College Licensing and Reputation Effects on the Labor Market

Fabiola Alba Vivar[⋆] José Flor-Toro[*] Matteo Magnaricotte[†]

March, 2024

Abstract

We study how better information on the quality of college education affects graduates' labor market outcomes. Between 2015 and 2021, Peru evaluated its existing colleges and awarded operating licenses to the 94 institutions meeting minimum quality standards. Using administrative labor market data and a staggered difference-in-differences approach, we find positive effects of positive news about graduates' human capital: within one year of the licensing announcement, wages increase by 8%, employment by 7%, hours worked by 8%, and the likelihood of being employed in a large firm and the public sector by 6% and 5%, respectively. Most effects are concentrated among graduates with shorter or no tenure at their current job, while we don't find significant effects for workers with longer tenure. This suggests that uncertainty about the productivity of workers is reduced over time, with public signals affecting workers' welfare.

We have benefited from data provided by the Peruvian Ministry of Education. We also gratefully acknowledge all the comments and suggestions from Alex Eble, Miguel Urquiola, Kiki Pop-Eleches, Bentley MacLeod, Sandra Black, Judy Scott-Clayton, Matt Notowidigdo, Chris Udry, Nicola Bianchi, Gaston Illanes, Cristian Maraví, Daniela Vidart and participants at NEUDC, LACEA, 9th UDEP-UBC Workshop for Young Economists, the Applied Microeconomics Seminar at Northwestern and the Development Colloquium and Applied Microeconomics Colloquium at Columbia.
[⋆] Teachers College at Columbia University, *fma2139@tc.columbia.edu,*, New York, NY.
[*] Northwestern University, *joseflortoro2021@u.northwestern.edu*, Evanston, IL.
[†] University of Chicago, *magnaricotte@uchicago.edu*, Chicago, IL.

1 Introduction

Reducing information asymmetries among market participants improves welfare in most theoretical models, but the empirical literature on the effects of mandatory information disclosure has yielded mixed results (Dranove and Jin, 2010; Ho et al., 2019). Labor markets are an important setting with informational asymmetries, yet little is known regarding the effects of releasing public signals about the quality of education at different colleges to firms. Colleges heavily invest to build their reputation and public signals of their quality are frequently released through rankings. Current evidence on the importance of college reputation for labor market outcomes is generally derived from changes in public information at the individual level (Macleod et al., 2017), or by comparing individuals with similar ability and knowledge but different affiliations (Anelli, 2020; Sekhri, 2020). Due to important empirical challenges, less is known about the effects of changes in college reputation. In this paper, we study how the release of information about college quality stemming from regulatory policy affects firms decisions and graduates' outcomes.

In 2015, the Peruvian Ministry of Education started the implementation of a higher education policy[1] that enforced compliance with a set of basic quality standards: colleges had to meet 8 quality requirements to receive an operational license and continue their activities. The licensing decisions were announced over the period 2016-2021 and resulted in the closure of 50 universities out of the existing 144.

We matched college records with monthly employment records which allows us to track labor market outcomes over the period 2014-2019 for each Peruvian who graduated college in the class of 2014, a year before the higher education reform begins. We take advantage of the staggered nature of licensing decisions to estimate a difference-in-

[1]Similar college regulations have been implemented in other countries in Latin America (like Brazil and Ecuador) as a response to stagnating achievement levels and trailing growth (Marta Ferreyra et al., 2017).

differences model by comparing changes in outcomes for individuals impacted by the decision through their college versus those whose college had yet to be affected. We conduct separate analyses for graduates of colleges that were granted or denied a license. This approach addresses the systematic differences in earnings trajectories of graduates from different colleges and provides us with suitable comparison groups.

Our analysis shows positive effects for graduates of colleges that were granted a license. We find that conditional on being employed, monthly wages increase by about USD 15 (or 8% of the baseline) on average during the first 12 months after the licensing decision. We also observe positive and significant effects on employment rates, hours worked, and the probability of working in a large firm and the public sector. These effects are heterogeneous, with individuals with shorter job tenure at the time the licensing decision was announced earning USD 50 higher monthly wages. Similar results are observed for other labor market outcomes, while we find no effects for individuals with longer job tenure.[2]

Our research builds upon prior literature studying the use of private or public signals in the hiring process. We expect the licensing process to affect labor market outcomes of university graduates because it provides more accurate information regarding the quality of education offered by various universities. Bassi and Nansamba (2022) shows that certifying workers' skills in Uganda led to more assortative matching and higher earnings conditional on employment. Bates (2020) shows that availability of objective benchmarks on the quality of potential hires increases mobility of the most productive workers. Carranza et al. (2022) assesses individual workers' skills and finds that credible public signals improve outcomes. In our setting, the regulator produces public signals about the quality of workers' education which can represent a proxy for productivity

[2] Additionally, we observe non-significant negative effects of the decision announcement for those who graduated from a college whichi did not get a license. However, any conclusion should be considered as suggestive due to the small sample.

(Rivera (2011) shows that educational credentials are the most common criterion used to evaluate resumes). Our finding highlights that significant improvements in market outcomes are produced by assessment of college quality, and not just of worker skills. In addition, we show that these public signals are most useful for workers with short or no job tenure.

Our research also contributes to the body of knowledge on college reputation. In a recent study, Eble and Hu (2022) shows how schools that changed names (to a more prestigious-sounding name) attracted more higher-aptitude students, and graduates from new renamed colleges had a small premium in an audit study. Similar to our work, this study shows how signals about college quality can impact labor market outcomes. Other studies have shown positive returns to college reputation (Macleod et al., 2017; Anelli, 2020; Sekhri, 2020).[3] In that sense, our work is closest to Macleod et al. (2017), who argue that college reputation partially substitutes for individual signals, when the latter are unavailable. They show that returns to reputation become smaller when more precise individual signals become available which is similar to the Peruvian context as well as many other economies like the US. Other recent work has focused on reputation in elite institutions, finding that accessing more reputable colleges can increase individuals' wages even when they do not appear to improve their graduates' skills (Anelli, 2020; Sekhri, 2020).[4] In our setting, firms are likely to update their beliefs regarding college graduates in response to the results of the licensing process. In contrast to papers that take reputation as fixed and use variation in the availability of individual-level signals, our research examines the impact of a policy that directly influences a college's reputation, and consequently, the labor market outcomes

[3] Several studies have estimated labor market returns of college attendance in different contexts (see recent examples in Grosz (2020); Montoya et al. (2018); Zimmerman (2014)).

[4] Arteaga (2018) also documents that demand for college graduates in an elite college in Colombia decreased following cuts to the university curriculum (i.e. a reduction in courses required for Economics majors), showing that employers react to changes in human capital of workers.

of its graduates. Our findings show that outcomes react to the policy in a manner consistent with the presence of asymmetric information about the quality of education among workers and with a process of on-the-job information production.

The next section discusses the relevant institutional context in the Peruvian higher education system. Section 3 describes the data used in our analysis. Section 4 presents the empirical strategy, while Section 5 presents and discusses our results. Section 6 concludes.

2 Background

2.1 Higher Education Regulation in Peru

In the early 1990s, following a severe economic crisis, Peru transitioned to an open market adopting market deregulation policies and promoting the private sector. These changes were in line with similar reforms enacted in other Latin American countries during the same time period. Among these reforms, some of them were focused on the education sector: with the approval of Law No. 882 in 1996, the Peruvian Congress reduced market entry barriers and allowed for-profit universities in the system.

Unlike the 90s, Peru experienced sustained economic growth in the following decade. Not surprisingly, access to higher education grew significantly and the number of colleges increased rapidly to match the demand. However, in later years, policymakers and public opinion showed concerns regarding the labor market outcomes of college graduates. Yamada et al. (2013) suggests that a reason for the deterioration in the quality of professionals is the lower level of skills of the last generations of students, coming from low-quality universities. This issue is part of a larger body of literature documenting disparities in the quality of higher education options in Peru (Díaz, 2008; Yamada et al., 2015). In an attempt to alleviate these concerns, the Peruvian Congress implemented a moratorium on the creation of new universities in 2012, with the aim of restricting the entry of low-quality institutions. The moratorium effectively prohibited the creation of both public and private universities and the opening of new branches. Subsequently, already-established universities undergo a licensing process, which is the focus of this paper and its detailed in the following section.

2.2 The Licensing Process

Following a major Higher Education Reform (Law No. 30220), the Peruvian government created the National Superintendence of Higher University Education (SUNEDU) in 2014. The following year, SUNEDU was tasked with the enforcement of minimum quality standards in the higher education system, through the licensing and the continued supervision of universities.[5] The conditions to obtain an operating license required compliance with the following requirements: (1) having clear academic objectives and (2) academic plans for each degree; (3) having good standing infrastructure and equipment; (4) having a research agenda; (5) faculty with at least a Master's or Ph.D. degree, and at least 25% of faculty should be full-time professors; (6) provision complementary services (like health and psychological services); (7) establishment of job placement mechanisms, such as job banks and (8) ensuring institutional transparency.[6]

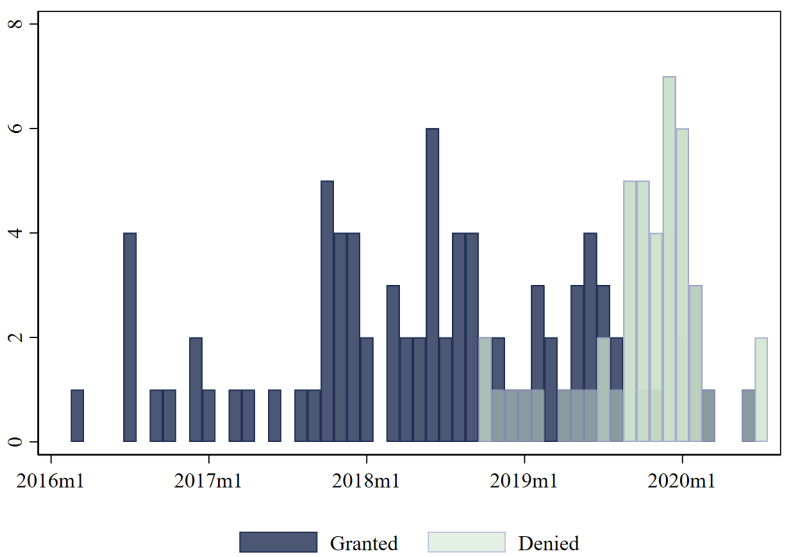
All universities in the country, whether public or private, were required to meet each of these minimum requirements without exception. Failing to meet even one of these standards was sufficient grounds for license denial. At the end of the licensing process in early 2021, a total of 50 universities out of 144 were denied an operating

[5]In addition to overseeing compliance with the Ministry of Education's regulations, SUNEDU has the authority to impose sanctions on institutions that fail to adhere to these rules. Its responsibilities extend to managing requests for changes to college names, monitoring the minimum requirements for degree-granting, publishing annual reports on the use of university benefits and the state of higher education in Peru, and administering statistics related to the sector.

[6]A document that compiles a minimum set of standards that universities should comply with, are publicly available here. Also, see Appendix A.1 for more details about these requirements.

license, which implied their closure within 2 years. Currently, the state of the licensing process is ambiguous since political opposition in the congress is trying to overturn this reform. In this paper, we focus on the announcements of the licensing decisions that happened between July 2016 and December 2019 due to data constraints, which will be further explained in the subsequent section. Figure 1 shows the distribution of licensing decisions over time. Although licenses were approved relatively evenly throughout this period, denials only commenced toward the end of 2018.

Figure 1: Licensing Decisions Over Time



It is also worth highlighting that the timing of decisions and announcements is not orthogonal to college quality metrics. In Appendix Figure A.1, we see how universities whose graduates enjoyed higher average wages and growth were more likely to be granted a license in the early months of the process. We can also see that after a first period of high wage growth, most wage trajectories become approximately linear. Nevertheless, elite universities were indeed more likely to get the license within the first months since the licensing process began. This follows the policymakers intuition that top universities should be able to get the license faster because they were more likely to comply with the requirements and establish a role model of college quality standards.

3 Data

In partnership with the Peruvian Ministry of Education, we matched educational records of recent graduates from multiple sources with their labor market outcomes. Mainly, we use a combination of two large administrative datasets. First, we collect administrative information on the educational achievement of all students who graduated from college between 2014 and 2019. This data set includes university attended, major, graduation year, and level of degree (BA, MA, etc.). In our case, we restrict our attention to bachelor-level graduates only. In our empirical analysis, we focus exclusively on the cohort that graduated in 2014, the year before the higher education reform started.

The second dataset consists of a panel that covers the period between January 2014 and November 2019 which includes monthly formal labor market outcomes for each individual, obtained from the Peruvian Ministry of Labor. This data comes from tax records and includes wages, number of hours worked, employer identification (anonymized), tenure, and sector. These two datasets are subsequently combined to obtain information about formal labor market outcomes for any BA graduate in 2014. It is important to highlight that this data does not include information about the informal sector, which employs about half of Peruvian college graduates. Our findings are subject to a significant limitation as the data does not cover the informal sector, which is a likely destination for recent graduates rather than unemployment. However, it is worth noting that wages in the informal sector are substantially lower on average and are typically below the minimum wage.

To generate our treatment variable, we use data obtained through SUNEDU's website which includes the outcome of the licensing process and the timing of the announcements. As depicted in Figure 1 and discussed earlier, this provides us with 50 colleges that were shut down and 94 that were granted a license. However, we only include licensing announcements until the end of 2019. For our empirical analysis, we exclude 5 elite universities from the sample. As seen in Figure 2, elite college graduates have substantially higher levels of income with wage trajectories that grow at a faster pace. In sum, elite college graduates earn 50 percent more than other college graduates, and this difference persists over time. Additionally, elite colleges were more likely to receive a license first, as confirmed by our use of machine learning techniques to predict the timing of licensing using the 2010 University Census (CENAUN) data. We find that indeed those elite colleges where ranked first on the probability of both getting the license and getting the license first.[7] In contrast, non-elite colleges are harder to predict in terms of quality and surprisingly more comparable. To summarize colleges by type in our sample, Table 1 shows relevant statistics for the variables in our data. We can observe that graduates from licensed universities have higher levels of income, are more likely to work in a large firm, and are also more likely to graduate from a public university.

