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Abstract

We evaluate the returns to signaling occupation-specific skills using unique administrative data from a nationwide certification program in Colombia. The program certifies skills and issues three certifi-

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cates: basic, intermediate, and advanced. We use regression discontinuity methods to compare workers' earnings around certificate-assignment thresholds. Signaling advanced occupation-specific skills yields significant returns: 9.7%, on average, within two years of certification. Instead, we find no effects from signaling basic or intermediate occupation-specific skills. Our analysis reveals that the primary mechanism behind the observed income effects associated with the advanced certificate is the ability to signal occupation-specific skills to potential employers.

JEL Codes: J01, J31, J44

1 Introduction

One of the fundamental drivers of low productivity in developing countries is the mismatch between workers and firms.[1] Among the primary explanations for this problem are the limited availability of information regarding the skills of prospective workers and the inability of local labor markets to effectively collect and disseminate this information. In addition, usual signaling devices (e.g., academic credentials, diplomas, and college reputation) are less likely to transfer valuable information to employers in developing economies for several reasons.[2] First, workers usually lack formal education and training. Second, for certain industries and sectors, there might not be enough variation in schooling among workers to infer productivity accurately. Third, traditional measures of academic ability may not reflect productivity in occupations that require skills that are mainly acquired on the job, constantly evolve with industry standards, or are not taught in formal academic institutions.[3]

Because of existing informational frictions and the imperfect role of edu-

1. See, for example, Bloom et al. (2010), Hall and Jones (1999), and McKenzie (2017).

2. For developed countries, it has been shown that academic credentials, diplomas, and college reputation can help to mitigate information problems by providing job seekers with indicators of their skills and offering firms valuable tools for screening and comparing candidates (Altonji and Pierret 2001; Arcidiacono et al. 2010; Bedard 2001; Clark and Martorell 2014).

3. Regarding the characteristics of the labor markets in developing countries, see, for example, Behrman (1999) and Rosenzweig (1988).

cation in forecasting occupation-specific productivity, there are reasons to think that policies aimed at providing accurate information about occupation-specific skills can generate significant efficiency gains. On the one hand, occupation-specific skills provide means for finding employment and long-run earnings growth for low-educated workers (Bandiera et al. 2020). Therefore, reducing information frictions likely has a positive impact on income and reduces income differentials among comparable workers.[4] On the other hand, such policies can rectify information disparities between incumbent and potential employers regarding occupation-specific productivity, thereby inducing the efficient allocation of workers and fostering wage growth (Greenwald 1986; Pinkston 2009; Schönberg 2007). Nonetheless, it remains unclear if those efficiency gains are expected only for workers entering the labor market or if they can also benefit more experienced workers.

In this paper, we identify the worker returns to signaling occupation-specific skills in the context of a developing country. We employ a sharp regression discontinuity design using unique administrative data to estimate these returns within a large population of experienced male workers. Our study focuses on a particular signaling device: a certificate issued by the Colombian National Training Service (SENA), a governmental organization responsible for evaluating and certifying workers' skills in Colombia. Starting in 2004, SENA implemented a rigorous evaluation procedure to assess occupation-specific skills acquired as a byproduct of work experience and to determine if those skills are up-to-date with the prevailing industry standards.[5] Program participants are assigned to one of four mutually exclusive and exhaustive categories on the basis of their performance on the certification exam: no certificate, basic, intermediate, or advanced. Each category is defined by sharp thresholds corresponding to different exam-score intervals. Therefore, the categories of the certificate represent distinct signal contents.

4. Recent literature has shown that providing credible information on workers' skills or recent job performance can largely improve workers' labor market outcomes (Abebe et al. 2021; Abel et al. 2020; Bassi and Nansamba 2022; Carranza et al. 2022).

5. The certificates under analysis are not legally required to practice the corresponding occupations.

In an ideal scenario, where certificates are randomly assigned, the wage variation across these predefined categories would capture the signaling value of obtaining a certificate. However, wage differentials not only reflect the signaling value but also encompass productivity disparities among workers and unobserved match-quality factors pertaining to the interaction between workers and firms. To address potential confounders, we leverage the sharp differences in scores required to obtain a particular certificate as a proxy for random assignment. We first focus on individuals who barely pass the exam and those who barely fail, assuming they are similar in all other dimensions that matter for productivity. Under certain conditions, passing status constitutes a valid approximation for random assignment for individuals with scores close to the passing cutoff (Cattaneo et al. 2020; Cattaneo and Titiunik 2022; Lee and Lemieux 2010). We use this insight to estimate the unbiased signaling returns of the basic certificate by comparing the earnings of the two groups within the two years after certification. We then extend this approach to estimate the returns of obtaining either an intermediate or an advanced certificate, which allows us to explore the distributional effects associated with the content of the signal. In addition, we use administrative data for program participants to investigate the potential mechanisms that lead to income growth and income differentials. Our analysis focuses on how obtaining a certificate impacts employment status (i.e., salaried work, self-employment, and unemployment) and how transitions between employers contribute to generating the observed returns.

