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ABSTRACT

Signaling Effects on the Labor Market: Winners and Losers of University Licensing in a Higher Education Reform

We investigate the effects of a higher education reform on the labor market outcomes of college graduates in Peru. The cornerstone of this piece of legislation was a licensing process whereby a newly created higher education superintendency evaluated every existing university on minimum quality criteria to grant or deny their operating license. We find that, conditionally on being employed, the effects of this reform on the college graduates of universities that were granted (denied) the license were two: an effect of around 6.5% (-9%) on monthly wages and a less precisely estimated effect of approximately 4 p.p. (-3.5 p.p.) on the probability of being formally employed. Our work provides evidence of the existence of winners and losers as a consequence of this ambitious higher education reform in Peru.

JEL Classification: I26, I28, J01, L14

Keywords: SUNEDU, university licensing, higher education reform, signaling effects

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1 Introduction

Many developing countries deregulated their higher education markets towards the end of the twentieth century in response to mounting demand for college education from rising high school graduates numbers (Yamada and Lavado, 2018). These countries allowed private for-profit and nonprofit institutions to enter this market, massively increasing the supply of higher education. For instance, between 1999 and 2013, gross enrollment in higher education in Latin America and the Caribbean doubled from 22% to 45% (UNESCO, 2023).

Peru was an extreme case of these market-friendly reforms in the education sector. The Legislative Decree 886 awarded some tax exemption benefits to promote business investment in all levels of education. As a result, in the 1996-2014 period, the number of total universities in Peru more than tripled from 45 to 140. Moreover, the number of private universities grew 210% rising from thirty in 1996 to ninety three in 2015 (MINEDU, 2023).

Critically, this promotion of private investment in the education sector occurred in a context of weak and limited oversight. Universities were essentially self-regulated by the *National Assembly of University Presidents*. There were no regulatory provisions assigning to any government body or third party the responsibility of enforcing higher education quality, nor providing the necessary resources to fulfill this function (Távara, 2018). This situation resulted in universities having almost complete autonomy without any evaluation mechanisms.

Naturally, the supply push in this deregulated context had a troublesome side, as Chong et al. (2023) document. While some high-quality universities were created, many low-quality institutions mushroomed. This originated fears of posterior unemployment or negative returns to investment in higher education from the point of view of families and students, not necessarily the university owners. Yamada et al. (2016) link these reforms with a higher probability of underemployment as well.

Public outcry followed these negative consequences of lower quality higher education, which pressured politicians to regulate this sector. Therefore, in one of the few policy reforms in recent years in Peru, two laws were approved by Congress. In 2012, Law 29771 instituted a five-year moratorium on the creation of new universities. In 2014, Law 30220 created SUNEDU, the *National Superintendency of University Education*. This public and autonomous organization was given, among other faculties, the role of granting or denying operating licenses. This policy decision aimed to verify that no university education service failed to meet basic quality standards (SUNEDU, 2015).

In 2015, SUNEDU designed and started the mandatory licensing process. They would grant or deny licenses depending on whether universities complied or not with basic quality conditions in organization, teaching, research, and infrastructure (SUNEDU, 2015). In the 2016-2022 period, all universities in Peru, private or public, had to participate in the licensing process. The breakdown of licensing decisions was as follows: 94 universities were granted a license, whereas 50 were denied it. This sent a clear information signal to all segments of society about the actual quality of each university and the training or education provided to their students.

The process of university accreditation in Peru has had a positive impact on the quality of education. This is evident in the increased research output of universities, with the number of published papers rising by 181% between 2016 and 2020. In addition, more universities now have at least a quarter of their faculty as full-time staff, with the percentage rising from 48% to 82% (SUNEDU, 2022).

However, while the effects of the licensing process on quality are well-documented, less is known about its impacts on college graduates. We argue that the licensing outcome of each university affected the labor market outcomes of its graduates. This is because, after the accreditation process, employers receive a clear signal about whether or not a college graduate has received an education that meets basic quality standards. We expect that the accreditation process has positive (negative) effects on the monthly wages and the probability of formal employment for college graduates from universities that have been granted (denied) an operating license.