4 Empirical Strategy

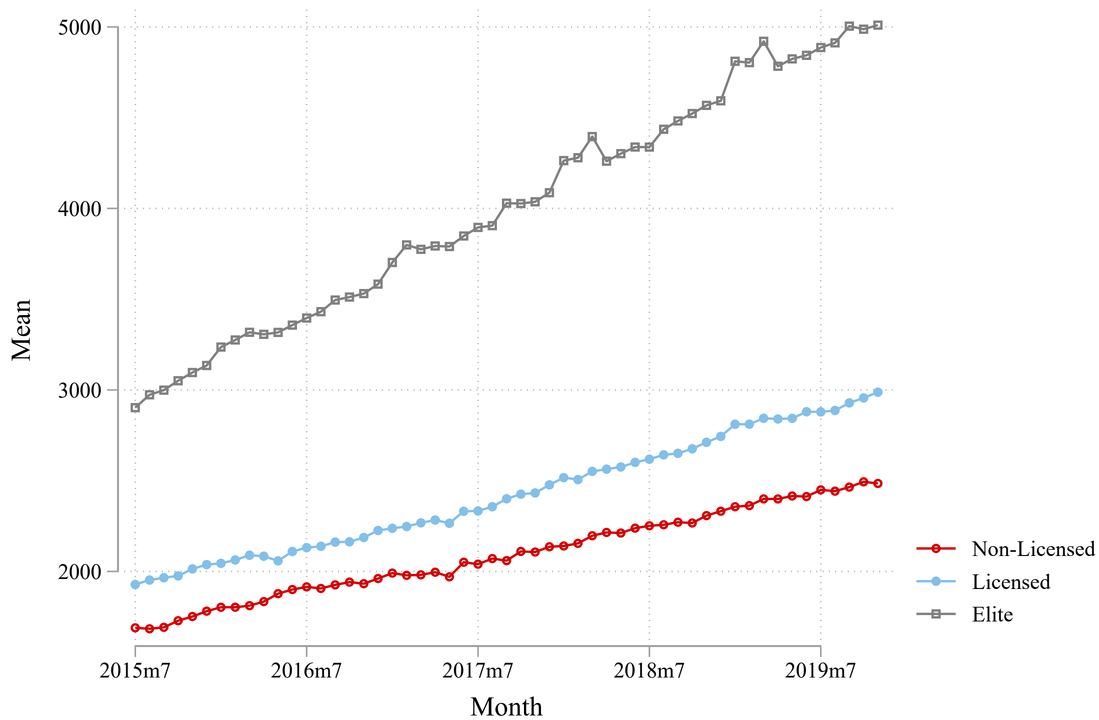
Our empirical strategy is based on a difference-in-differences (DiD) approach with staggered treatment, given the roll-out of the licensing decisions. We assume a model of the type:

$$y_{t,i} = \sum_{\tau} \sum_{c'} \beta_{\tau,c'} D\{c' = c(i)\} D\{\tau = t - g(c(i))\} + \psi_t + \mu_i + e_{t,i} \tag{1}$$

where $g(c(i))$ is the period in which the licensing decision was announced for college

[7]See Appendix A.2 for more details about these results.

Figure 2: Average Monthly Wages of Recent Graduates



$c(i)$ attended by individual i, and t indexes different months. $\beta_{\tau,c}$ is the parameter of interest: the effect of exposure to the license shock on outcome $y_{t,i}$ (e.g. earnings). The term $\beta_{\tau,c}$ highlights the possibility of effects being heterogeneous for different colleges (c) and depending on exposure length $(t - g(c(i)))$. [8]

One important aspect to define is a proper comparison group. Given that all colleges were part of the licensing process, all of them obtained a licensing result. We define two types of treatment: *Granted* for those universities which obtained a license and *Denied* for those that did not obtain a license. Because universities that will be granted a license are unlikely to offer a proper comparison to universities that are denied one, and vice versa, we estimate separate models depending on the type of treatment. The

[8]In our setting, heterogeneous treatment effects are likely to arise from heterogeneity in the employers' beliefs update induced by the results of the licensing decision.

Table 1: Summary Statistics

	(1) Total	(2) Granted	(3) Denied
Employed	0.490	0.492	0.472
	(0.500)	(0.500)	(0.499)
Wages	2412.0	2443.1	2104.3
	(1728.0)	(1748.7)	(1473.2)
Hours Worked	197.7	197.6	198.6
	(60.24)	(60.28)	(59.82)
Tenure	16.31	16.27	16.68
	(14.65)	(14.63)	(14.87)
Public Employer	0.0989	0.0988	0.100
	(0.299)	(0.298)	(0.300)
Large Firm	0.712	0.715	0.676
	(0.453)	(0.451)	(0.468)
Public University	0.390	0.431	0
	(0.488)	(0.495)	(0)
Female	0.532	0.529	0.559
	(0.499)	(0.499)	(0.497)
Engineering Major	0.245	0.247	0.229
	(0.430)	(0.431)	(0.420)
Health Major	0.115	0.113	0.134
	(0.319)	(0.316)	(0.341)
Law and Buss. Major	0.512	0.504	0.583
	(0.500)	(0.500)	(0.493)
Education Major	0.0432	0.0438	0.0374
	(0.203)	(0.205)	(0.190)
Observations	3,754,202	3,396,081	358,121

Notes. Data sources are confidential and anonymized administrative data from the Peruvian Ministry of Education and the Peruvian Ministry of Labor. We use monthly labor market data from 2014-2019. Wages are measured in Nuevos Soles ($PEN = 0.3USD$). Elite colleges are excluded from this sample.

focus of this paper is on the ones who obtained the license. Nevertheless, we also provide results for those who got the license denied. In both cases, we include individuals who graduated with a bachelor's degree in the 2014 class as described in the previous section.

Allowing for heterogeneity and dynamics in the typical difference-in-difference staggered design requires us to avoid standard "two-way fixed effects" (TWFE) regressions, as they have been shown to be problematic in such setups (Goodman-Bacon (2021), Baker et al. (2021)). The frailties of TWFE estimations come from the inclusion of already-treated groups within the comparison group: if treatment effects are heterogeneous, the TWFE estimator will be biased.[9] Several recent papers have introduced solutions to address these problems, by making sure that only never-treated or not-yet-treated units are included in the comparison group. Similar to the basic difference in differences, these papers rely on parallel trends assumptions to build consistent estimators that do not suffer from the same problems.[10]

Our difference-in-differences methodology requires two important assumptions: first, the *staggered treatment adoption* assumption which requires that once a unit participates in the treatment, they remain treated and the treatment status cannot go on and off. In our setting, the universities that were granted or denied an operating license did not change their status. Second, the *parallel trends assumption based on no-yet-treated units* where we can use the no-yet-treated groups as valid comparison groups.

We follow an approach similar to the one introduced by Cengiz et al. (2019).[11] This approach looks at each treatment occurrence in isolation, sidestepping the problem introduced by staggered treatment. Because this approach builds event-specific datasets and stacks them on top of each other, it is also known as "stacked regression". For each licensing event (which can comprise several universities if their events are contemporaneous) we select a window of 12 months before and after the treatment event; control

[9]Dynamic effects, e.g. when treatment effect is growing as time from the event passes, also lead to misspecification and inconsistency when a constant effect is assumed. This can be addressed by estimating treatment effects relative to event time (Borusyak et al. (2021)).

[10]See as examples of such new estimators Callaway and Sant'Anna (2021), Borusyak et al. (2021), and Sun and Abraham (2020).

[11]As a robustness check, we also follow Callaway and Sant'Anna (2021) to estimate the main results of the license decision and we find similar results.

units are chosen among those that are no-yet-treated during this window. Each dataset can then be indexed by g, the timing of the licensing event of the included treated units. For each dataset g, we estimate time fixed effects and individual fixed effects.

The treatment dummy is the only control shared across datasets: the estimated ATT will be a weighted average of the single ATTs that could be obtained from each dataset. Because the timing of treatment is unique in each dataset g, we can impose conditions on job tenure before treatment occurs. This allows us to obtain treatment effects for individuals who were just hired, by comparing them to individuals who were hired at the same time but who graduated from different colleges. We can then estimate our results conditional on tenure being short (0-2 months) or long (more than 10 months) and observe whether the certification value of the licensing decision varies along this dimension.

Finally, we address potential issues with identification. Difference-in-differences approaches require parallel trends to hold for treatment and control units. From Figure A.1 we can see that graduates from a group of licensed universities have systematically higher wages and enjoys faster wage growth over time. These universities are among the earliest treated ones and are considered elite universities in Peru. We provide evidence that the parallel trends assumption for the outcomes of graduates of those universities is unlikely to hold as seen in Figure A.1 and through a machine learning exercise that shows how these universities had a higher likelihood to get the license first (more details are described in Appendix A.2). For this reason, we exclude elite universities since they are unlikely to be affected by the licensing process and those graduates have systematically higher wages compared to the average population.

5 Results

5.1 The impact of the licensing decisions

First, we study the effects of the positive licensing decisions on main labor market outcomes following Cengiz et al. (2019) as detailed in the previous section.

5.1.1 Main Results

We look at the labor market results for those who graduated from a college that obtained a license. As seen in Table 2, graduates from universities that got the license enjoy higher wages, are more likely to be employed, work more hours, and are also more likely be employed in a large firm and the public sector during the first 12 months after the announcement. The positive signal of the licensing process also increased employment rates by 7% and the total amount of hours worked per month increased by 6 hours per month on average. When it comes to job quality, we also find that graduates from these licensed colleges are more likely to be employed in the public sector and work in the public sector, which is consistent with the fact that public employers have stricter hiring procedures that typically require diploma certifications. More importantly, we observe a significant increase in monthly wages. In column (1) we calculate wages conditional on being employed and the magnitude of the wage increase is equivalent to USD15 per month. When computing the overall wage increase for all college graduates, we find an increase of 8%, which is comparable to the typical adjustments of the Peruvian minimum monthly wage.

We can also visualize these effects on an event study as seen in Figure 3 where monthly wages increase significantly during the entire period studied, reaching increments up to USD 40 per month as seen in Figure 3 panel (b). Similarly, Figure 3 panel (d) shows how employment rates substantially increase over time in pair with wages

Table 2: Difference-in-Differences Estimates for ATT

	Wage	Wage (Unc.)	Empl.	Hours	Large	Public
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	45.03**	73.29***	0.03***	6.257***	0.018***	0.005*
	(18.29)	(15.89)	(0.0058)	(1.115)	(0.0038)	(0.0029)
Mean	2295.2	911.4	0.398	76.06	0.283	0.0847
N	1014700	2563383	2563383	2563383	2563383	2563383

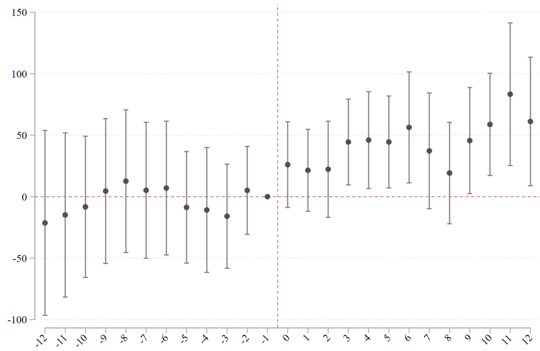
Notes. *** $p < 0.01$, ** $p < 0.05$,* $p < 0.10$. Regressions include individual, major, and job tenure fixed effects. Time fixed effects at the monthly level are estimated separately for individuals with different major and job tenure. ATTs are calculated for the first 12 months after the license announcement. Standard errors clustered at the college level are in parenthesis. Column (1) shows the effects for average wages conditional on being employed, while Column (2) shows the total effect for wages unconditionally. Monthly wages are measured in Nuevos Soles (PEN) ($PEN \approx USD0.3$). Columns (3), (5), and (6) are reported in percentage points; column (4) is measured in hours.

and the total amount of hours worked per month and the probability of working in large firm. However, the likelihood of working in the public sector seems rather stable over time as shown in panel (f). Notice that these event studies can help visualize how likely we are to satisfying our parallel trends assumption. All event study graphs report pointwise confidence intervals, but we are in the process of implementing simultaneous confidence bands as recommended in Olea and Plagborg-Møller (2018). The current version of Figure 3 shows either no evidence of pre-trends or suggestive trends that might lead us to underestimate the ATT (see panels (b), (c), and (d)).

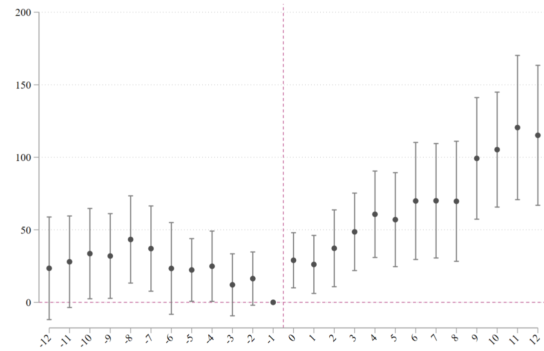
5.2 Heterogeneous Impact by Groups

We turn to studying the heterogeneous effects of the licensing by groups, including gender, major and whether the worker's university is a private or public institution. We focus on the wage effects we observed in the previous section. As seen in Figure 4 there is no relevant differential effect by gender when it comes to the wage premium obtained by graduates whose college obtained a license. Additionally, we find that the effect for public college graduates is almost double that of private college graduates, even though the two are not statistically different. It is important to highlight that in the Peru-

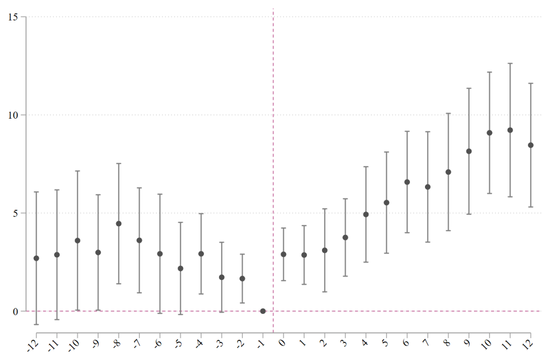
Figure 3: Event Study for Graduates of Licensed Universities



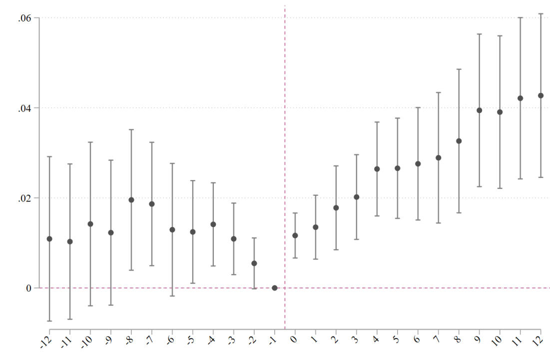
(a) Wages



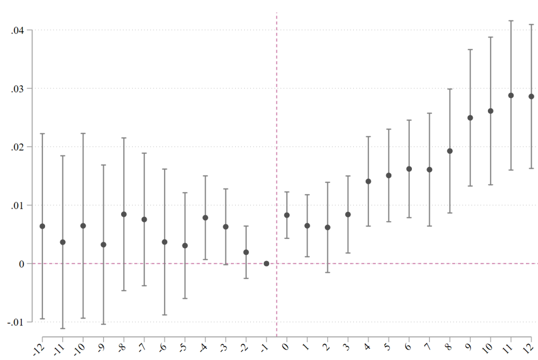
(b) Wages (Unconditional)