Several features of our study set it apart from previous literature. First, we estimate the returns to signaling occupation-specific skills, whereas previous literature has examined mostly the effects of signaling academic aptitude as a proxy for productivity.[6] There are strong arguments suggesting occupation-specific skills are valuable and key to explaining post-schooling

6. Relevant papers in this literature are Bedard (2001), Clark and Martorell (2014), Macleod et al. (2017), and Tyler et al. (2000). Using data from an elite university in Colombia, Arteaga (2018) discusses the importance of signaling for college graduates. As we mentioned before, more recently, a few studies have focused on the value of signaling noncognitive skills (Bassi and Nansamba 2022), general skills at the hiring stage (Abel et al. 2020; Carranza et al. 2022), or field-specific skills (Busso et al. 2023).

wage growth.[7] Nonetheless, limited attention has been devoted to analyzing the consequences of providing reliable information about occupation-specific skills. Some exceptions can be found in the emerging literature studying the returns to occupation certification, predominantly in the context of developed economies, with estimates that span from no effect to a 13% increase in income.[8] However, for the most part, this literature has used imprecise (self-reported) certification measures, and only a few studies have national-level data, preventing them from examining the effects across various segments of the economy. In addition, most papers rely on observable characteristics to estimate the effects of certification, and therefore, it is unclear whether self-selection into certification leads to biased estimates.

Second, our study design is able to isolate the returns to signaling occupation-specific skills from confounding channels, such as education. In our analysis, individuals are primarily full-time experienced workers who have completed their formal education. The skills they signal are acquired mainly on the job, as a byproduct of experience, rather than through formal education. In addition, the program tests skills without facilitating investment in human capital through lectures or training.[9] Importantly, we provide evidence spanning a wide group of occupations from a national sample of program participants. Therefore, our conclusions are not restricted to particular firms or sectors. In addition, since our data cover the two-year period after certification, we can evaluate how long the effects take to man-

7. Regarding the theoretical importance of task-specific skills, or more generally occupation-specific skills, see, for example, Becker (2009) and Gibbons and Waldman (1999, 2004). For empirical papers discussing the value of occupation-specific skills, see, for example, Kambourov and Manovskii (2009), Neal (1995), Parent (2000), Poletaev and Robinson (2008), and Sanders and Taber (2012). Finally, regarding the importance of skills for post-schooling wage growth, see Rubinstein and Weiss (2006) and Sanders and Taber (2012).

8. This literature further concludes that the effects of licensing on labor market outcomes are larger than the effects of certification. Unlike certification, occupational licensing mandates that individuals can engage in a particular occupation only if they satisfy specific predetermined criteria for competence. See, for example, Albert (2017), Kleiner and Krueger (2013), Kleiner and Vorotnikov (2017), and Xia (2021). In addition, the literature finds that the effects of certification are larger among less-educated individuals (Baird et al. 2021), suggesting the potential role of certification as a signal of skills in situations when general measures of human capital are not available.

9. It is possible that participants in the certification program are still investing in human capital by studying for the exam. Our empirical methodology allows us to deal credibly with this issue.

ifest and how permanent they are.

A third contribution to the literature is the possibility of studying the effects on experienced workers. In contrast, most of the literature evaluates the returns to signaling skills when workers first enter the labor market or only a few years into the labor market.[10] The effects on experienced workers have been consistently understudied, and it is unclear whether signaling skills can still generate returns even after agents have accumulated significant experience in the labor market. In fact, our findings suggest that this population group captures significant returns. In such a way, we provide novel evidence about the importance of information frictions on post-schooling income growth.

Lastly, limited attention has been given in the literature to signals that convey information about different skill levels. Previous studies have focused mainly on dichotomous signals and whether or not the worker possesses an occupational certificate.[11] We are among the first to provide direct evidence of the distributional effects of displaying signals with different content.[12] Our context enables us to do so because the signaling device categorizes workers' skills into four mutually exclusive and exhaustive categories, each defined by a sharp threshold.

