered rollout of Facebook across U.S. colleges between 2004 and 2006. Initially launched at Harvard in February 2004, Facebook gradually expanded access to students at other universities before becoming publicly available in September 2006. During this period, 775 U.S. colleges gained access at different times. Once an institution was onboarded, any student with a valid university email address could join the platform. As noted by Brügger (2015) and Wilson et al. (2012), adoption was rapid and widespread, especially among undergraduate students.

The staggered introduction of Facebook generates quasi-experimental variation in social media exposure during college. Combined with high reported take-up rates, this allows us to estimate the effects of social media exposure on future earnings. Using the PSEO dataset which include aggregate earnings of graduates one, five and ten years after graduation we find that exposure to the social has a negative and persistent effect on wages: having Facebook for the entirety of undergraduates studies with respect to not being exposed, is predicted to decrease median wages by 3,9% in the year after graduation with the effect not being completely absorbed after five years. The effect can be framed in a simple work-leisure framework, whereby access to the social distracts students form studying, lowering their GPA and thus reducing their bargaining power and consequently wage in the labor market.

The rest of the paper is structured as follows: section 2 will present the data sources and the creation of the measure of exposure to Facebook. Section 3 introduces our main regression model and discuss precisely identification assumptions. Results are presented in section 4 and heterogeneity analysis is briefly performed in section 5. In section 6 some placebo tests are performed. Section 7 discusses the limitations of the present study and concludes.

2 Data

We use two sources of data, the first comes from the replication files of Braghieri et al. (2022), which use Wayback Machine to recover the introduction dates of Facebook in a total of 842 US colleges.

For earnings we use the Post-Secondary Employment Outcomes (PSEO) Earnings, a dataset collected every three years since 2001 by the United States Census Bureau, which provides aggregate data of graduate earnings at the 25th, 50th, and 75th percentiles, one, five, and ten years after graduation, by institution, degree level, degree field, and graduation cohort. Each observation aggregates three subsequent cohorts together, that is earnings of graduates in 2001 are together with the ones of graduates in 2002 and 2003 provided they did the same major at the same institution. Participation is voluntary, and several states and private institutions are not able or willing to share their students' data. Hence, after combining the datasets, we are able to match 111 universities, which will be considered our treated sample (as they introduced Facebook before it was publicly available) [1], their distribution on the USA states is displayed in fig. 1

Given that we cannot observe actual data on the usage of Facebook per institution and major, we choose to restrict our analysis to undergraduates, as there is evidence of high usage of Facebook among such students, with take-up rates as high as 86% (Braghieri et al., 2022). Our main explanatory variable is built by taking the difference between Facebook public release and introduction of Facebook in the specific institution. It is normalized so to range from zero (no exposure during bachelor's studies) to one (full exposure). Thus, it is defined at the institution-cohort level and for each three-years cohorts group it represent the share of undergraduate years in which that cohort had access to Facebook. Given the timing of the observations and three-years cohort-aggregation structure of the PSEO dataset, which groups together graduates from 2001-2003,

[1] Of these, the University of Georgia gained access to social media the earliest, on the 21 of August of 2004.

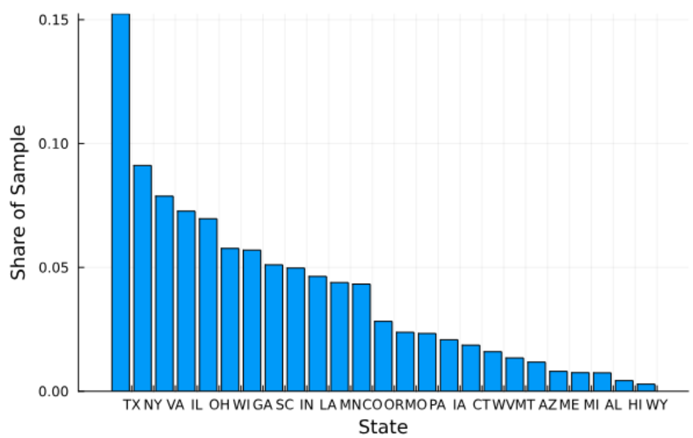

Figure 1: Distribution by state of early adopters institutions in matched sample

2004-2006, 2007-2009 and so on, we are force to consider graduates in 2009, which commenced undergraduate in 2005 as exposed as graduates in 2007 and 2008 even though if their university was an early beneficiary of Facebook they would have entered already with it.