To study the impacts of the licensing process on the employment outcomes of college graduates, we employ data from two sources. First, we use the National Household Survey (ENAHO), a detailed questionnaire applied to a nationally representative sample on a rolling basis, with quarterly releases. We specifically take advantage of its education and employment sections. Second, we analyze administrative data obtained from SUNEDU about the licensing process. This enables us to identify when universities received their licensing outcomes and whether they were granted or denied the license.

In a previous effort, Alba et al. (2022) shed light on this issue using administrative data from payroll records. Even though their high-frequency panel data supposes an advantage, their study has some shortcomings. The authors acknowledge and discuss one of them, that their data only captures the formal labor market. In Peru, only about a third of all workers are formal workers, so tax records data cannot capture information on most of the labor market. Additionally, graduates from universities who were denied the license are more likely to have been non-formal workers even before the licensing process, which makes the tax records data unfit to evaluate the effects of a denied license. A second limitation is that they work with data on college graduates only. This means they must use not-yet-treated graduates as their control group. In other words, to estimate the effects of the licensing process for college graduates from universities that were granted (denied) the license, they use college graduates from universities that had not yet been granted (denied) such license, but eventually were. This yields non-comparable results for both treatments because the effects are estimated against different bases.

Our contribution to the understanding of the effects of the licensing process on the labor market outcomes is three-fold. First, to accurately represent the nationwide effects of the licensing process, we need to use data that covers the entire labor market. Using ENAHO is a step further in this matter. Second, we use high school graduates as a control group for both treatments. This allows us to estimate the effects of both outcomes against the same control group, making them comparable. Moreover, using a different and lower educational attainment group makes our results easier to interpret and more policy-relevant. Third, since our data includes both informal and formal workers, we can estimate the effect of the licensing process on the probability of having formal employment.

We find significant effects for both licensing outcomes. Specifically, conditional on being a dependent worker, the licensing process had positive (negative) effects on the labor market outcomes of college graduates from universities who were granted (denied) the license. These effects were around 6.5% (-9%) on monthly wages and 4pp. (-3.5pp.) on the probability of being employed in the formal sector. However, it is worth noting that while these second set of results bear the expected signs, they are only statistically significant when we consider a successful licensing outcome as the treatment of interest. This is evidence that the reputational consequences of the system-wide reform had both winners and losers.

The rest of this document is organized in the following way. Section 2 describes our data. Section 3 develops our identification strategy. Section 4 presents our results. Section 5 discusses the sensitivity of our results to sample refinements. Section 6 includes alternative specifications. Section 7 covers some extensions. Finally, Section 8 concludes.

2 Data

2.1 SUNEDU

Detailed information about the licensing process and its results is publicly available from SUNEDU. This includes application timelines and evaluation criteria. More importantly, it recounts exactly when each university was granted or denied the operating license. These two licensing outcomes are two mutually exclusive results that serve as treatments for this paper.

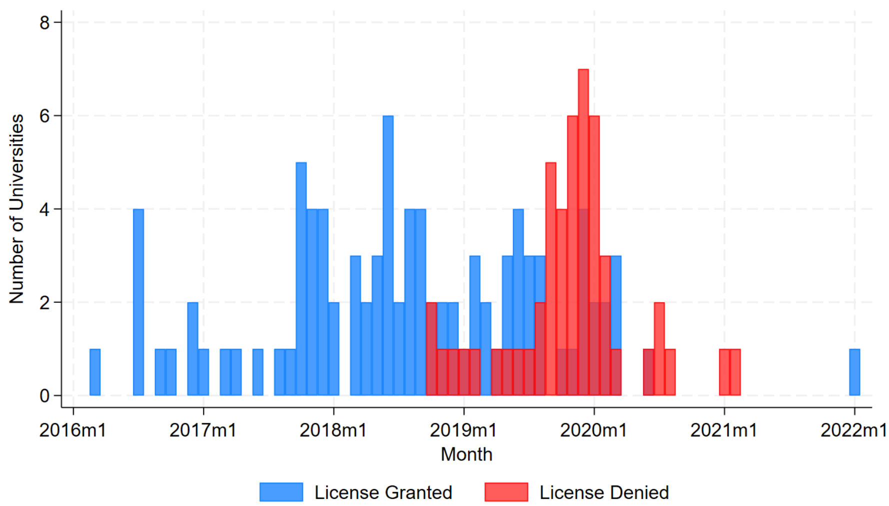
Additional granular information on the documentary and in-situ review for each university is also available. SUNEDU's assessment consisted of a rubric of fifty-five indicators grouped into eight basic quality categories.[1] It is important to note that SUNEDU planned and executed the licensing application process in a gradual fashion by dividing all universities into nine application groups based on its foundation date. These groups determined the order in which universities applied for the operating license. This has two implications. First, decisions were not handed on a unique period. Second, the licensing application groups were heterogeneous. Table (1) provides a comparison of the licensing application groups, while Figure (1) depicts a timeline of decisions.