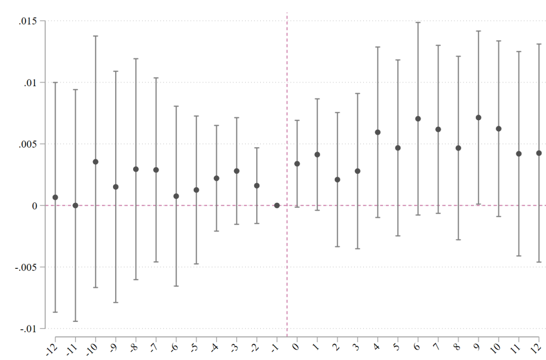
(c) Total Hours



(d) Employment



(e) Large Firm

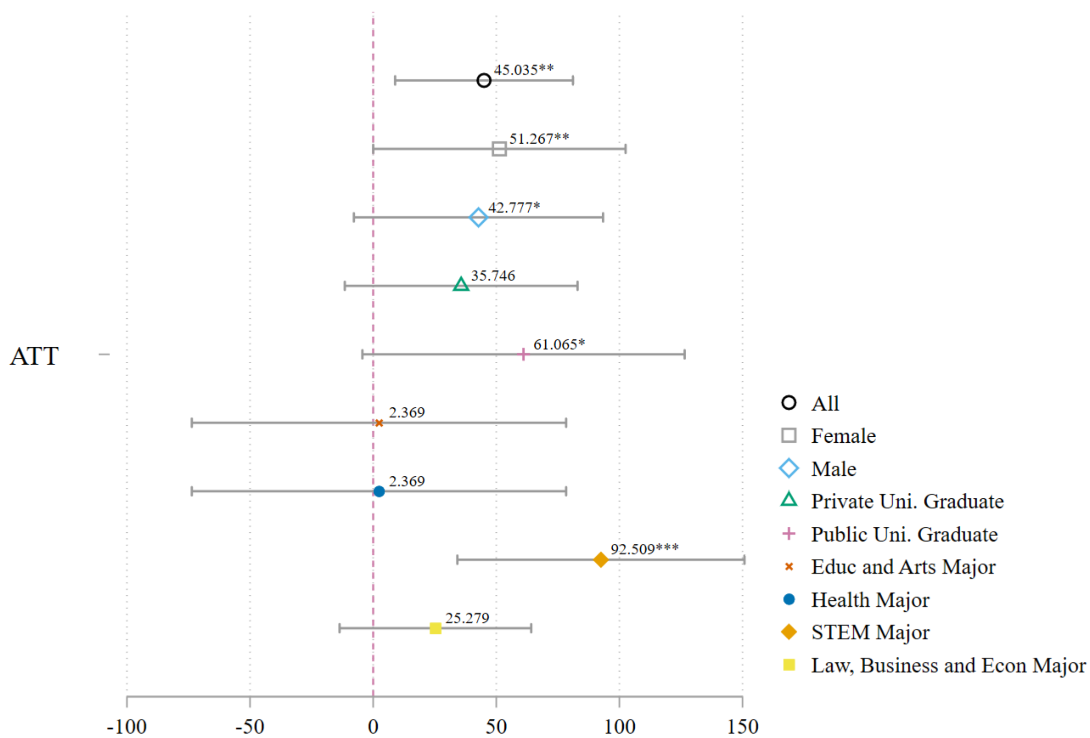


(f) Public Employer

Notes. Regressions include individual, major, and job tenure fixed effects. Time fixed effects at the monthly level are estimated separately for individuals with different major and job tenure. Confidence intervals are testing pointwise hypothesis and have no adjustment. Errors are clustered at the college level. Panel (a) shows the effects for average wages conditional on being employed, while panel (b) shows the total effect for wages unconditionally. Monthly wages are measured in Nuevos Soles (PEN) ($PEN \approx USD0.3$). Effects in panels (d), (e), and (f) are measured in percentage points; effects in panel (c) is measured in hours.

vian higher education market, private universities are less selective in comparison with public universities which are not only more competitive but also tuition-free, attracting talented students. In this sense, private universities without an established reputation (as elite private universities might have) could have seen the license announcement as a more relevant positive signal. However, we observe that public college graduates are the ones who obtained most of the wage benefits.[12] Finally, the estimate for STEM graduates is much higher than that of other majors, with a point estimate of about USD30, or double that estimated for the whole sample.

Figure 4: Estimated Wage Effects by Groups



Notes. *** $p < 0.01$, ** $p < 0.05$,* $p < 0.10$.Regressions include individual, major, tenure and month-fixed effects. ATTs are calculated for the first 12 months after the license announcement.

[12]See Flor-Toro and Magnaricotte (2021) who discuss the differences between private and public universities in Peru.

5.3 Heterogeneous Impact by Tenure

In this section, we focus on the heterogeneous effects of the positive licensing decisions by tenure. For this analysis, we impose conditions on job tenure right before treatment occurs. We can estimate our results conditional on tenure being short (0-2 months) or long (more than 10 months).

Table 3 shows the results for short tenure on Panel (a) and for long tenure in Panel (b). We find significant positive effects on wages for individuals with short tenure as well as employment rates, hours worked, the likelihood of working on a large firm. The magnitude of the effect is approximately USD 50 per month or an increase of 6 percent relative to the mean wage in our data. We do not find significant effects on the likelihood of working in the public sector. On the other hand, individuals with longer tenure do not appear to experience significant gains in any labor market outcome except for employment rates and the likelihood of working in a large firm. Treatment appears to lower tenure and increase employment, which is consistent with individuals moving across jobs but they do not obtain any wage premium.

Figures 5 and 6 shows the dynamics of treatment effects estimated for each of the outcomes and samples used in Table 3. In Figure 5 we can see that pre-treatment coefficients are generally small and not significant for all outcomes. The estimates for wages in panel (a) show that the effect is increasing over time, reaching up to 200 Peruvian Soles or an 8% increase compared to the mean wages in the data. This is quite an important effect in light of the fact that the increase realized within 1 year from the announcement. Employment rates also see an increase after 6 months of the announcement up to 0.04 or an 8% increase compared to the mean employment rate in the data. In contrast, the dynamics shown in Figure 6 for those with long tenure are noisier. Nonetheless, we see a small increase in employment rates suggesting that they were more likely to remain in the formal labor market, especially in large firms.

Table 3: ATT of a Positive Signal for Individuals by Tenure

Panel A: Short Tenure

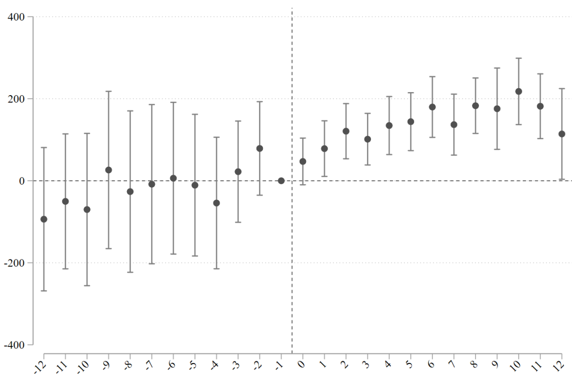
	Wage	Wage (Unc.)	Empl.	Hours	Large	Public
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	147.4***	164.8***	0.048***	10.18***	0.032**	-0.006
	(29.59)	(44.18)	(0.0158)	(3.857)	(0.0162)	(0.00790)
Mean	2106.6	1296.3	0.616	118.0	0.438	0.125
N	141179	229694	229694	229694	229694	229694

Panel B: Long Tenure

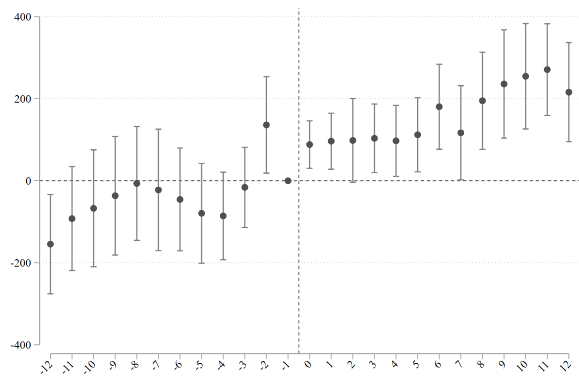
	Wage	Wage (Unc.)	Empl.	Hours	Large	Public
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	15.08	58.96	0.035*	4.501	0.037*	-0.004
	(42.19)	(51.54)	(0.0195)	(4.254)	(0.0186)	(0.0140)
Mean	2356.7	2137.0	0.907	176.2	0.664	0.133
N	109098	120377	120377	120377	120377	120377

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions include individual, major, and month fixed effects. ATTs are calculated following the estimator for the first 12 months after the license announcement. Standard errors are in parenthesis. Monthly wages are measured in Nuevos Soles (PEN) ($1\ PEN \approx 0.3 USD$). Short-tenure workers are those who were working at their main job for less than 3 months. Long-tenure workers are those who were working at their main job for more than 10 months.

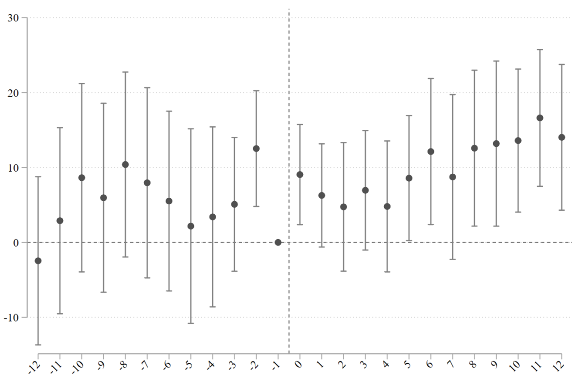
Figure 5: Effects of a Positive Signal on Individuals with Short Tenure



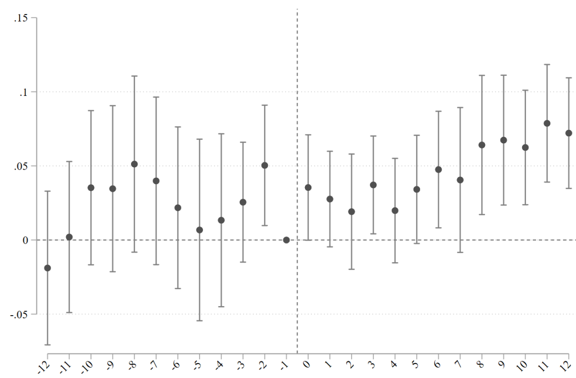
(a) Wages



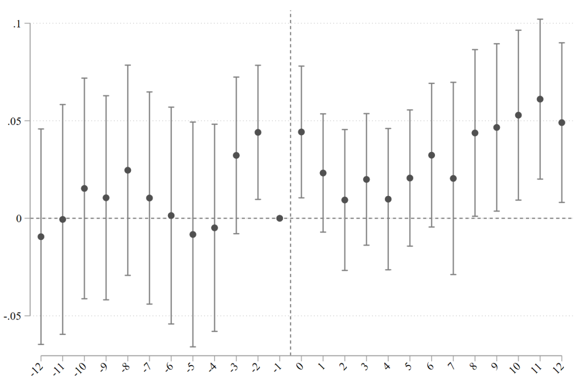
(b) Wages (Unconditional)



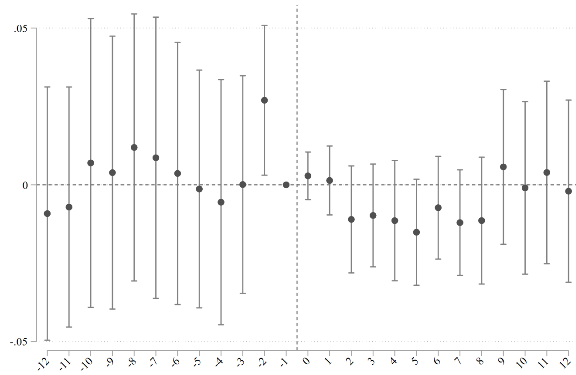
(c) Total Hours



(d) Employment



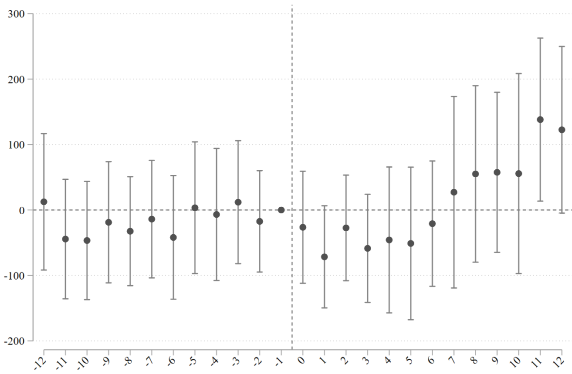
(e) Large Firm



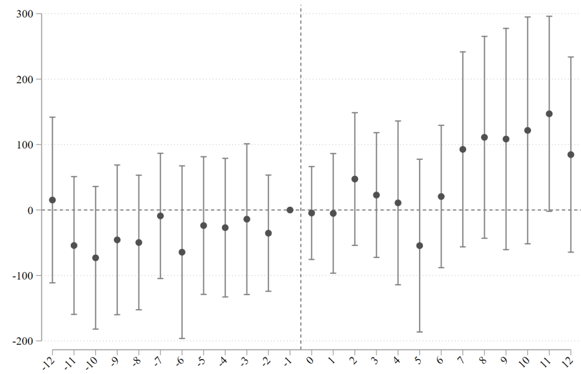
(f) Public Employer

Notes. Regressions include individual, major, and month fixed effects. Monthly wages are measured in Nuevos Soles (PEN) (1 $PEN \approx 0.3USD$). Short-tenure workers are those who were working at their main job for less than 3 months.