Our estimates reveal no effects from signaling basic or intermediate occupation-specific skills. This result is expected from the perspective of traditional signaling models since most program participants obtain basic or intermediate

10. Regarding the value of academic credentials, see, for example, Arcidiacono et al. (2010), Bedard (2001), Clark and Martorell (2014), and Machin et al. (2020). More recently, the literature has focused on the value of signaling general skills (Abel et al. 2020), noncognitive skills (Bassi and Nansamba 2022), and field-specific skills (Busso et al. 2023). In all cases, these papers focus on young workers entering the labor market. For papers evaluating the labor market returns to the GED, see for example, Cameron and Heckman (1993), Jepsen et al. (2016), and Tyler et al. (2000). This literature focuses on individuals, typically aged between 18 and 25, who have recently entered the labor market.

11. Examples of papers analyzing dichotomous signals are Clark and Martorell (2014), Jepsen et al. (2016), Machin et al. (2020), and Tyler et al. (2000). The literature studying the economic importance of certificates is relatively new. The following papers provide important contributions in this area: Albert (2017), Kleiner and Krueger (2013), and Kleiner and Vorotnikov (2017).

12. Another paper that provides an analysis of signals with different contents is Bassi and Nansamba (2022).

certificates. As such, evidence is compatible with the idea of firms operating within a pooling equilibrium, wherein they pay wages based on average productivity. Consequently, only workers capable of signaling productivity levels above the average are likely to experience wage adjustments.

Indeed, our findings indicate that signaling advanced occupation-specific skills yields large and significant returns. Our estimates show that obtaining an advanced certificate generates an average increase in income of 9.7% during the two years following certification. We provide evidence indicating that the primary mechanism driving the observed effects on income is the potential to signal occupation-specific skills to prospective employers. First, we find that self-employed individuals at the time of certification transition to salaried work within the year following certification. Remarkably, these individuals experience an average income increase of 15.5% in the second year. Second, we estimate large effects on income for salaried workers at the time of certification (10.7%), as well as an average 46.8% increase in the probability of having a job-to-job transition. These findings suggest that the certificate can also be a valuable tool for salaried workers, enabling them to convey critical skill-related information to potential employers.

Notably, our results show that highly experienced workers can still improve their wages through certification, which is compatible with the existence of information asymmetries (Kahn 2013; Pinkston 2009). We argue that this phenomenon can be attributed to the certificate's unique ability to provide insights into the individual's adherence to current occupation standards, which is rarely discerned from resumes and may be easier to evaluate for an incumbent employer. In such a way, our findings provide compelling evidence that information frictions remain critical even after workers have accumulated significant experience.

Finally, we offer suggestive evidence indicating that some of the estimated effects on income among salaried workers originate within the firm. While pure learning within the firm could theoretically explain wage adjustments for workers entering the labor force or even workers with low tenure, the same mechanism does not provide a satisfactory answer to rationalize the returns among the most experienced workers. We argue that the characteristics of program participants make it unlikely that returns originate from behavioral responses from either (i) current employers, who might modify their productivity expectations or use the certificate as an efficient screening tool for justifying promotions, or (ii) workers, who might alter their self-assessment of labor market prospects and productivity. Therefore, we favor the narrative that incumbent firms adjust wages to retain valuable workers who, due to the certificate, are more likely to leave and work for other firms.

Overall, our findings suggest that mitigating information frictions through certification can provide substantial advantages by disclosing pertinent information to prospective employers. In alignment with the insights of Bandiera et al. (2020), our results underscore the significant impact of certifying skills in fostering earnings growth and facilitating job transitions. Moreover, our findings highlight the potential of signaling occupation-specific skills to benefit individuals who have accumulated considerable experience in the labor market. This includes not only those without salaried employment but also experienced workers already entrenched in the workforce.

The rest of the paper is structured as follows. In Section 2, we provide a detailed description of the program's key features. In Section 3, we describe the sample of program participants and elaborate on the procedure for obtaining information on labor market outcomes during and after applying for the certificate. We outline the empirical strategy employed to estimate the causal effects of obtaining a certificate in Section 4. In Section 5, we present the core findings. In Section 6, we delve into the mechanisms behind our main results. Finally, we conclude in Section 7.