[1]These categories (number of indicators) were the following: academic offering and study plans (8); the existence of compatible educational supply (7); appropriate infrastructure and equipment (15); research plans (8); capable teaching staff and proportion of full-time professors (4); complementary educational services (8); labor market insertion mechanisms (4); and university transparency (1).

Table 1: Licensing Process Groups

Application Group	Count	Granted	Public	Province	Average Age
1	15	12	6	8	109
2	15	11	5	8	61
3	16	11	5	9	34
4	17	11	5	14	32
5	19	11	7	12	27
6	18	12	6	9	25
7	17	12	5	13	23
8	19	11	8	10	16
9	9	4	2	4	10

Figure 1: Licensing Process Timeline



2.2 ENAHO

The National Household Survey (ENAHO) is a questionnaire administered by the National Institute of Statistics and Informatics (INEI) to a nationally representative sample of homes. Data is collected on a rolling basis (every month), but the actual data sets are released quarterly. The survey covers a variety of topics, but we are interested in its demographics, education, and employment sections.

The education section of the questionnaire collects data on every person who lives in a sampled household that is at least three years old. From this section, we extract data on education attainment and education enrollment. Since 2014, ENAHO has asked college graduates where they obtained their degrees as well. This section is particularly important to identify the two educational attainment groups whose outcomes we will compare as part of our identification strategy: those who are high school graduates, and those who are college graduates.

The employment section of the survey gathers data on every person who lives in a sampled household that is at least fourteen years old. There are no other eligibility restrictions to respond to this section of the survey. This means that considerations such as whether one is employed or not, or whether one's employment is formal or informal do not prevent anyone from answering this section of the survey. From this section, we obtain our two dependent variables, which we define below.

- **Monthly Income:** Monthly income in soles (local currency) from the primary source of income, defined only for those who have a dependent job as their primary source of income. In cases when the survey respondent reports being paid in a frequency other than monthly, we adjust their income to reflect a monthly salary.[2] This variable is log-transformed before being used in regressions.

- **Formal Employment:** An indicator that takes the value of one if the survey respondent is a formal employee and zero otherwise, defined only for those who have a dependent job as their primary source of income.

2.3 Descriptive Statistics

We employ ENAHO data from 2014-Q1 to 2022-Q4. To obtain our relevant sample, we restrict it to people who are either *only* high school graduates or college graduates.[3] Second, regarding age restrictions, we keep people who were between twenty and forty-five years of age when they responded to the survey, provided they were born after 1975.

[2] One U.S Dollar is roughly 3.7 Peruvian Soles

[3] Because the group of high school graduates serves as a control group, it is important that their skills signaling is not contaminated by incomplete tertiary studies. Therefore, people who graduated from high school and have incomplete studies towards a posterior degree are excluded from the sample regardless of whether this incomplete degree is a technical or professional one. Likewise, people who finished graduate studies are also excluded from the sample.

We merge the data from ENAHO with that of SUNEDU linking them through the name of the university where the college graduate obtained their undergraduate degree (this variable is missing for the high school graduates). Once the merge is complete, every observation belongs to one of three groups: (i) a group of high school graduates, (ii) a group of college graduates from a university that was granted a license, or (iii) a group of college graduates from a university which was denied a license. The first group will be our control group across all analyses. The second and third groups, depending on when they answered the survey, can be assigned to one of our treatment groups (license granted or license denied). This will be further explained in the next section. Table (2) compares demographics and labor market outcomes across these three groups. We report the number of individuals and universities that constitute each of these groups. In addition, we characterize them through their mean age, the share of females, their average monthly primary income, and the share that holds formal salaried employment.