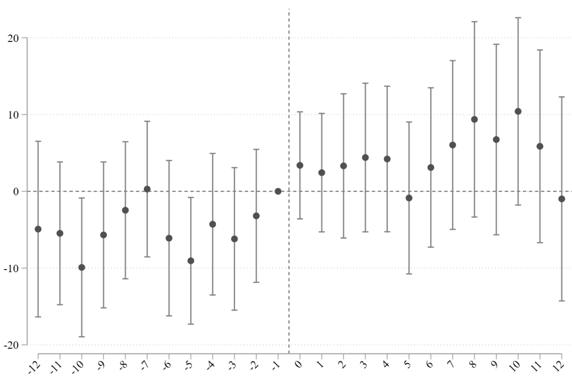
Figure 6: Effects of a Positive Signal on Individuals with Long Tenure



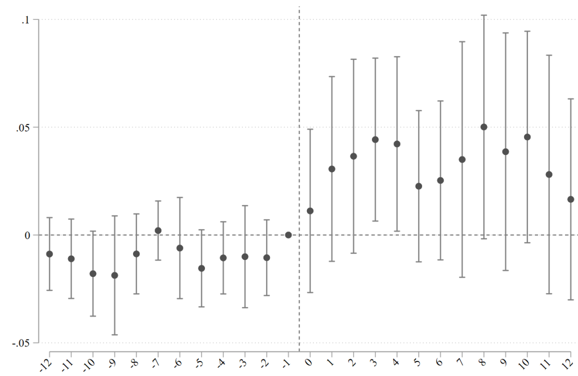
(a) Wages



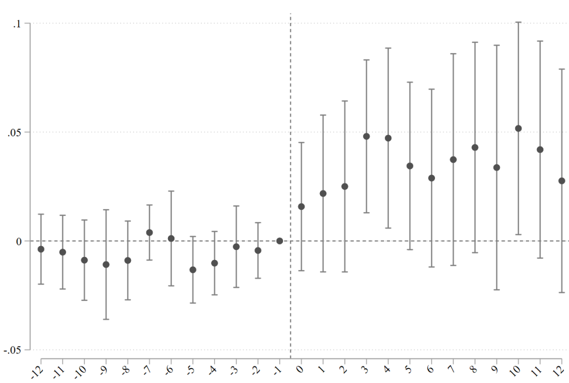
(b) Wages (Unconditional)



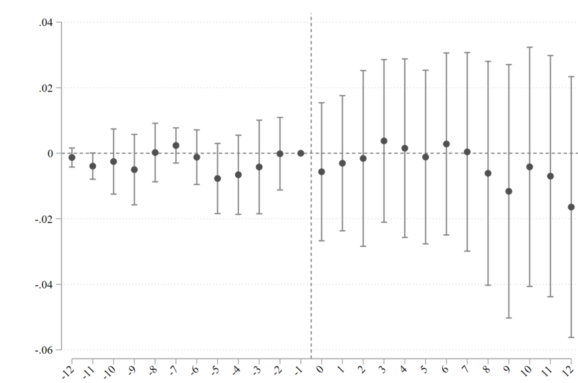
(c) Total Hours



(d) Employment



(e) Large Firm



(f) Public Employer

Notes. Regressions include individual, major, and month fixed effects. Monthly wages are measured in Nuevos Soles (PEN) (1 $PEN \approx 0.3USD$). Long-tenure workers are those who were working at their main job for more than 10 months.

5.4 Discussion

Our findings indicate that obtaining a license had a positive impact on the labor conditions of former graduates from licensed colleges, particularly in terms of higher wages and employment rates. Interestingly, the effects were different depending on the tenure of individuals at their job before the public announcement. Those with a short tenure of 0-3 months experienced an increase in monthly wages of 147 Nuevos Soles (PEN) or around USD 50 during the first year after the announcement. This wage increase was linked to an additional workday per month. Moreover, they were more likely to work in large firms, which typically provide better labor conditions such as private health insurance. On the other hand, individuals with longer tenure (more than 10 months) at their job at the time of the announcement had a higher probability of employment. This was not accompanied by a significant increase in monthly wages, suggesting that they changed jobs to get other types of benefits.

Unfortunately, our dataset does not provide a precise estimation of the effects of license denial. However, the evidence that we could collect suggests that the impact was probably not strongly negative for those who work in the formal sector. This could be attributed to the fact that several universities in this group were already known to offer low-quality education before the licensing process, and hence employers may not have revised their beliefs after the announcement. Therefore, additional analysis with alternative methods and larger sample sizes may be required to better understand the actual effects of license denial.

Our findings should be interpreted in light of the fact that our data only covers formal labor market outcomes. Peru is a country that, to this day, has a large amount of labor informality, even among college-educated workers. Nonetheless, as the formal sector typically offers greater protections and benefits for workers, our study highlights relevant benefits from the licensing process, with no evidence of downsides.

6 Conclusion

In this paper, we studied the effects that signal produced during a college licensing process had on college graduates' labor market outcomes. Our results indicate that the announcement of a college complying with quality standards leads to a positive effect on wages, particularly for individuals with short tenure, resulting in increased turnover. We also do not find effects for those with long tenure suggesting that the effect on this positive signal is only relevant when the employer has little information regarding their employees.

However, we were unable to precisely estimate the effects of negative signals, such as license denials, due to data limitations. Nevertheless, the current evidence suggests that labor market outcomes of graduates from these universities were unlikely to be negatively affect in a meaningful way.

Certification of education quality can benefit college graduates by improving their match with employers and increasing their ability to bargain better working conditions. Our study suggests that benefits are mainly affecting workers whose productivity was only briefly observed by their employers. Workers with longer tenure appear only to enter the labor market without capitalizing on the information released.

Further exploration of how workers and employers learn from the information released, and how this affects their bargaining process, could increase the ability of scholars to understand when and to what extent regulation can benefit the proper functioning of labor markets through certification and information production.

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A Appendix

A.1 Additional Figures and Tables

A.1.1 Additional Figures

Figure A.1: Average Monthly Wages by University

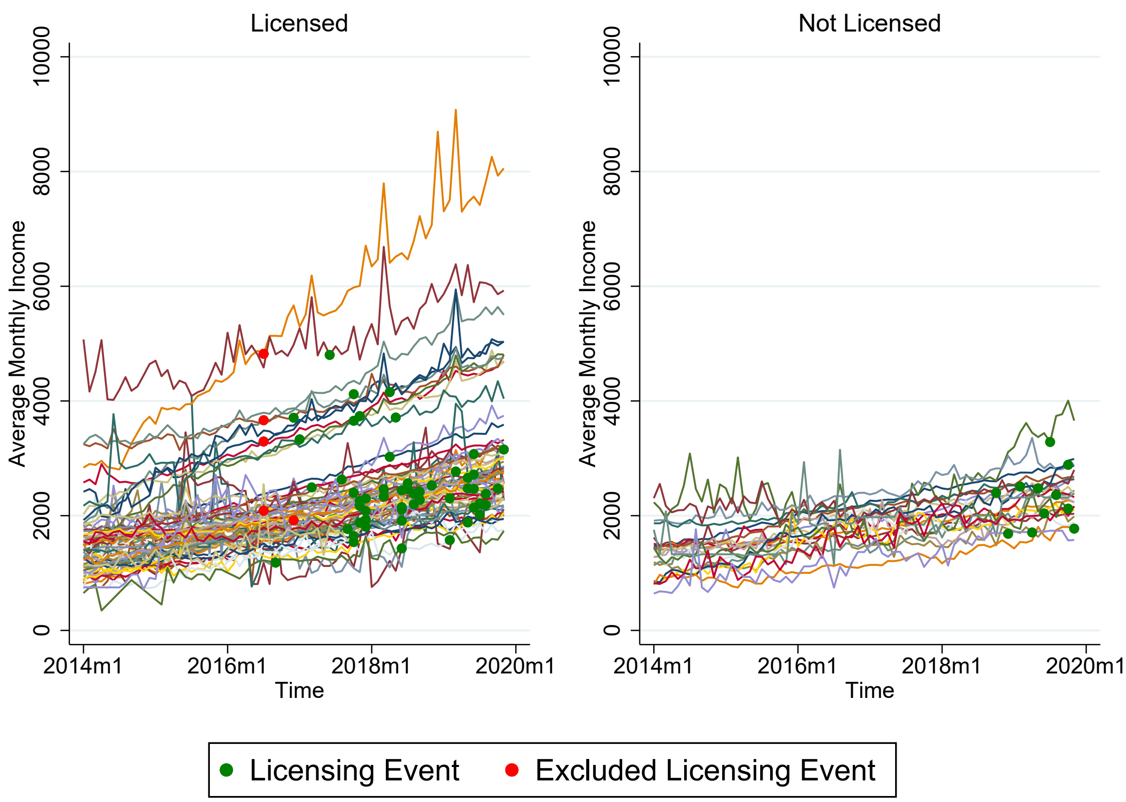


Table A.1: ATT Estimates of Granted License Colleges following Callaway and Sant'Anna (2021)

	Post-Treatment		**Pre-Treatment**	
	ATT	(s.e.)	Placebo	(s.e.)
Wages (PEN)	67.360 ***	(12.62)	-2.358	(21.66)
Employment	0.004 **	(0.00)	0.000	(0.00)
Hours Worked	-0.738	(0.87)	-0.809	(1.08)
Tenure	-0.463 *	(0.20)	-0.135 *	(0.08)
Public Employer	0.001	(0.00)	0.001	(0.00)
Large Firm	-0.003	(0.00)	-0.002	(0.00)

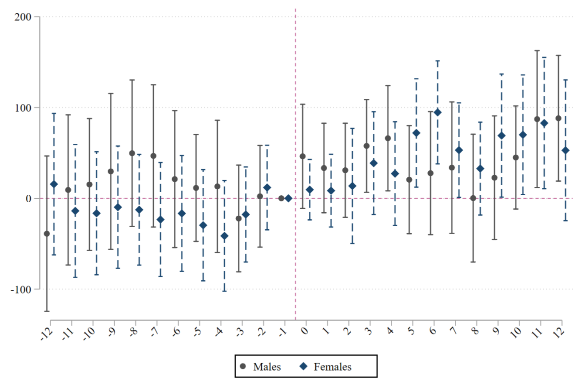
Notes. *** $p < 0.01$, ** $p < 0.05$,* $p < 0.10$. Regressions include individual and month fixed effects. ATTs are calculated using the Callaway and Sant'Anna (2021) estimator for the first 12 months after the license announcement. ATT (Pre) are the average treatment effects 12 months before the treatment. SE (Pre) are the standard errors for the ATT(Pre) estimates. Monthly wages are measured in Nuevos Soles (PEN) ($PEN \approx 0.3USD$). Tenure is measured as the total amount of working months in their main job.

Table A.2: ATT Estimates of Denied License Colleges following Callaway and Sant'Anna (2021)

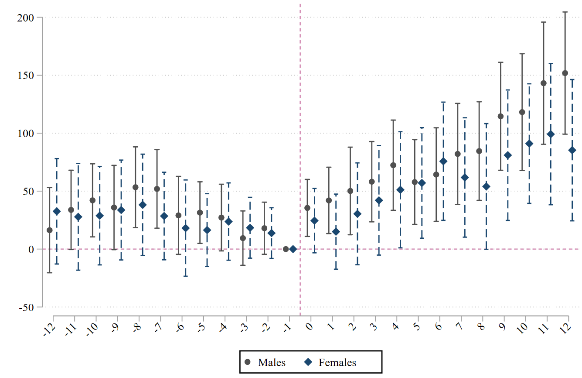
	Post-Treatment		**Pre-Treatment**	
	ATT	(s.e.)	Placebo	(s.e.)
Wages (PEN)	-44.915	(51.42)	41.761	(44.09)
Employment	-0.005	(0.02)	0.001	(0.00)
Hours Worked	-5.338	(4.19)	0.453	(4.43)
Tenure	-1.975	(2.70)	0.549 *	(0.30)
Public Employer	-0.013 *	(0.01)	-0.003	(0.00)
Large Firm	0.011	(0.01)	0.003	(0.00

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Regressions include individual and month fixed effects. ATTs are calculated using the Callaway and Sant'Anna (2021) estimator for the first 12 months after the license announcement. ATT (Pre) are the average treatment effects 12 months before the treatment. Standard errors are in parenthesis. Monthly wages are measured in Nuevos Soles (PEN) (1 $PEN \approx 0.3USD$). Tenure is measured as the total amount of working months in their main job.

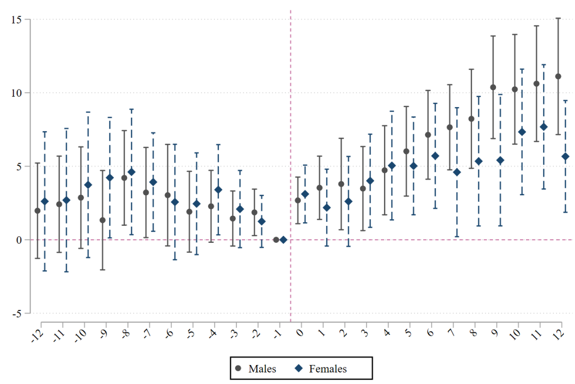
Figure A.2: Event Study for Graduates of Licensed Universities By Gender



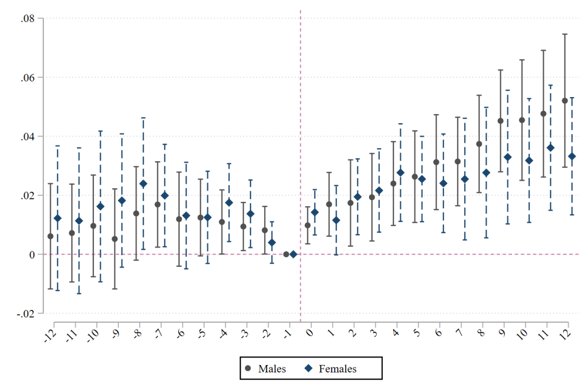
(a) Wages



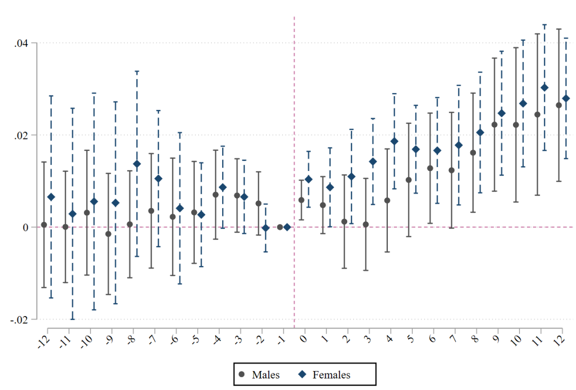
(b) Wages (Unconditional)



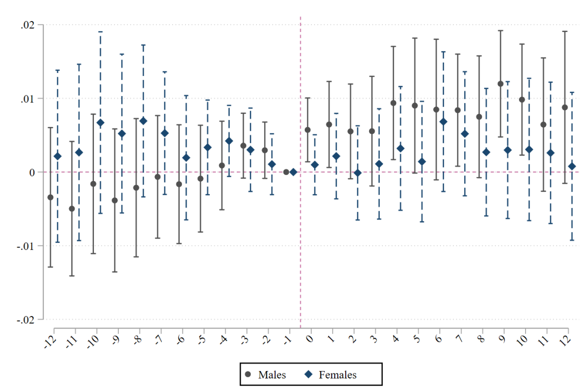
(c) Total Hours



(d) Employment

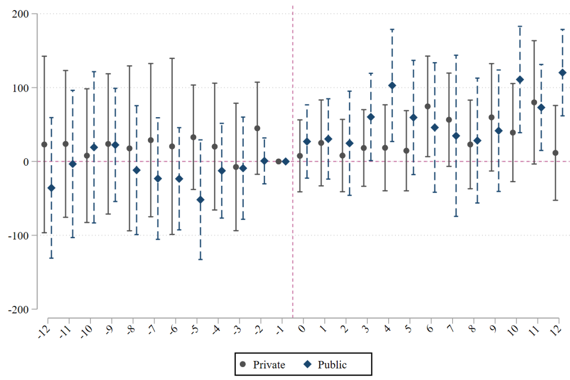


(e) Large Firm

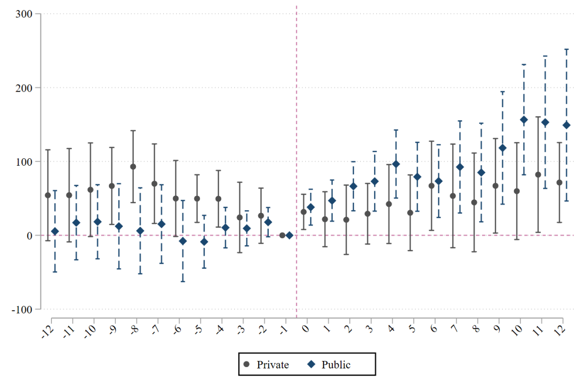


(f) Public Employer

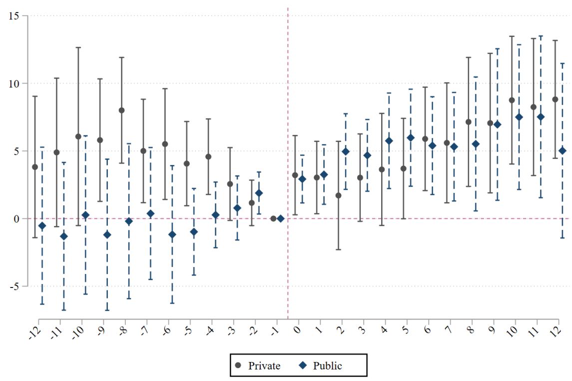
Figure A.3: Event Study for Graduates of Licensed Universities By Type of College