3 Empirical Strategy

Our main model is:

$$log(earnings)_{c,i,m} = \beta exposure_{c,i} + \delta_c + \xi_i \times \gamma_m + \epsilon$$

Where δ_C, ξ_I, γ_M are fixed effects for cohorts of graduation, study institution and degree major, respectively.

The regression is run in the subsample containing information about graduates between 2001-2003 and 2007-2009 [2] , clustering the standard errors at the major-institution level. Under the assumption of constant selectivity into education institution and majors we can use data from the former cohorts as "pre-treatment" observations and data from the latter as "post-treatment" ones. Identification is then achieved under an additional assumption, the parallel trends assumption, which in our context can be expressed spelled out as constant relative percentage distances between wages conditioning on of same major in treated and untreated institutions absent the treatment. In other words, parallel trends is equal to asseting that, in percentage terms, the wages of graduates in the same graduation-year group and from same major, absent the treatment, would have evolved equally among treated and untreated institutions, that is, among university who had access to Facebook prior to its release to the public in February 2006 and those who had not, respectively. Practically, our two

[2] We exclude cohorts 2004-2006 as their exposure to treatment is unclear, results including them are displayed in section 8.2.

assumptions are that graduates wages of graduates in 2001-2003 to be a good proxy for the wages graduates in 2007-2009 would have earned had them completed their bachelor's in the same year, field and institution (1) and that the distance in earnings among graduate of the same major in different universities to be stable over the years of the analysis (2).

4 Results

Figure 2 displays the main results of the analysis for median wage, one, five, and ten years after graduation, while Table 8.2 in the appendix also includes the 25th and 75th percentiles of income distribution. On average, being exposed to Facebook for the entirety of the undergraduate program is estimated to reduce by more than 3,5% your wage in the year following graduation across all percentiles, with median wages being the most affected: a decrease of -3,9% is estimated for this group, vis a vis the -3,6% and -3,7% of the lowest and highest percentiles, respectively. The effect reduces to around -1,1% after five years and becomes zero after ten years, highlighting the high persistence of the shock.

We further characterized the interaction between the dependent and the main explanatory variable, checking whether the relation is concave or convex. We do so by including the square of exposure as an additional regression to our main specification. We find the newly added term to have a positive coefficient, implying that the rate at which the wage decreases with exposure is higher the shorter the length of exposure to Facebook. [3]

We rationalize these findings in a work-leisure framework: the more students are exposed to social media, the less they study, reducing GPA and eventually

[3] Regression tables are displayed in the appendix, Table 8.1.

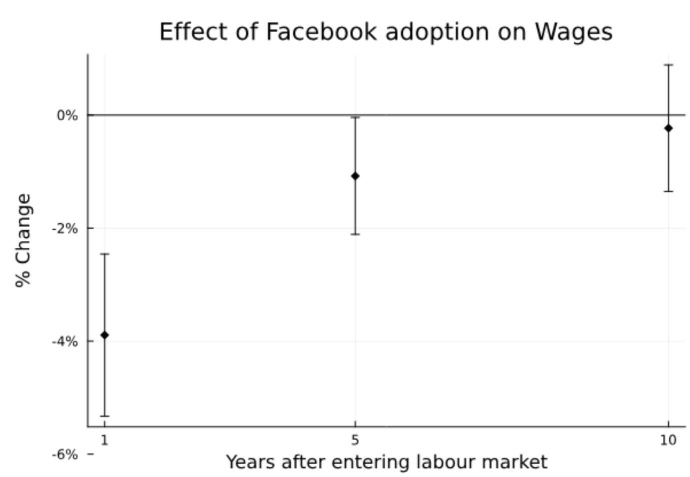

Figure 2: Estimated coefficients from the main model

obtaining lower wages in the labor market. Yet, the effect is stronger at the beginning: probably the adoption of the social demands more attention at the beginning, disrupting more established schedules, and is then integrated into a new study-leisure routine as time passes.