2 Program Description

Since 2004, the Colombian National Training Service (SENA), a government agency in Colombia, has been responsible for implementing a nationwide certification program.[13] In Colombia, technical norms define the tasks and activities specific to different occupations and the up-to-date quality standards governing the production and provision of goods and services within those occupations. These norms are drafted and continuously revised by industry skill councils and are approved by the government. Based on the criteria defined by such norms, the certification program aims to assess and certify the knowledge and skills that workers acquire through their work experience, as well as the currency with occupational standards. In doing so, the program is tailored to occupations where knowledge is mostly acquired outside of formal education institutions, indirectly targeting lower-educated individuals.

From its inception, the Colombian government has recognized this program as a pivotal policy to enhance firms' productivity and bolster their competitiveness. During the past decade, the program has gone through a significant expansion, resulting in SENA being entrusted with continually expanding participation, free of charge, across the country. To date, SENA issues certificates in 912 technical norms, which have been developed by 74 industry skill councils representing the major sectors of the economy.[14] During 2019, SENA certified approximately 243,000 workers across 117 different locations.[15]

The policy's underlying objectives are to reduce the costs associated with identifying productive workers, streamline personnel selection processes, and minimize potential mismatches between firms and workers. Furthermore, the policy provides workers with means, i.e., certificates, to publicly showcase their skills and currency with occupational standards. This, in turn, aims to foster smoother transitions into more lucrative employment

13. The two primary legal dispositions governing this program are Decreto 933/2003 and Decreto 4108/2011.

14. The six most popular technical norms, accounting for 24% of certifications between 2017 and 2019, were: serving customers following service procedures, handling food in compliance with current regulations, controlling access to restricted areas based on service characteristics and regulations, operating forklifts following technical manuals, and promoting safe and healthy practices in work environments.

15. In general, candidates can take the exam for all norms in any municipality. The primary constraint is the waiting time, as they may have to wait for an instructor from a different location to visit and assist with the practical test. However, SENA does not consider this issue a significant barrier for participants to attain certification.

opportunities, thereby curbing unemployment rates among participants.

Participants enter the program hoping to be certified in a particular technical norm. To obtain the certificate, they must provide evidence of proficiency in executing the task and work activities defined by such a norm, as well as their knowledge of the prevailing quality standards. As a result, the certificate contains valuable information about the skills and knowledge required to perform a specific occupation, in accordance with contemporary standards. We refer to such skills and knowledge as occupation-specific skills.[16] To initiate the certification process, participants must demonstrate at least six months of experience in a given occupation. Typically, the process is completed within four weeks. Additionally, since technical norms are continuously revised and updated, the certificate remains valid for three years.

To obtain the certificate, individuals must take a two-part exam. The first part, known as the competence exam, entails participants performing a series of tasks and work activities under the observation of a panel of SENA officials. Evaluators assign a pass/fail grade based on the participants' performance. Since all participants must showcase relevant work experience to start the certification process, most of them successfully pass this stage (see Table 1). The second part of the exam involves a multiple-choice knowledge test. This test evaluates participants' understanding of the various concepts related to the occupation and the prevailing quality standards prescribed by the technical norm. SENA administers the exam, which is designed using a randomly selected set of predefined questions.[17] Therefore, the exam's difficulty is constant across participants. The exam

16. For instance, the technical norms pertaining to plumbing primarily outline the tasks and work activities related to installing and repairing piping fixtures and systems. These norms also define proper network installation, functionality, and durability standards. As a result, the certification program evaluates if individuals can perform occupation-specific activities efficiently while producing outcomes of higher quality and durability.

17. While the technical norm itself is publicly available, the question bank is not accessible. According to SENA, the question bank contains more than 100,000 questions for all the different technical norms. This question bank undergoes continual enhancement and revision to adapt to the evolving standards of a particular occupation. It is important to add that the number of questions in the competence exam ranges from 18 to 44. The specific number of questions for a particular norm depends on the number of tasks and activities described by the norm.

is graded by a computer on a scale of 0 to 100 points. Using computerized grading ensures that SENA officials cannot manipulate the results. The score determines the level of certification conferred by SENA. Individuals who score below 30 points do not get a certificate, even if they pass the first part. Participants scoring between 30 and 59.9 points receive a basic certificate, while those scoring between 60 and 89.9 points are granted an intermediate certificate. Lastly, participants who score 90 or higher obtain an advanced certificate. Participants are only informed of the certification level attained, and the exact grade remains confidential.

According to SENA's guidelines, participants can improve their certification level by undertaking the second part of the examination in the subsequent fiscal year, leading to infrequent exam retakes among individuals. In fact, our data show that only 0.5% of participants retake the knowledge test. Furthermore, the lack of information about how close participants are to the certification cutoff likely discourages retaking, even among those who scored just below a given cutoff.