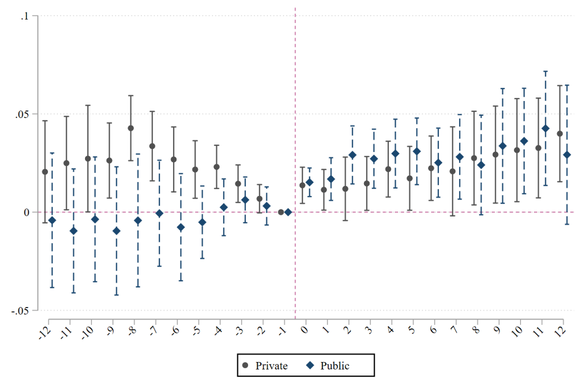
(a) Wages



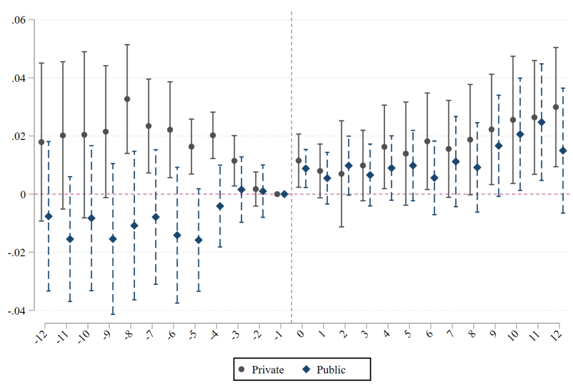
(b) Wages (Unconditional)



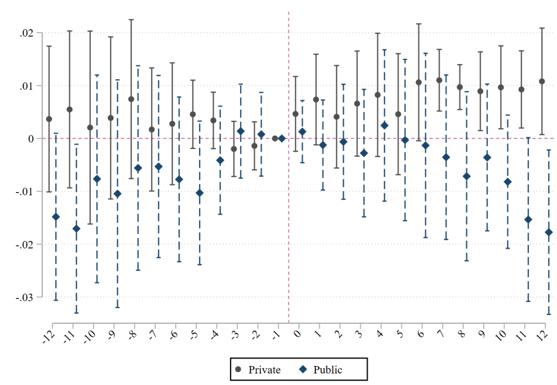
(c) Total Hours



(d) Employment

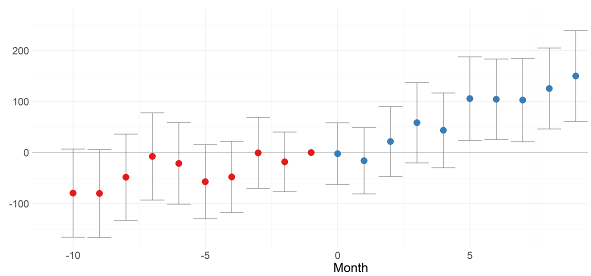


(e) Large Firm

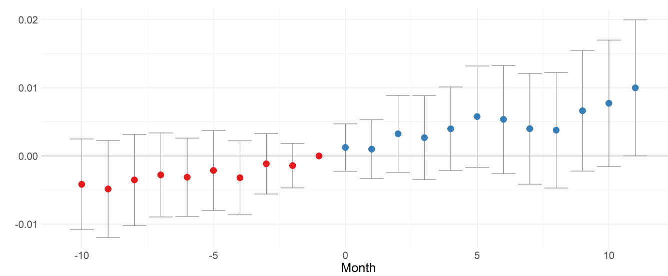


(f) Public Employer

Figure A.4: Event Study for Graduates of Licensed Universities following Callaway and Sant'Anna (2021)



(a) Wages



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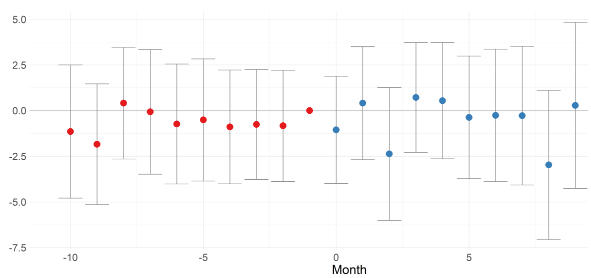
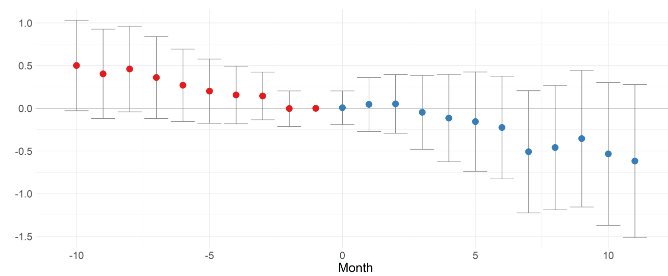
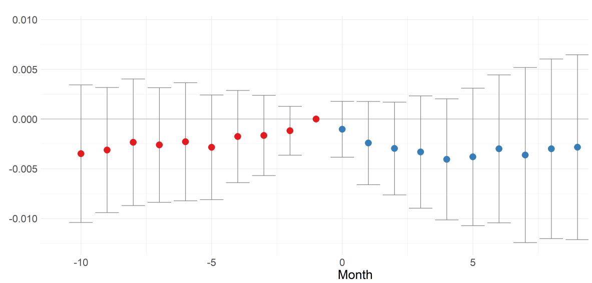


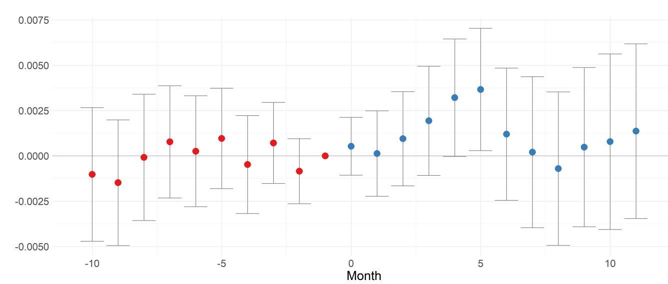
(c) Total Hours



(d) Tenure

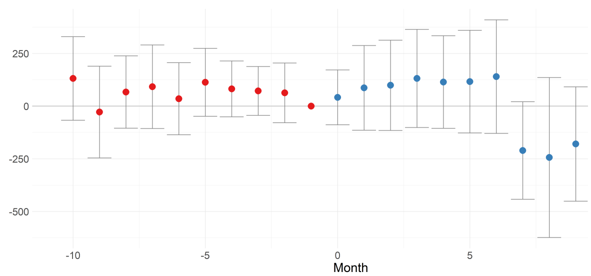


(e) Large Firm

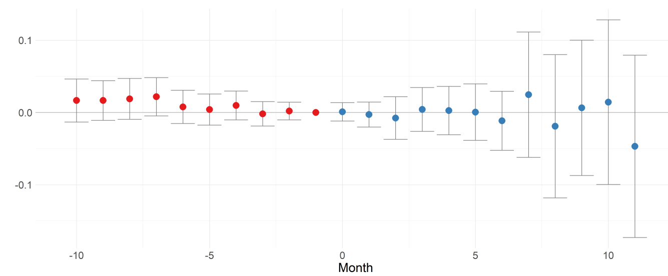


(f) Public Employer

Figure A.5: Event Study for Graduates of Unlicensed Universities following Callaway and Sant'Anna (2021)



(a) Wages



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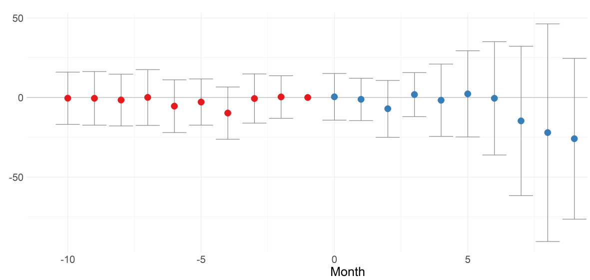
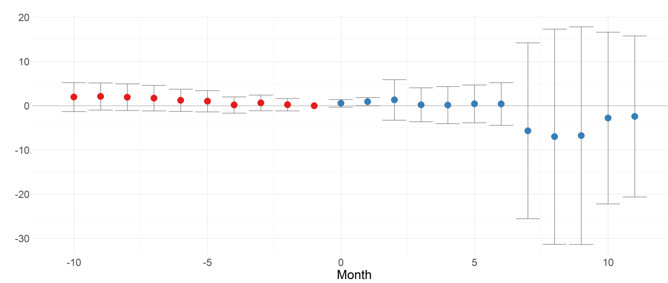
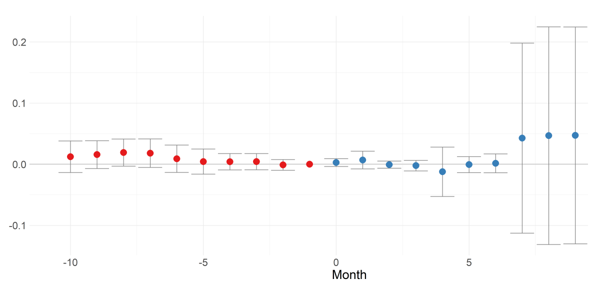


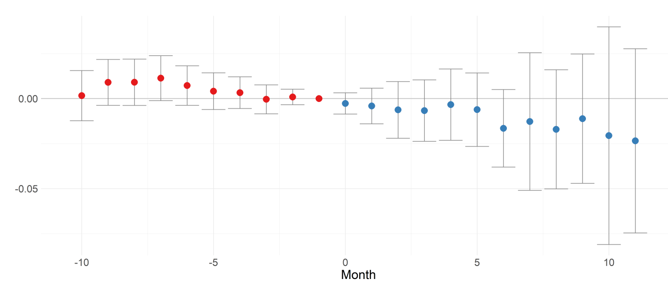
(c) Total Hours



(d) Tenure

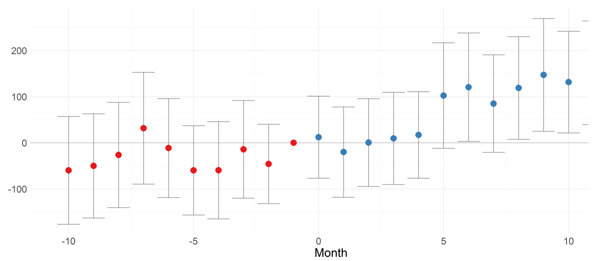


(e) Large Firm

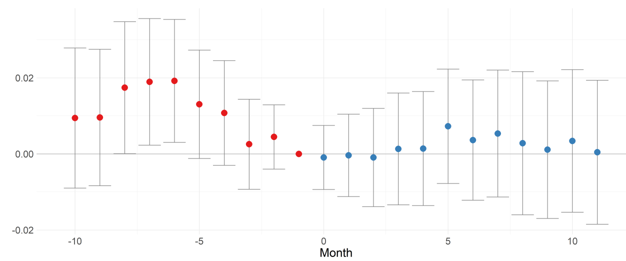


(f) Public Employer

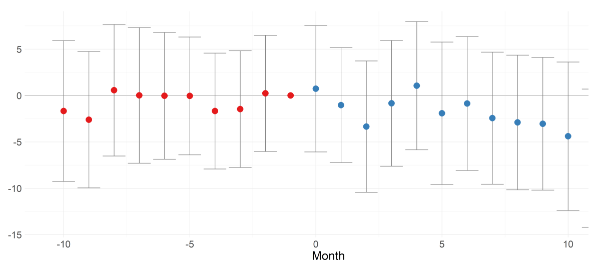
Figure A.6: Event Study for Female Graduates of Licensed Universities



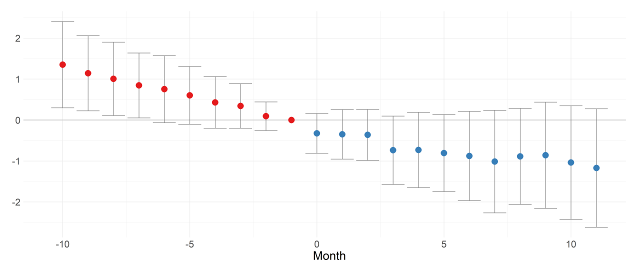
(a) Wage



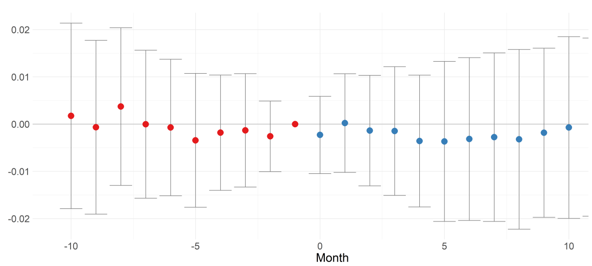
(b) Employment



(c) Total Hours



(d) Tenure



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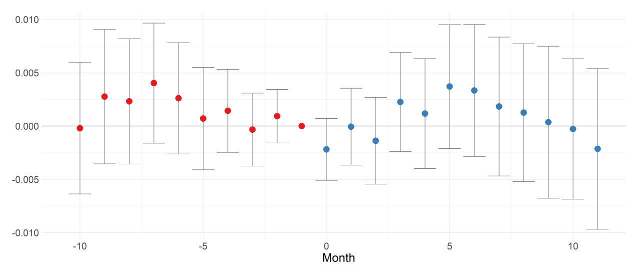
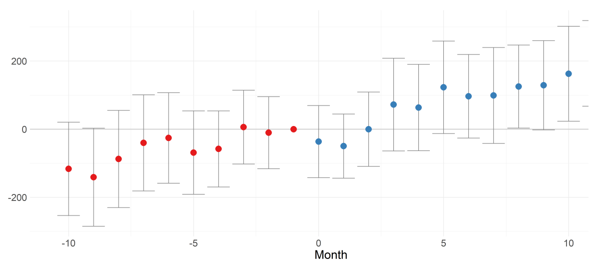
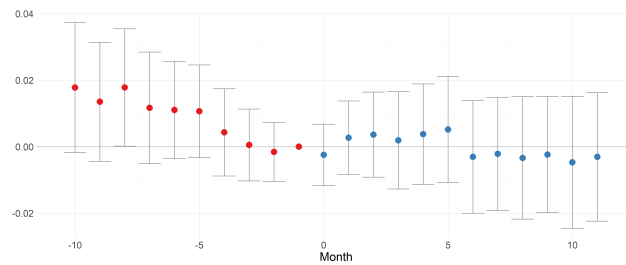