5 Heterogeneity

We then conduct heterogeneity analysis with the objective of understanding which field of study was mostly affected by the reduction in income. After organizing majors into four groups: STEM, Humanities, Social Sciences, and Others, we estimate the following triple differences model:

$$\begin{aligned} log(earnings)_{c,i,m} =& \beta_1(exposure_{c,i} \times Field_{c,i,m}) \\ &+ \beta_2 exposure_{c,i} \\ &+ \beta_3(Field_{c,i,m} \times \delta_c) \\ &+ \delta_c + \xi_i \times \gamma_m + \epsilon_{c,i,m} \end{aligned}$$

Results are displayed in fig. 3. Albeit there is no clear subgroup driving the results, the most affected group seems to be that of humanities students, while the lowest decrease in point estimate terms is recorded among wages of graduates in social sciences. Yet, the substantial overlap of most standard errors makes it hard to draw group-specific conclusions.

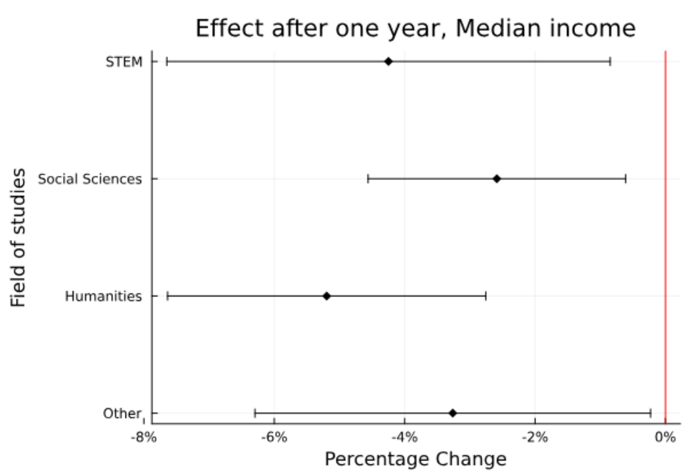

Figure 3: Results from Heterogeneity analysis, Median income

6 Placebo tests & sensitivity analysis

We test the credibility of our results in two ways. First, we provide evidence in favor of our identification assumptions by artificially assigning to cohorts 2004-2006, 2010-2012, 2013-2015, 2016-2019 and 2019-2021 the same level of exposure to Facebook as graduates from the same institution in 2007-2009 were subject to. Our placebo analysis for testing PTA consists of running the model's main specification several times, each time considering as treated one of the above cohorts and as controls the graduates in the three years before. Null effects support the solidity of PTA, as they hint at no difference between university graduates of the same major in different years, both before Facebook introduction and in the period where everyone had equal access to the social media. Results are displayed in section 8.3. Out of the 7 placebo comparisons in no case we find negative and statistically significant coefficient at a confidence level lower than 10% (yet we find positive effect when comparing median and Q3 earnings of graduates in 2019-2021 with the ones of 2016-2018).

As a second test, we conduct randomization inference. Concentrating on the effect one year after treatment, in the original sample (2001-2003 and 2007-2010) we randomly reassign the exposure measure to different universities in the treatment years, ten thousand times, running the model after each shuffle. Thus obtaining a distribution of coefficients against which we compare the ones estimated in our main regression, the results are displayed in fig. 4. For each percentile, we find our estimate to be statistically different from the distribution, implying that the probability that such a measure was found by chance is close to zero.