Table 2: Descriptive Statistics

	Overall	High School	Granted Graduates	Denied Graduates
Age	30.52	30.19	31.65	31.65
	(6.57)	(6.71)	(5.92)	(6.03)
Female	0.37	0.33	0.51	0.54
	(0.48)	(0.47)	(0.50)	(0.50)
Montly Salary	1,307.40	1,079.16	2,101.08	2,031.78
	(994.79)	(709.02)	(1,376.28)	(1,328.52)
Formal Salaried Employment	0.38	0.30	0.68	0.64
	(0.49)	(0.46)	(0.47)	(0.48)
Universities	96	0	62	34
Observations	39,892	30,852	7,086	1,954

Notes: Data comes from ENAHO 2014-Q1 to 2022-Q4. We limit the dataset to people aged 20-45, born after 1975, employed in a dependent job, and whose educational attainment is either high school only or with a college degree (excluding people with graduate degrees). One US Dollar is roughly 3,70 Soles. Data includes 96 out of the 144 universities that applied for a license.

3 Empirical Strategy

3.1 Difference-in-Differences

We employ a difference-in-differences identification strategy to estimate the effects of the licensing process on the labor market of college graduates. We estimate separate effects for the *license granted* and *license denied* decisions. Because universities received their licensing outcomes at different points in time spanning five years, this is a case of staggered treatment adoption. In such a setting, Goodman-Bacon (2021) demonstrates that the traditional two-way fixed effects approach can be problematic under heterogeneous treatment effects. We cannot theoretically rule out heterogeneous treatment effects in the context of the licensing process. Universities applied for licensing based on a timeline conforming to their foundation year. Therefore, being a college graduate from a particular licensing group was already a labor-market signal that could change a potential effect of the licensing process. In other words, the moment each university received its licensing outcome is not orthogonal to its quality, which lends credibility to possible heterogenous effects.

Furthermore, two-way fixed effects estimates may lack interpretability because they are the result of a weighted sum of all possible canonical difference-in-differences estimations (where these weights can even take negative values). Another frailty of two-way fixed effects comes in the various comparisons that are embedded in its causal estimate, which includes using not-yet-treated units as controls. While a researcher may find this comparison useful in certain cases, we argue that since all universities participated in the licensing process, a more convenient estimate would include only pure controls: never-treated individuals.

Several alternatives to two-way fixed effects have been developed in recent literature. These include those of Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfœuille (2020), Sun and Abraham (2021), and Athey and Imbens (2018). We follow Callaway and Sant'Anna (2021) approach to difference-in-differences using only never-treated units as controls. They propose estimating group and time-specific treatment effects based on the date of treatment adoption and length of treatment exposure. These are then aggregated in several complementary ways which are convenient to interpret.

For the purposes of this paper, the never-treated individuals are those whose education attainment group is only high school. Furthermore, we define treatment groups based on the date on which each university was granted or denied the functioning license. Specifically, universities are grouped by the semester in which they were granted or denied the functioning license.

3.2 Treatment Definitions

We establish two mutually exclusive treatments: (i) being a college graduate from a university that obtained a license, and (ii) being a college graduate from a university that was denied a license. For each individual, these treatments activate upon SUNEDU's decision to grant or deny the license to their alma mater. We observe college graduates from each university before and after SUNEDU granted or denied their license. Therefore, for any given college graduate, we must determine their treatment status depending on the date when they answered the ENAHO questionnaire. We do this considering the following rules:

- **Licensed-Granted Treatment:** A person who graduated from a university that got granted a license in semester t_o is considered *license-granted treated* if they were interviewed in semester $t_o + 1$ or later. It is considered not treated if it was interviewed before semester t_o.[4]
- **License-Denied Treatment:** A person who graduated from a university that got denied a license in semester t_o is considered *license-denied treated* if they were interviewed in semester $t_o + 1$ or later. It is considered not treated if it was interviewed before semester t_o.[5]

[4]We discard all observations from people who are interviewed in the same semester in which their *alma mater* was granted its license. We aim to properly identify a person's treated status as posterior to the decision release. If we failed to do this, there would be cases in which we would be attributing treated status to people who were interviewed before SUNEDU announced the decision concerning their university.

[5]Similarly, we discard all observations from people who are interviewed in the same semester in which their *alma mater* was denied the license.