(f) Public Employer

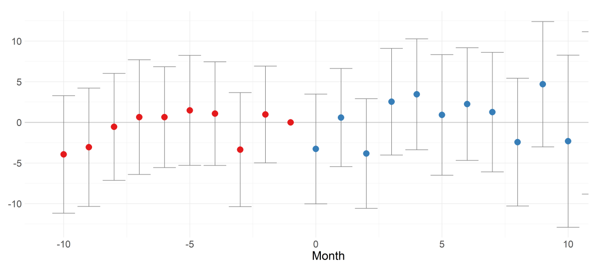
Figure A.7: Event Study for Male Graduates of Licensed Universities



(a) Wage



(b) Employment



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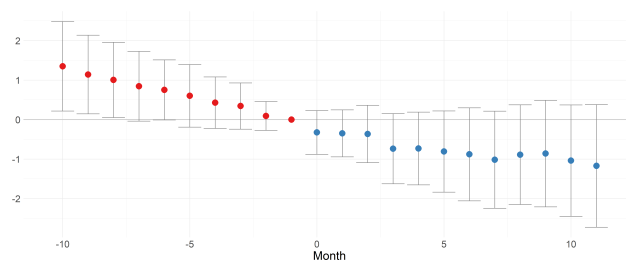

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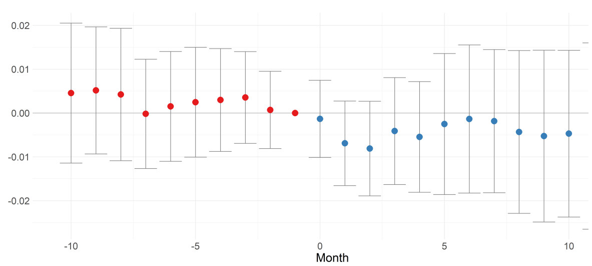

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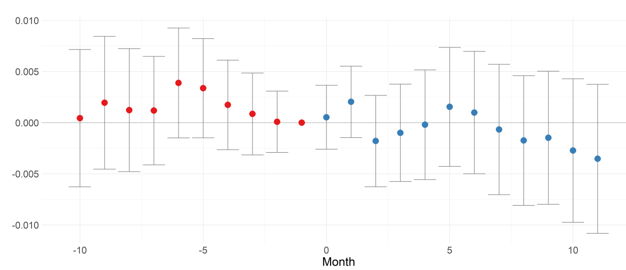
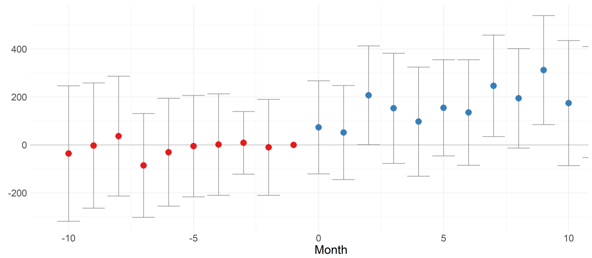
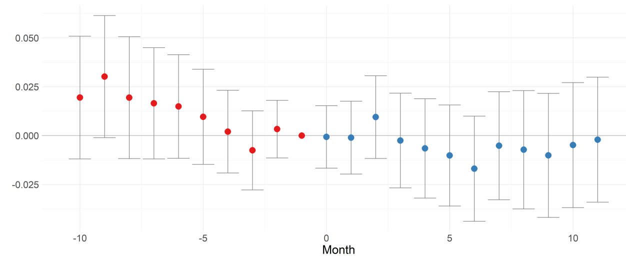


(f) Public Employer

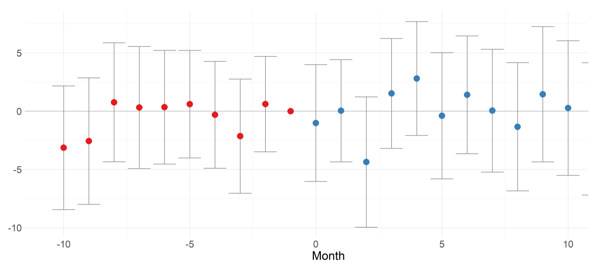
Figure A.8: Event Study for Graduates of Public Licensed Universities



(a) Wage



(b) Employment



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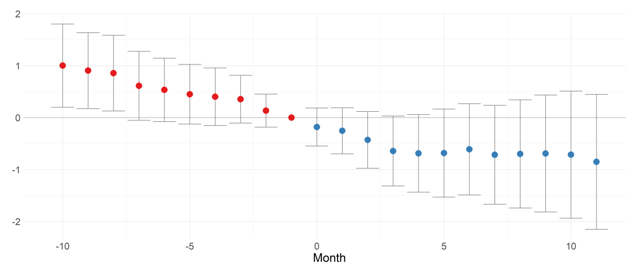

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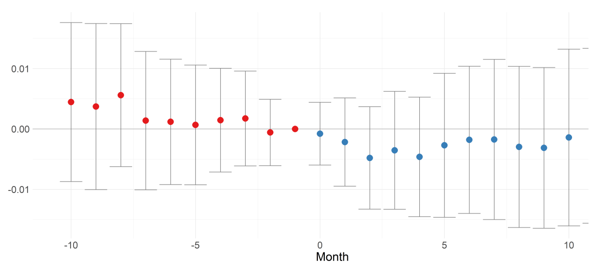

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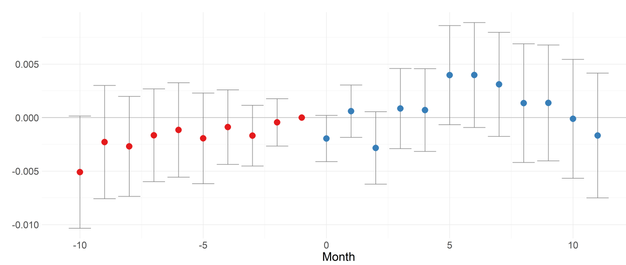
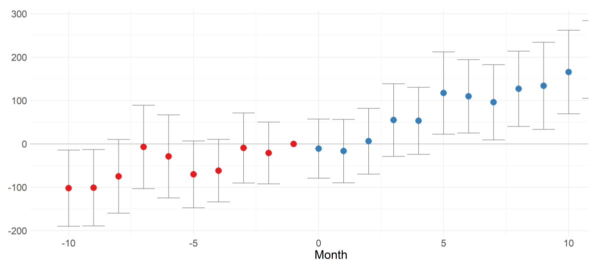
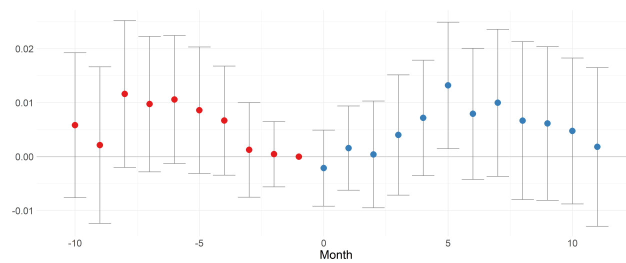


(f) Public Employer

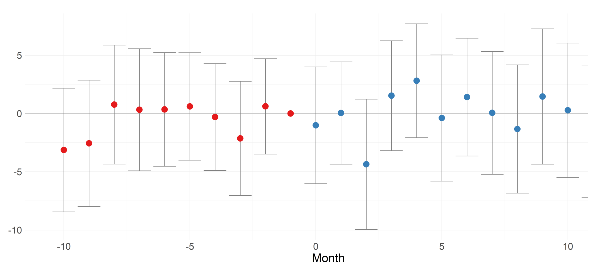
Figure A.9: Event Study for Graduates of Private Licensed Universities



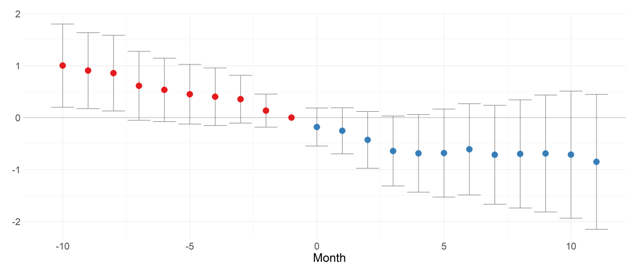
(a) Wage



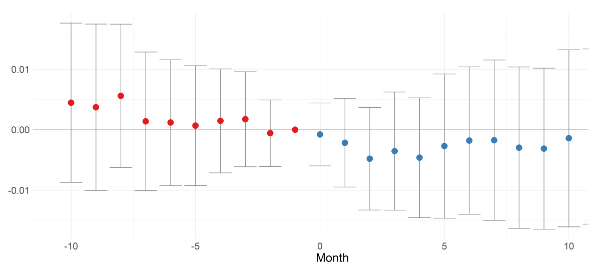
(b) Employment



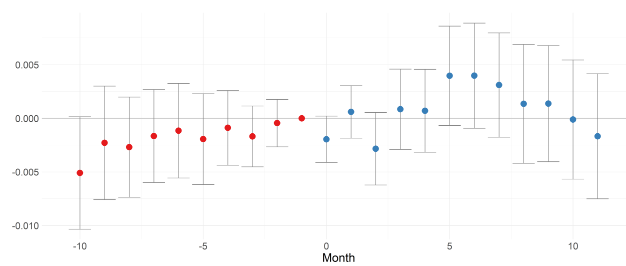
(c) Total Hours



(d) Tenure

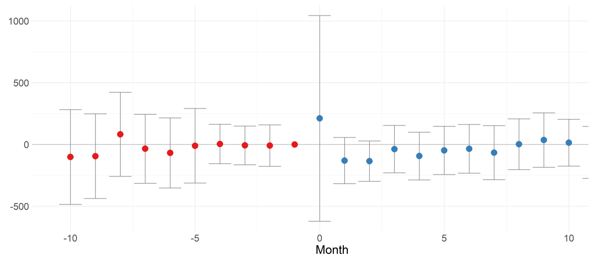


(e) Large Firm

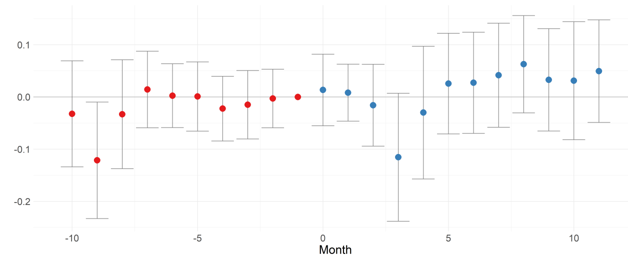


(f) Public Employer

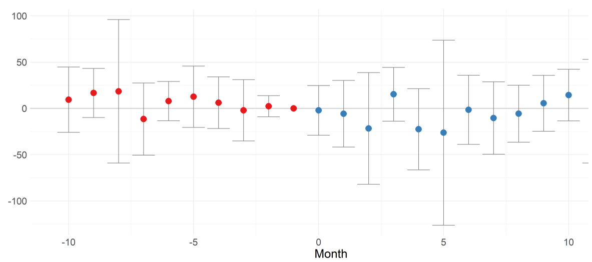
Figure A.10: Event Study for Education Graduates of Licensed Universities



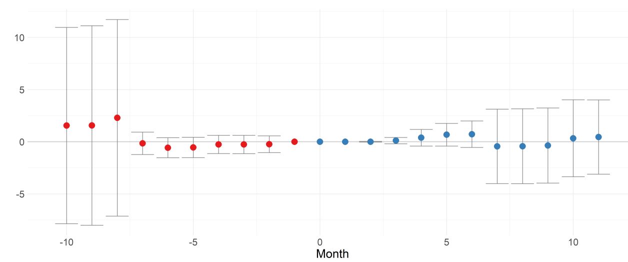
(a) Wage



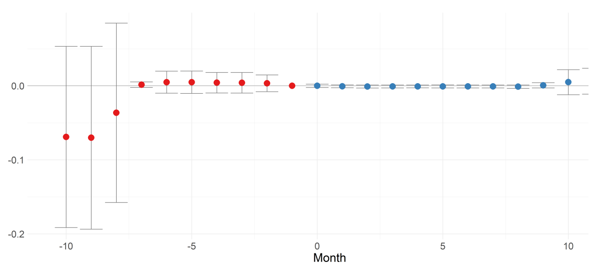
(b) Employment



(c) Total Hours



(d) Tenure



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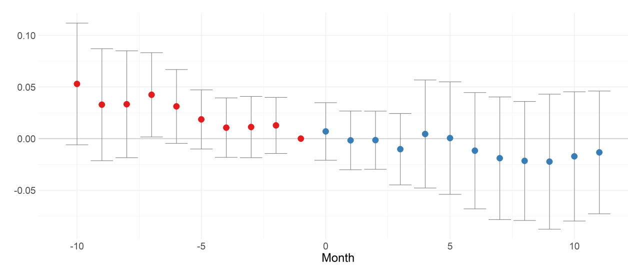

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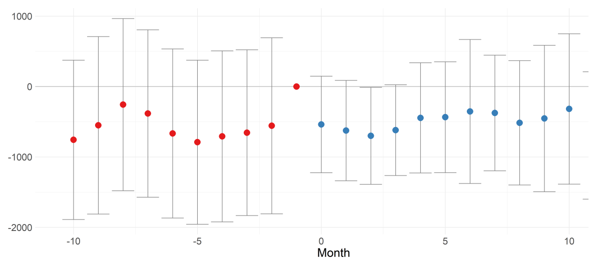
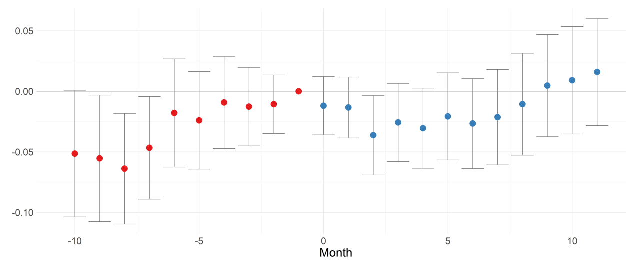
Figure A.11: Event Study for Health Graduates of Licensed Universities