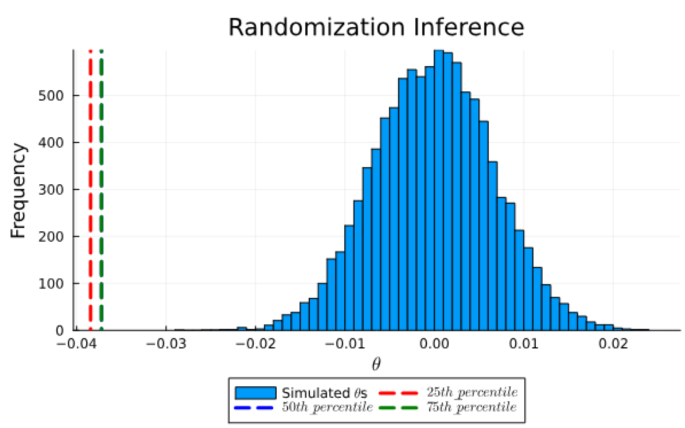

Figure 4: Randomization inference for wages one year after graduation

7 Conclusions

Exploiting the natural experiment created by the Facebook staggered expansions into colleges, this paper provided quasi-experimental estimates for the effect of exposure to the social media on the profile of wages of former university students one, five, and ten years after graduation, finding a negative and relatively persistent effect. Section two presented the PSEO data and data on the introduction of Facebook into colleges. It further discussed the way in which the main regressor - the measure of exposure to Facebook - was created. Section three presented the main TWFE model adopted for the analysis while section four presented the results, that suggest that exposure to Facebook for the whole duration of undergraduates studies is associated with a decrease of $\sim 4\%$ of your wage if compared to no exposure to Facebook at all, further analysis of relation among the two variables seems to suggest diminishing negative effects of social media exposure on wages. We make sense of these results in a basic work-leisure framework according to which the social media reduced the time students spent studying, thereby lowering GPA and finally wages in the labor market. Section five briefly explores heterogeneity, finding the effect to be more severe among students of humanities and STEM subjects, with Social Sciences students being the relatively less affected category. Robustness is performed in section six.

This study presents several limitations, the biggest being the aggregation of data in groups of three cohorts. This weakens our analysis in two ways: first, it forces us not to properly consider the exposure of graduates in 2009. As they started university in 2005, they should be assigned less exposure than older cohorts in universities treated before August 2005. Still, we are forced to consider them as exposed as students who entered college in 2003 and 2004. Secondly, it limits our ability to control for the 2008 crisis. In fact, the cohort fixed effects included in our model capture just a weighted average of the common shock that those cohorts experience, potentially biasing our estimates.

References

Braghieri, L., Levy, R., and Makarin, A. (2022). Social media and mental health. *American Economic Review*, 112(11):3660–93.

Brügger, N. (2015). A brief history of facebook as a media text: The development of an empty structure. *First Monday*.

Wilson, R. E., Gosling, S. D., and Graham, L. T. (2012). A review of facebook research in the social sciences. *Perspectives on psychological science*, 7(3):203–220.

8 Appendix

8.1 Main Results - Tables

	log(earnings) one year after graduation		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
FB Exposure	-0.037***	-0.039***	-0.036***
	(0.009)	(0.007)	(0.007)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	18,509	18,509	18,509
R^2	0.930	0.943	0.934

	log(earnings) five years after graduation		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
FB Exposure	-0.016*	-0.011*	-0.011*
	(0.007)	(0.005)	(0.006)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	18,192	18,192	18,192
R^2	0.948	0.959	0.952

	log(earnings) ten years after graduation		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
FB Exposure	-0.003	-0.002	0.000
	(0.007)	(0.006)	(0.007)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	18,118	18,118	18,118
R^2	0.947	0.958	0.953

Table 1: Regression results for log(earnings) at the 25th, 50th, and 75th percentiles across 1, 5, and 10 years after graduation

	log(earnings) one year after graduation		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Exposure	-0.912***	-0.872***	-0.584**
	(0.265)	(0.227)	(0.225)
Exposure^2	0.452***	0.431***	0.284*
	(0.137)	(0.117)	(0.116)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	18,509	18,509	18,509
R^2	0.930	0.943	0.934
Within R^2	0.003	0.004	0.003

	log(earnings) five years after graduation		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Exposure	-0.889***	-0.590***	-0.519**
	(0.210)	(0.170)	(0.183)
Exposure^2	0.452***	0.300***	0.263**
	(0.108)	(0.088)	(0.094)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	18,192	18,192	18,192
R^2	0.948	0.959	0.952
Within R^2	0.003	0.002	0.001

	log(earnings) ten years after graduation		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Exposure	-1.750***	-1.772***	-1.900***
	(0.202)	(0.177)	(0.212)
Exposure^2	0.903***	0.915***	0.982***
	(0.104)	(0.091)	(0.109)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	18,118	18,118	18,118
R^2	0.947	0.959	0.953
Within R^2	0.008	0.010	0.009

Table 2: Regression results with quadratic exposure terms for log(earnings) at the 25th, 50th, and 75th percentiles, one, five, and ten years after graduation.