4 Results

Table 3: Main Results

	License Granted		License Denied	
	Monthly Income	Formal Employment	Monthly Income	Formal Employment
	(1)	(2)	(3)	(4)
Pre Decision Average	-0.0035	-0.0030	-0.0283	0.0092
	(0.0079)	(0.0057)	(0.0199)	(0.0157)
	[0.5921]	[0.6669]	[0.1540]	[0.5561]
Post Decision Average	0.0651**	0.0419*	-0.0882*	-0.0349
	(0.0307)	(0.0221)	(0.0494)	(0.0377)
	[0.0341]	[0.0579]	[0.0739]	[0.3547]
C&S ATT	0.0643**	0.0395**	-0.0903*	-0.0356
	(0.0307)	(0.0220)	(0.0494)	(0.0378)
	[0.0362]	[0.0399]	[0.0677]	[0.3461]
Observations	33,391	33,897	21,765	22,111
Treated Observations	6,358	6,452	1,684	1,713

Notes: We follow Callaway & Sant'Anna (2021). The first column header is the licensing decision relevant to that column. The second column header is the dependent variable. We report three coefficients. **Pre-Decision Average:** The average of the estimated coefficients for the semesters before SUNEDU's decision. **Post-Decision Average:** The average of the estimated coefficients for the semesters after SUNEDU's decision. **C&S ATT:** The weighted estimator proposed by Callaway & Sant'Anna (2021). Standard errors are reported in parenthesis and clustered at the decision group level. P-values are reported in brackets.

4.1 License-Granted Treatment

We first focus on estimating the effect of a positive licensing decision. Two refinements are needed before the estimations. First, we limit the study to six semesters before and after each licensing decision. Second, we limit the universe of licensed universities we include in the analysis to those who got their licenses on or after semester 2018-I.

We perform this second step because of a plausible concern that the universities that received their operating licenses in the two previous years were already deemed as high-quality ones by the labor market. This would cause their graduates' wages and employment prospectus to have a historic evolution typical of high achievers, which would violate the parallel trends assumption of a difference-in-differences identification strategy. In fact, Alba et al. (2022) found evidence supporting this claim and limited their analysis to those universities that were granted a license after May 2018.

Table (3) reports our main results. Columns (1) and 2) are concerned with the effect of a positive licensing decision on monthly income and formal employment, respectively. First, concerning parallel trends, we examine the statistical significance of the pre-treatment average estimate, which is always null and with very large p-values. We find that SUNEDU's decision to grant a license had a positive effect of around 6.5% on the monthly wages of the graduates of these universities. Furthermore, this decision also increased the probability that these graduates hold a formal job at around 4 p.p.

4.2 License-Denied Treatment

We now move on to estimating the effect of a negative licensing decision. In terms of the study window, we limit the study to four semesters before and after each denial decision, but we do not impose any restriction on which universities whose licenses got denied we include in the analysis. This is because, arguably, employers knew less about lower-quality universities.

Table (3) reports this set of results. Columns (3) and (4) are the ones where the relevant treatment is a negative licensing decision. Again, the average of the pre-treatment estimates is also non-significant. We find that the effect of SUNEDU's license denial on the monthly income of people who graduated from those universities is negative around 9%. However, we fail to obtain significant results when we examine the effect of a denied license on the probability of having formal employment. It is important to notice that the number of *license-denied treated* individuals is way lower than those of *license-granted treated* ones, which could explain why the estimated effects of a negative licensing decision are more imprecise.

5 Sensitivity Analysis

Tables (4) & (5) include further refinements to the sample of college graduates which ultimately impacts the number of treated individuals in the analysis. We previously mentioned that we make sure that all control individuals are high school graduates who did not pursue any additional education, even if incomplete. This is especially important for control units because if they did attend a university for some time, SUNEDU's licensing decisions could arguably impact their labor market outcomes as well.