(a) Wage



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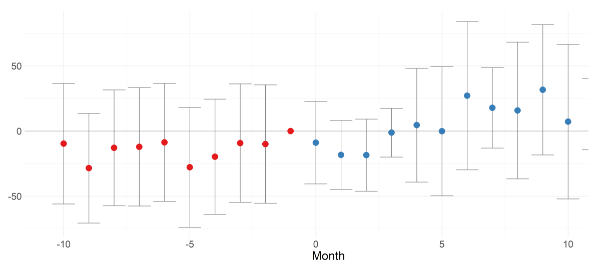
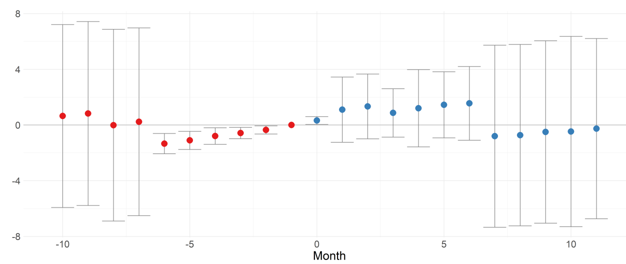
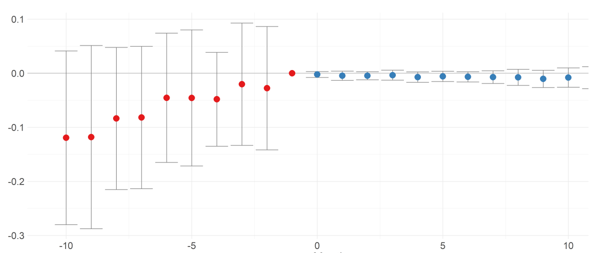


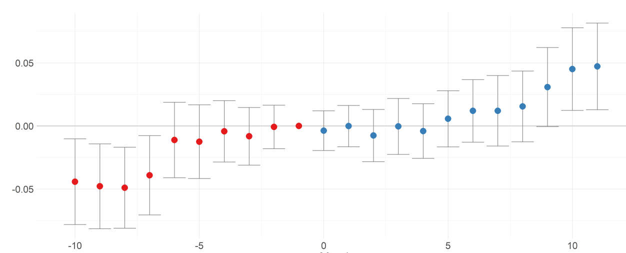
(c) Total Hours



(d) Tenure

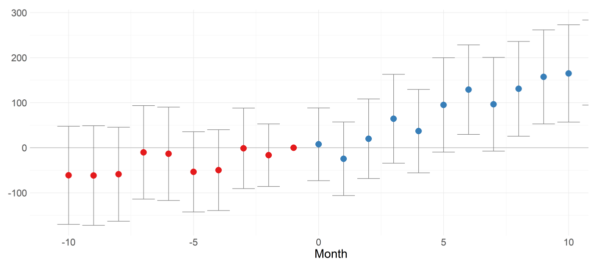


(e) Large Firm

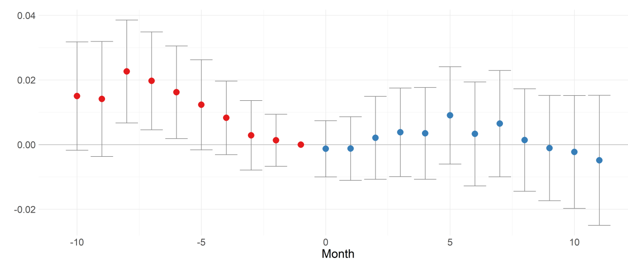


(f) Public Employer

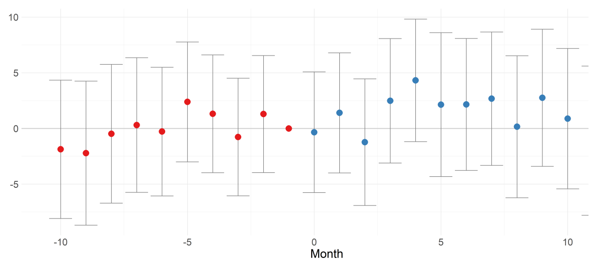
Figure A.12: Event Study for Services (Law, Administration and Economics) Graduates of Licensed Universities



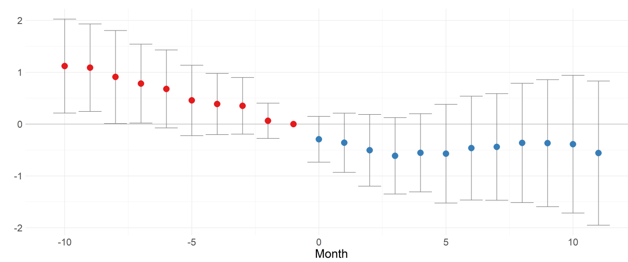
(a) Wage



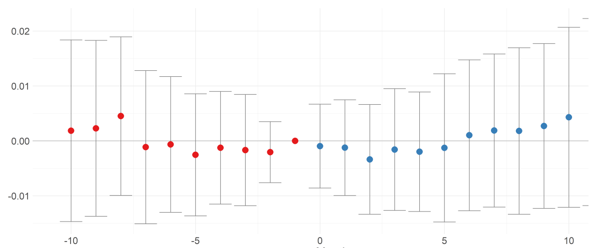
(b) Employment



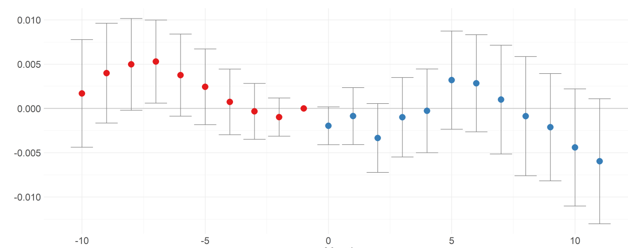
(c) Total Hours



(d) Tenure

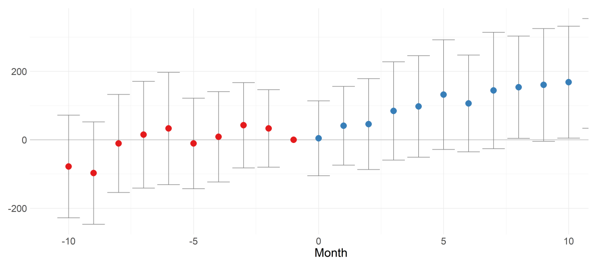


(e) Large Firm

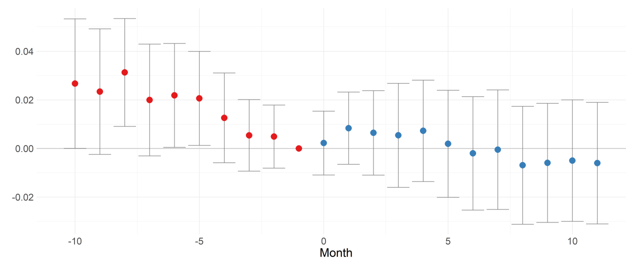


(f) Public Employer

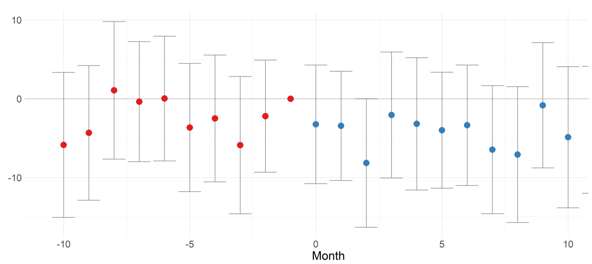
Figure A.13: Event Study for Engineering Graduates of Licensed Universities



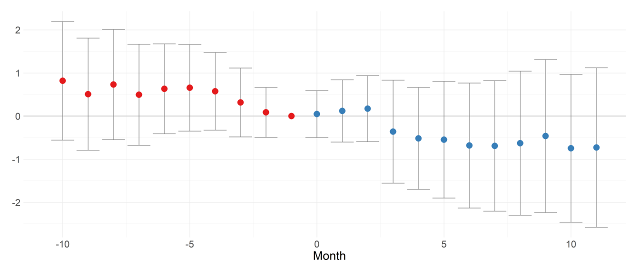
(a) Wage



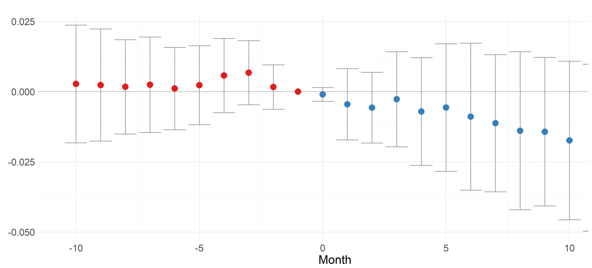
(b) Employment



(c) Total Hours



(d) Tenure



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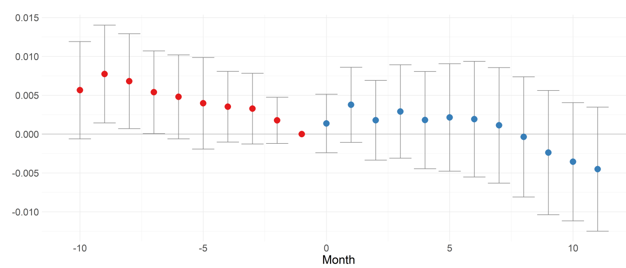


(f) Public Employer

A.2 Licensing Requirements

SUNEDU implemented a licensing process that demanded universities to comply with 8 main requirements. *All* requirements were mandatory and failing to comply in one was enough to get the licence denied.

The requirements were the following:

1. **Academic objectives.** Universities should have clear paths for students to obtain degrees and diplomas. They are also required to have an academic curriculum for each degree and academic plans to improve them.

2. **Academic plan.** Universities must offer degrees that respond to current labor market demands and that are relevant to the context. They should also offer degrees that have both human and economic resources which are sustainable over time.

3. **Infrastructure and equipment.** Universities must have a good standing infrastructure with rooms exclusively for institutional purposes and guaranteed utilities (water, electricity, internet access, and sanitation). They also should have relevant laboratories according to the degrees they offer.

4. **Research agenda.** Universities must also produce relevant research and have a registry of the research they produce. They were also required to have active research faculty and follow ethical research regulations.

5. **Faculty.** Universities should have no less than 25 percent of full-time faculty. Professors should have a transparent hiring process and have good academic records (an MA or a Ph.D. diploma).

6. **Complementary services.** Universities should also offer complementary services to students such as basic health services, a minimum of 3 sports groups,

cultural services, library access, social and psychological services.)

7. **Job placement mechanisms.** Universities should provide a job bank and search for strategic alliances with the public and private sectors. They should also have an office to follow up with graduates.

8. **Institutional transparency.** Universities must make publicly available the following: institutional goals, academic rules and calendars, admissions logistics (calendar and available seats), school fees, academic plans, faculty names, and faculty openings.

A.3 Predicting the Licensing Process

A.3.1 Predicting Licensing

In this section, we study if the licensing decisions were predictable. We rely on data from the University Census Data (CENAUN) implemented on 2010, a few years before the beginning of the higher education reform, and machine learning techniques to predict which universities have a higher likelihood of getting the license. The CENAUN provides comprehensive information for all colleges that existed before 2010 and it contains relevant variables regarding infrastructure, professors, management, and students. We utilized approximately 100 variables in our analysis.

First, we explore different machine learning approaches such as lasso regressions, Logistic regressions, Decision Tree Models and the k-nearest neighbors algorithm in order to predict the licensing status. The later showed the highest level of accuracy among those 4 approaches. The k-nearest algorithm had a test-set score of 0,92. We also used k-fold validation and we choose an optimal $k = 15$ parameter using GridSearch. As anticipated, the algorithm performs well in predicting the licensing outcomes for elite universities, but its accuracy decreases for lower-ranked universities, as shown in Figure A.14. We also compare these results with income measures, which serve as a proxy for college quality and find similar results.

A.3.2 Predicting Timing if License

Second, we implement a survival analysis and time-to-event prediction with PyTorch to predict the license timing. Specifically, we used a Cox-Time regression, which is a continuous-time method that does not require discretization of the time scale. We also create a simple neural net with two hidden layers, ReLU activations, batch norm

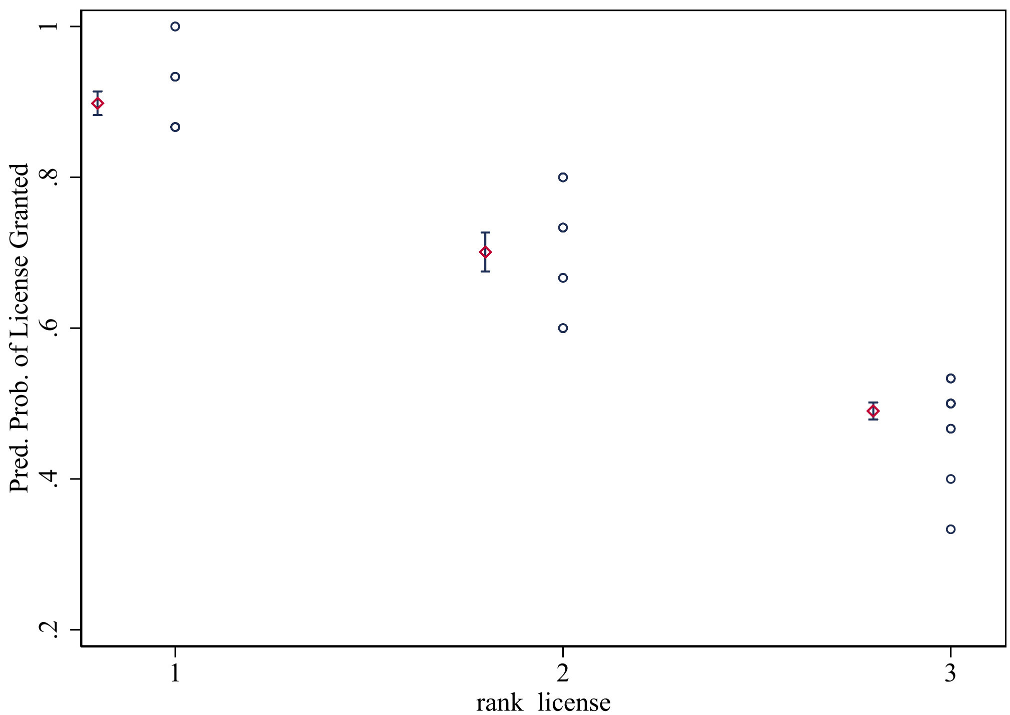


Figure A.14: Predicted Probability of Getting the License by Rank and dropout. From these estimates, we are able to obtain the probability of getting the license first. These estimates allowed us to obtain the probability of obtaining the license first, which we used to rank the order in which universities obtained a decision and compare it with the actual order. As seen in Figure A.15, the correlation between the predicted rank and real one is positive. However, we can see that it is more accurate for the first events than the last ones. These first announcements coincide with the elite universities that have a high probability of getting the license as seen in the previous analysis.