8.2 Main specification - Including 2004

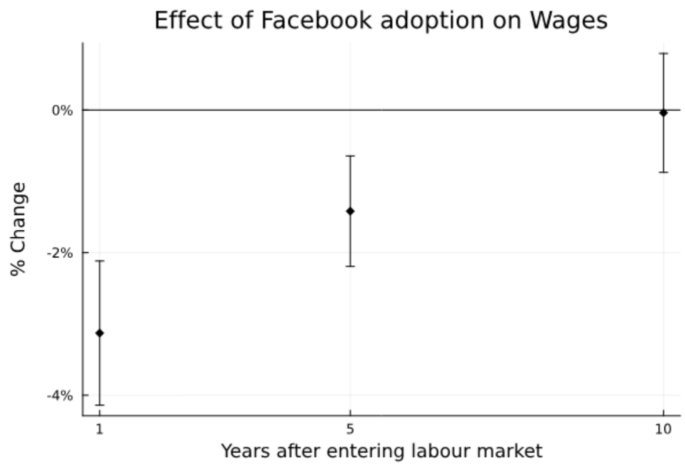

Figure 5: Main model estimates including 2004 as control, 50th percentile

	log(earnings) one year after graduation		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Exposure	-0.027***	-0.031***	-0.030***
	(0.006)	(0.005)	(0.005)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
grad_cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	33,891	33,891	33,891
R^2	0.931	0.943	0.930

	log(earnings) five years after graduation		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Exposure	-0.016**	-0.014***	-0.013**
	(0.005)	(0.004)	(0.004)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
grad_cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	33,158	33,158	33,158
R^2	0.941	0.955	0.944

	log(earnings) ten years after graduation		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Exposure	-0.003	0.000	-0.003
	(0.005)	(0.004)	(0.005)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
grad_cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	32,991	32,991	32,991
R^2	0.938	0.956	0.950

Table 3: Regression results including the 2004-2006 cohort as controls. Log(earnings) at the 25th, 50th, and 75th percentiles across 1, 5, and 10 years after graduation

8.3 Placebo

	Log(Earnings) 1 Year After Graduation Placebo Cohort: 2004, Control: 2001		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Synth Exp	-0.007	-0.004	-0.003
	(0.008)	(0.007)	(0.007)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	19,093	19,093	19,093

	Log(Earnings) 1 Year After Graduation Placebo Cohort: 2013, Control: 2010		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Synth Exp	-0.010	-0.008	-0.004
	(0.006)	(0.005)	(0.006)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	28,768	28,768	28,768

	Log(Earnings) 1 Year After Graduation Placebo Cohort: 2016, Control: 2013		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Synth Exp	0.009	0.015	0.017
	(0.006)	(0.005)	(0.006)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	30,431	30,431	30,431

	Log(Earnings) 1 Year After Graduation Placebo Cohort: 2019, Control: 2016		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Synth Exp	-0.008	-0.008	-0.008
	(0.006)	(0.005)	(0.005)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	29,635	29,635	29,635

Table 4: Regression results using synthetic exposure for cohorts 2001–2019 on log(earnings) one year after graduation at different percentiles. Includes major, institution, cohort, and major-institution fixed effects. Cluster-robust standard errors in parentheses.

	Log(Earnings) 5 Years After Graduation Placebo Cohort: 2004, Control: 2003		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Synth Exp	-0.010	-0.004	-0.006
	(0.006)	(0.005)	(0.006)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	18,673	18,673	18,673
R^2	0.953	0.965	0.955

	Log(Earnings) 5 Years After Graduation Placebo Cohort: 2013, Control: 2010		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Synth Exp	-0.004	-0.002	0.001
	(0.005)	(0.004)	(0.004)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	28,346	28,346	28,346
R^2	0.962	0.972	0.963

Table 5: Regression estimates using synthetic exposure for various cohorts on log(earnings) five years after graduation at different percentiles. Includes major, institution, cohort, and major-institution fixed effects. Cluster-robust standard errors in parentheses.

	Log(Earnings) 10 Years After Graduation Placebo Cohort: 2004, Control: 2001		
	25^{th} Percentile	**50^{th} Percentile**	**75^{th} Percentile**
Synth Exp	-0.002	-0.008	-0.004
	(0.006)	(0.005)	(0.006)
Major Fixed Effects	Yes	Yes	Yes
Institution Fixed Effects	Yes	Yes	Yes
Cohort Fixed Effects	Yes	Yes	Yes
Major & Institution Fixed Effects	Yes	Yes	Yes
Observations	18,451	18,451	18,451
R^2	0.950	0.965	0.960

Table 6: Regression estimates from placebo analysis using synthetic exposure, for log(earnings) 10 years after graduation across percentiles. The placebo treatment group consists of 2004-2006 cohorts, with the control group from 2001-2003.