Table 4: License Granted Sensitivity

	Monthly Income				Formal Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C&S ATT	0.0643**	0.0632**	0.0595*	0.0562*	0.0395*	0.0382*	0.0382*	0.0337
	(0.0307)	(0.0308)	(0.0309)	(0.0315)	(0.0220)	(0.0221)	(0.0223)	(0.0226)
	[0.0362]	[0.0399]	[0.0544]	[0.0741]	[0.0729]	[0.0837]	[0.0868]	[0.1357]
Observations	33,391	33,372	33,282	33,084	33,897	33,877	33,786	33,583
Treated Observations	6,358	6,339	6,249	6,051	6,452	6,432	6,341	6,138

Notes: We follow Callaway & Sant'Anna (2021). Columns sequentially restrict the sample. **Columns 1 & 5** include all college graduates from universities that were granted the license. These columns are our main results. **Columns 2 & 6** drop college graduates who report being enrolled in institutes. **Columns 3 & 7** drop college graduates who report being enrolled in an undergraduate degree. **Columns 4 & 8** drop college graduates who report being enrolled in a graduate degree. **C&S ATT:** The weighted estimator proposed by Callaway & Sant'Anna (2021). Standard errors are reported in parenthesis and clustered at the decision group level. P-values are reported in brackets.

Table 5: License Denied Sensitivity

	Monthly Income				Formal Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C&S ATT	-0.0903*	-0.0861*	-0.0887*	-0.0977*	-0.0356	-0.0328	-0.0353	-0.0353
	(0.0494)	(0.0496)	(0.0500)	(0.0502)	(0.0378)	(0.0379)	(0.0380)	(0.0383)
	[0.0677]	[0.0829]	[0.0760]	[0.0516]	[0.3461]	[0.3857]	[0.3536]	[0.3559]
Observations	21,765	21,758	21,735	21,709	22,111	22,104	22,079	22,053
Treated Observations	1,684	1,677	1,654	1,628	1,713	1,706	1,681	1,655

Notes: We follow Callaway & Sant'Anna (2021). Columns sequentially restrict the sample. **Columns 1 & 5** include with all college graduates from universities that were denied the license. These columns are our main results. **Columns 2 & 6** drop college graduates who report being enrolled in institutes. **Columns 3 & 7** drop college graduates who report being enrolled in an undergraduate degree. **Columns 4 & 8** drop college graduates who report being enrolled in a graduate degree. **C&S ATT:** The weighted estimator proposed by Callaway & Sant'Anna (2021). Standard errors are reported in parenthesis and clustered at the decision group level. P-values are reported in brackets.

When it comes to college graduates, we made sure not to include people who hold graduate degrees. Even so, we have some cases where people who only hold an undergraduate degree report that they are enrolled in some education program at the time of the ENAHO survey. In the next two tables, columns gradually remove these observations. Columns (2) & (6) drop people who report being enrolled in technical instruction institutes. Columns (3) & (7) drop people who report being enrolled in a university for an additional undergraduate degree. Columns (4) & (8) drop people who report being enrolled in a graduate program.

When we focus on the effect of a positive license decision, we find that these exclusions cost precision to the causal estimate on monthly income. Specifically, estimations go from being significant at the 5% to the 10%. This precision cost is greater when the dependent variable is the formal employment indicator. When the full set of exclusions is imposed, the post-treatment average barely misses the statistical significance threshold ($p - val = 0.1080$). However, in all cases, the sign is the same. The coefficients themselves shrink but not considerably. On the other hand, shifting attention to the effects of a negative license decision, these exclusions do not alter any results in a consequential manner. If anything, when all the exclusions are imposed, precision on the effect on monthly income is increased ($p - value = 0.0591$ versus $p - val = 0.0761$). Nevertheless, exclusions do not improve estimations of the probability of having formal employment.

Finally, it is worth noting that the very decision of a college graduate to pursue additional education could have been influenced by SUNEDU's licensing decision concerning their university. This justifies having included these people in our main results. In other words, we argue that the inclusion of these people in the main analysis does not bias our results. Instead, removing these individuals allows us to estimate the effects of the licensing process without considering the additional education mechanism. That is, the effect of the licensing process only through the additional information about one institution, not considering any behavioral response it may have induced on the college graduates.

6 Alternative Specifications

In this section, we compare our Callaway and Sant'Anna (2021) main results with those that esteem from estimating two-way fixed effects or stacked difference-in-differences. We maintain our decision groups unchanged. That is, we still consider universities that were granted or denied the operating license in the same semester as one group for both of the alternative specifications.

In Table (6) we focus on the effects of positive licensing outcomes. Both alternative approaches improve the precision of our estimates. When we consider monthly income as our dependent variable, the robustness checks yield slightly lower estimates. However, the estimates are extremely similar when the dependent variable is the formal employment indicator. On the other hand, in Table (7), we are concerned with the consequences of negative licensing outcomes, where difference-in-differences estimated via two-way fixed effects or stacked regressions fail to uncover statistically significant effects.