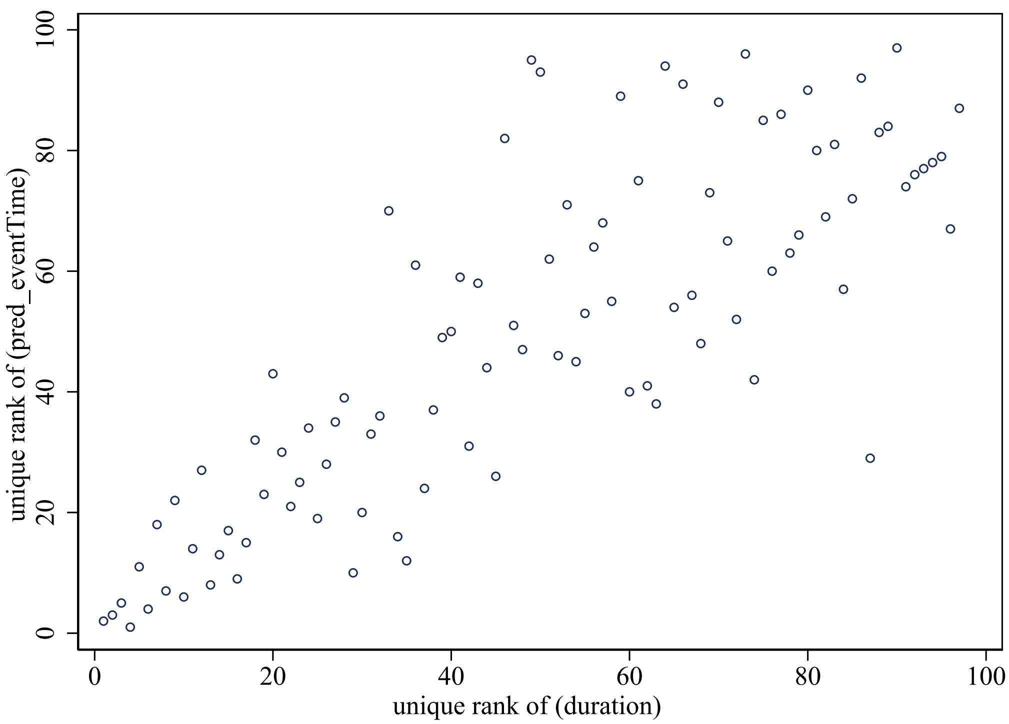


Figure A.15: Predicted Probability of Getting the License First vs. Real
Note: this graph shows the correlation of the predicted rank of getting the licensed versus the actual rank.

A.4 License Denied

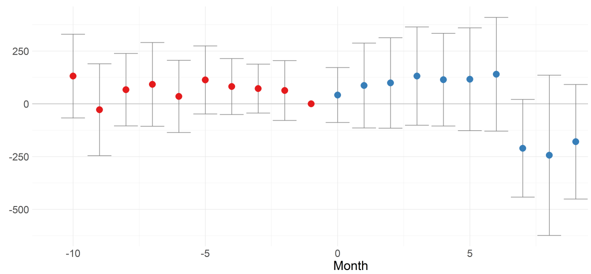
We also look at the results for those who graduated from a college whose license was denied. Using the same administrative data as described in the paper, we implement the Callaway and Sant'Anna (2021) estimator for this analysis. We find no significant effects in all outcomes on average during the first 12 months after the license denial announcement, except for a small reduction on the likelihood to work in the public sector. Results on wages, hours worked, and tenure also suggest a negative impact but this is not statistically significant. We also find similar results by gender (see Appendix Figure A.17 and Appendix Figure A.18). It is worth highlighting that, unlike the previous results, the sample used for these estimations is smaller and the results reported are noisier as seen on the event study plots in Figure A.16. The main reason behind the smaller sample is that not only these colleges have fewer students enrolled but also their graduates had a higher probability of being in the informal sector.

Table A.3: ATT Estimates of Denied License Colleges

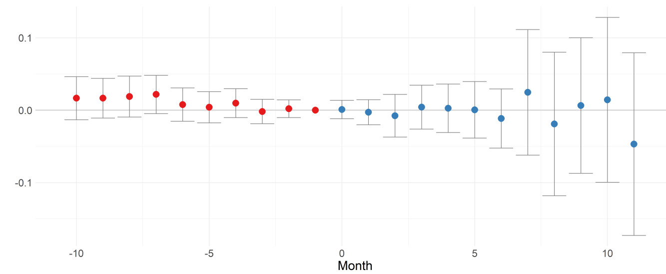
	Post-Treatment		**Pre-Treatment**	
	ATT	(s.e.)	Placebo	(s.e.)
Wages (PEN)	-44.915	(51.42)	41.761	(44.09)
Employment	-0.005	(0.02)	0.001	(0.00)
Hours Worked	-5.338	(4.19)	0.453	(4.43)
Tenure	-1.975	(2.70)	0.549 *	(0.30)
Public Employer	-0.013 *	(0.01)	-0.003	(0.00)
Large Firm	0.011	(0.01)	0.003	(0.00

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Regressions include individual and month fixed effects. ATTs are calculated using the Callaway and Sant'Anna (2021) estimator for the first 12 months after the license announcement. ATT (Pre) are the average treatment effects 12 months before the treatment. Standard errors are in parenthesis. Monthly wages are measured in Nuevos Soles (PEN) ($1\ PEN \approx 0.3 USD$). Tenure is measured as the total amount of working months in their main job.

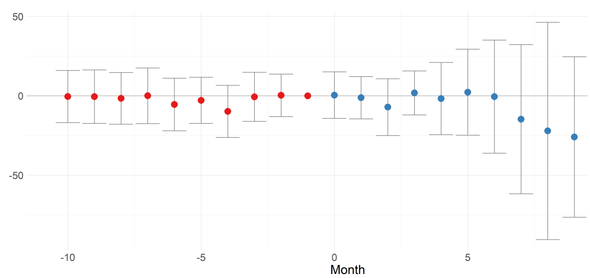
Figure A.16: Event Study for Graduates of Unlicensed Universities



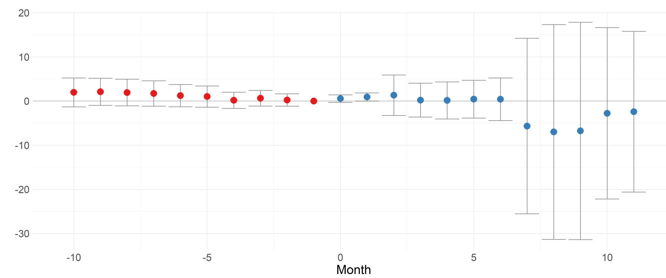
(a) Wages



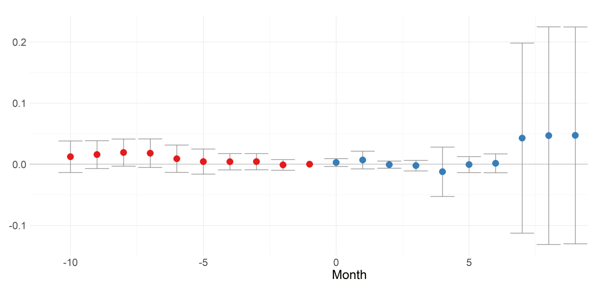
(b) Employment



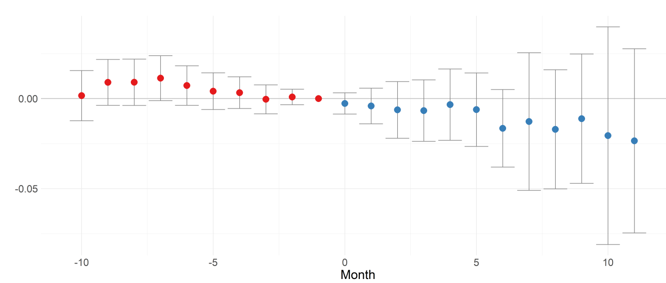
(c) Total Hours



(d) Tenure

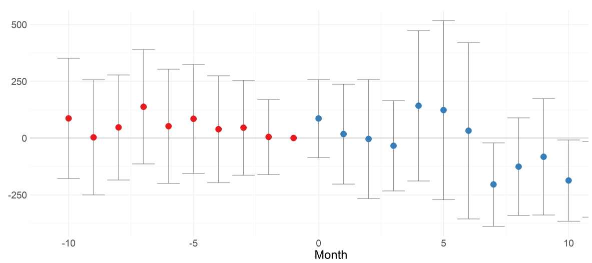


(e) Large Firm

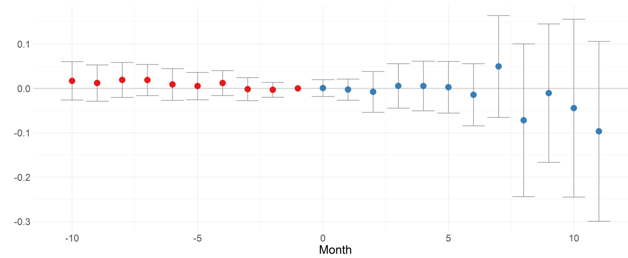


(f) Public Employer

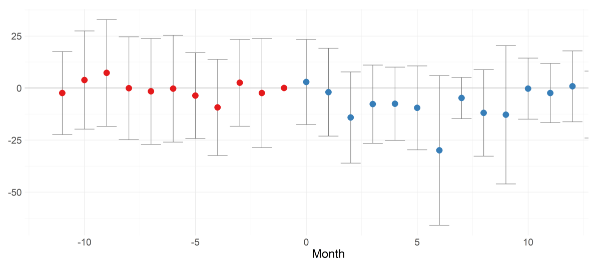
Figure A.17: Event Study for Female Graduates of Unlicensed Universities



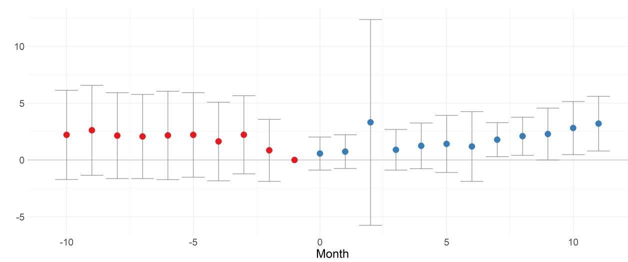
(a) Wage



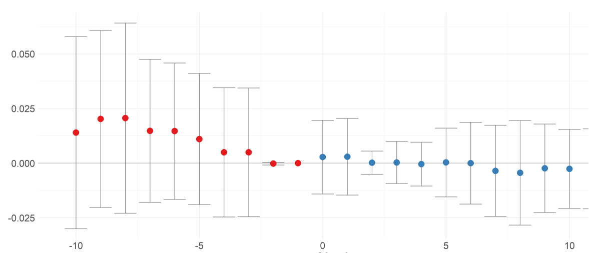
(b) Employment



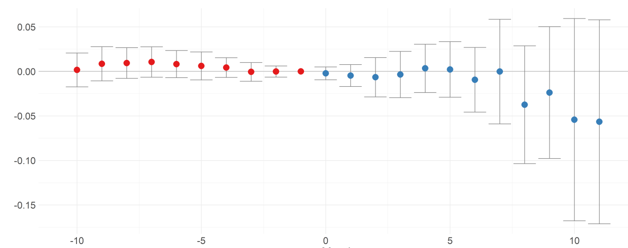
(c) Total Hours



(d) Tenure

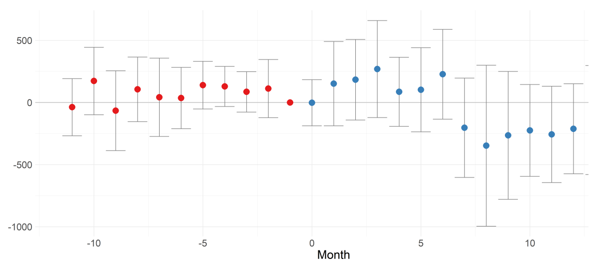


(e) Large Firm

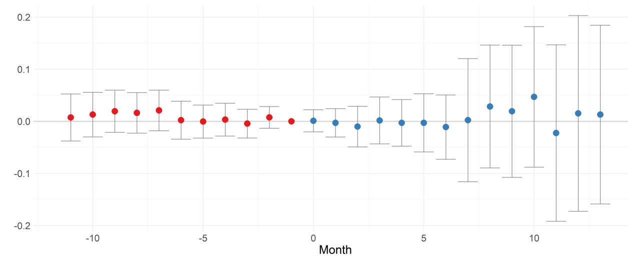


(f) Public Employer

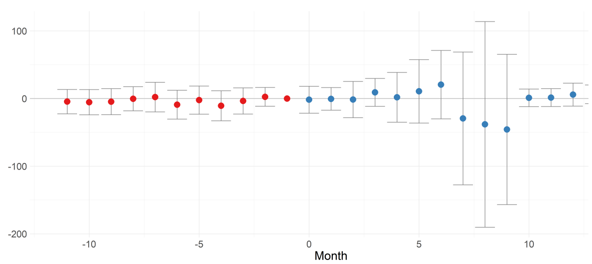
Figure A.18: Event Study for Male Graduates of Unlicensed Universities



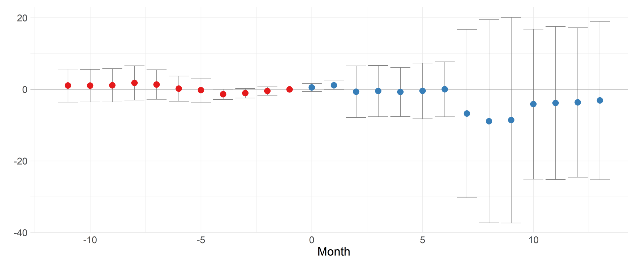
(a) Wage



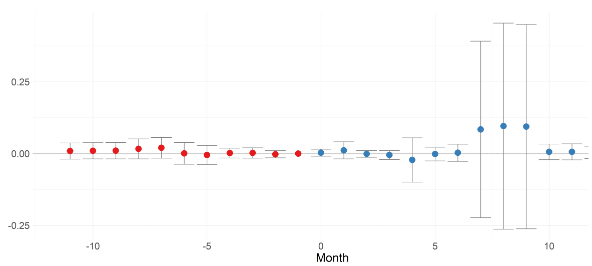
(b) Employment



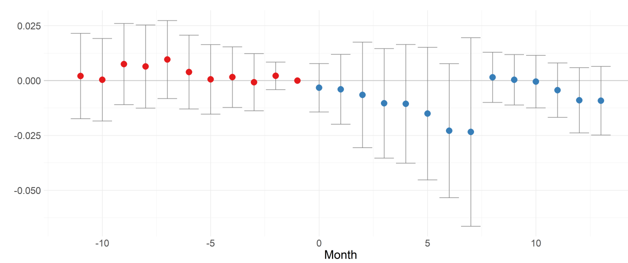
(c) Total Hours



(d) Tenure



(e) Large Firm



(f) Public Employer