Table 6: License Granted Robustness

	Monthly Income			Formal Employment		
	C&S	TWFE	SDID	C&S	TWFE	SDID
ATT	0.0643**	0.0484**	0.0500***	0.0395*	0.0389**	0.0394**
	(0.0307)	(0.0149)	(0.0139)	(0.0220)	(0.0144)	(0.0139)
	[0.0362]	[0.0176]	[0.0042]	[0.0729]	[0.0356]	[0.0161]
Observations	33,391	36,725	188,560	33,897	37,304	191,564
Treated Observations	6,358	6,358	6,358	6,452	6,452	6,452

Notes: Each column is a difference-in-differences model. **Columns C&S** follow Callaway & Sant'Anna (2021). **Columns TWFE** fit a two-way fixed effects model. **Columns SDID** estimate a stacked difference-in-differences model. Standard errors are reported in parenthesis and clustered at the decision group level. P-values are reported in brackets.

Table 7: License Denied Robustness

	Monthly Income			Formal Employment		
	C&S	TWFE	SDID	C&S	TWFE	SDID
ATT	-0.0903*	-0.0272	-0.0270	-0.0356	0.0012	0.0000
	(0.0494)	(0.0253)	(0.0255)	(0.0378)	(0.0275)	(0.0266)
	[0.0677]	[0.3244]	[0.3136]	[0.3461]	[0.9654]	[0.9989]
Observations	21,765	32,051	183,886	22,111	32,565	186,825
Treated Observations	1,684	1,684	1,684	1,713	1,713	1,713

Notes: Each column is a difference-in-differences model. **Columns C&S** follow Callaway & Sant'Anna (2021). **Columns TWFE** fit a two-way fixed effects model. **Columns SDID** estimate a stacked difference-in-differences model. Standard errors are reported in parenthesis and clustered at the decision group level. P-values are reported in brackets.

7 Extension - Quarterly Analysis

In this section, we defined our treatment groups at the quarter level as opposed to the semester level. The rationale behind this exercise is two-fold. First, we group fewer universities in a treatment group by defining them using a shorter period. Second, we try to respect the structure of ENAHO as much as possible, considering their quarterly releases. Put simply, this extension serves as a stress test to our main results, considering that the number of treated individuals is low: around 19% in the license granted analysis and only about 8% in the license denied one. We present the results of the analysis at the quarterly level in Table (8)

Following Callaway and Sant'Anna (2021), we now estimate twice as many two-by-two comparisons. The natural implication is that there are fewer treated individuals in each of these two-by-two estimations. Even more so, because there are now fewer universities in each treatment group, some of these comparisons are unfeasible. This occurs when there are no observations for a given decision group in a given quarter. Ultimately, this means that observations are dropped out of the estimation because of the more stringent treatment groups. This can be easily observed by comparing the observation counts in the table below and the one in the main results.

Table 8: Quarterly Analysis

	License Granted		License Denied	
	Monthly Income	Formal Employment	Monthly Income	Formal Employment
	(1)	(2)	(3)	(4)
C&S ATT	0.0864**	0.0965***	-0.0567	-0.0552
	(0.0429)	(0.0338)	(0.0764)	(0.0524)
	[0.0438]	[0.0043]	[0.4584]	[0.2919]
Observations	31,003	31,484	19,881	20,197
Treated Observations	5,232	5,316	1,567	1,594

Notes: We follow Callaway & Sant'Anna (2021). The first column header is the licensing decision relevant to that column. The second column header is the dependent variable. We report three coefficients. **Pre-Decision Average:** The average of the estimated coefficients for the semesters before SUNEDU's decision. **Post-Decision Average:** The average of the estimated coefficients for the semesters after SUNEDU's decision. **C&S ATT:** The weighted estimator proposed by Callaway & Sant'Anna (2021). Standard errors are reported in parenthesis and clustered at the decision group level. P-values are reported in brackets.

The quarterly analysis has advantages and disadvantages. On the one hand, the more narrowly defined treatment cohorts enable us to exploit more granular variation to obtain new estimates. Another benefit is that the quarterly analysis more closely resembles both the pace at which SUNEDU announced decisions and the frequency in which ENAHO is released. On the other hand, given our available sample of college graduates, this more detailed analysis comes at the heavy cost of dropping observations. Therefore, the differences between our main results and this extension should be interpreted cautiously, considering that they could well be explained by sample differences. We argue that our main results come from a grouping strategy that weights granularity and power concerns.

That said, the quarterly analysis yields larger effects of a positive licensing decision on both monthly income and formal employment (compare 8.64% against 6.43% and 9.65pp. to 3.95pp.). Even more, it results in a more precisely estimated effect on the second dependent variable. Nevertheless, it fails to identify statistically significant effects of negative licensing outcomes.

8 Conclusions

Using nationally representative data, we study the labor market effects of a higher education reform in Peru. Breaking with decades of self-regulation, this piece of legislation started a licensing process whereby every existing university was evaluated to determine whether it met basic quality criteria. We argue that the outcome of each university in this process sent a signal to employers about the quality of education that their workers and prospective applicants received.

We find that the licensing process had positive effects on the labor market outcomes of college graduates from universities that were granted a license. More specifically, a license-granting decision from SUNEDU had an effect of around 6.5% on their monthly incomes. They were also 4pp. more likely to be formally employed, with legal benefits. This does not mean that the reform had only positive consequences. On the contrary, a negative licensing decision reduced the monthly income of college graduates from universities that were denied a license by approximately 9%. Albeit not precisely estimated, this negative outcome is associated with a decrease of around 3.5 pp. in their probability of having formally employment.

These results are evidence that the Peruvian labor market incorporated the quality signals that the higher education reform produced. Furthermore, they underscore the importance of designing much needed reforms considering the potential costs they can have on some people. Finally, research on this reform has faced severe data limitations concerning college graduates from universities that were denied the license. We recommend policy-makers to deepen information collection efforts that enable researchers to more reliably study the aftermath of this reform.

References

F. Alba, J. Flor-Toro, and M. Magnaricotte. *College Licensing and Reputation Effects on the Labor Market*. PhD thesis, Northwestern University, 2022.

S. Athey and G. Imbens. Design-based analysis in difference-in-differences settings with staggered adoptions. *National Bureau of Economic Research*, 2018.

B. Callaway and P. H. Sant'Anna. Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230, 2021. ISSN 0304-4076. doi: https://doi.org/10.1016/j.jeconom.2020.12.001. URL https://www.sciencedirect.com/science/article/pii/S0304407620303948. Themed Issue: Treatment Effect 1.

A. Chong, P. Lavado, and G. Yamada. 'quick and dirty': Deregulation and expansion of national higher education: Be careful of what you ask for. *International Center for Public Policy*, 2023.

C. de Chaisemartin and X. D'Haultfœuille. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96, September 2020. doi: 10.1257/aer.20181169. URL https://www.aeaweb.org/articles?id=10.1257/aer.20181169.

A. Goodman-Bacon. Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277, 2021. ISSN 0304-4076. doi: https://doi.org/10.1016/j.jeconom.2021.03.014. URL https://www.sciencedirect.com/science/article/pii/S0304407621001445. Themed Issue: Treatment Effect 1.

MINEDU. La universidad en cifras. Technical report, Ministerio de Educación, 2023.

L. Sun and S. Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199, 2021. ISSN 0304-4076. doi: https://doi.org/10.1016/j.jeconom.2020.09.006. URL https://www.sciencedirect.com/science/article/pii/S030440762030378X. Themed Issue: Treatment Effect 1.

SUNEDU. El modelo de licenciamiento y su implementación en el sistema universitario peruano. Technical report, SUNEDU, 2015.

SUNEDU. Iii informe bienal sobre la realidad universitaria en el perú. Technical report, SUNEDU, 2022.

J. Távara. Gobernanza y regulación del sistema universitario peruano: luces y sombras de una nueva reforma. *Pontificia Universidad Católica del Perú*, 2018.

UNESCO. Institute for statistics (uis) - database. Technical report, 2023. URL http://data.uis.unesco.org/.

G. Yamada and P. Lavado. *Educación superior y empleo en el Peru: una brecha persistente*. Fondo Editorial de la Universidad del Pacífico, 2018.

G. Yamada, P. Lavado, and J. Martinez. An unfulfilled promise? higher education quality and professional underemployment in peru. *IZA Discussion Papers*, 2016.