A certificate typically includes the participant's name, identifier number, certificate expiration date, awarded certificate level, and the specific technical norm for which the participant has been certified (see Figure OA1 in online Appendix A). Employers can access the certificate information by entering the workers' identification number into SENA's web portal. Therefore, SENA provides the same information to workers and employers, making it unlikely that participants hide the certificate when unsatisfied with the outcome.

In general, no legal barriers prevent workers from continuing their current occupation, even if they do not obtain certification in the relevant technical norm. However, an exception exists for specific technical norms that apply to regulated occupations. Regulated occupations involve tasks where workers face exceptional hazards, or where failure to comply with the prevailing technical standards could lead to unacceptable risks for consumers and workers.[18] For such occupations, certification is mandatory and granted

18. Some examples of technical norms regarding occupations involving situations where workers face exceptional hazards include those related to tasks performed at elevated

only upon achieving a minimum score of 90 points on the knowledge test. Hence, workers who score below 90 are not certified and should not practice such occupations. Within our dataset, technical norms related to regulated occupations comprise less than 7% of the observations, and we choose to exclude them from the analysis. This exclusion is mainly motivated by the fact that the 90-point threshold leads to distinct and incomparable outcomes for technical norms associated with regulated occupations and those associated with non-regulated occupations. While participants scoring above 90 receive an advanced certificate, regardless of the underlying occupation, participants who score below this threshold would not obtain a certificate in the case of technical norms associated with regulated occupations, and they would receive an intermediate certificate in the case of technical norms associated with non-regulated occupations.

Our analysis of the certification program relies on administrative data provided by SENA, which covers all participants seeking certification in technical norms linked to non-regulated occupations from January 2017 to December 2019. The causal analysis leverages the discontinuity observed in the certification levels (i.e., basic, intermediate, advanced) that arise from variations in underlying scores near the three respective cutoffs (i.e., 30, 60, and 90). SENA has meticulously documented participants' demographic characteristics and the specific technical norms for which they sought certification. Over the course of this period, the program issued approximately 627,000 distinct certificates to more than 470,000 participants.[19] It is important to highlight that the institutional context remained consistent throughout the study period. Factors such as the number of evaluators, program coverage, and exam format remained unchanged since 2017. Section 3.1 provides additional information regarding SENA's data.

heights or the evaluation of equipment utilizing natural gas as an energy source. Examples of activities in which failure to comply with the technical standards could lead to unacceptable risks include installing and maintaining home networks for natural gas distribution and water purification procedures.

19. The number of certificates exceeds the number of participants due to individuals being eligible for certification in multiple technical norms. In our analysis in Section 5, we focus on the returns to the first certificate.

3 Data

Our analysis relies on two sources of information. First, we use SENA's novel administrative data with information about all participants in the certification program between 2017 and 2019. Second, given that our primary data on program participants do not contain information on labor market outcomes after certification, we use administrative records from contributions to the social security system to obtain income and employment status information.

3.1 SENA

We obtained data from SENA on all individuals who started the certification process between January 2017 and December 2019. The data contain information on the technical norm individuals applied to be certified on, the scores on the two-part exam, the test date, employment status at the time of certification, and socio-demographic information, such as educational achievement, age, and geographic location. In total, the data set contains information on 627,340 applications for certification.[20] Table 1 presents descriptive statistics for the complete dataset.

The sample comprises predominantly male individuals (68.4%). As mentioned before, we focus on the sample of men since responses from women may be obscured by (i) changes in home production activities that are not accounted for in our data and (ii) differential priors about productivity, which is outside the scope of this paper. However, as discussed in Section 5.3, estimates using the full sample of men and women are compatible with our core results. As shown in the second column of Table 1, men in the sample have, on average, 38.5 years old. Consistent with the type of occupations targeted by the certification program, there is a large share of low-educated individuals: Only 4% of the sample have a college degree or more, and 66% have completed high school at most.

As previously mentioned, the first part of the exam is generally considered

20. This figure excludes 41,675 applications for certification on technical norms related to regulated occupations.

a pass for nearly all participants and therefore does not actually determine their eligibility for the certificate. In fact, the pass rate for the sample of men stands at 99%. The mean score for the second part of the exam among the sample of men is 82 points. Approximately 1% of workers fail to attain a certificate, whereas 13%, 40% and 47% acquire basic, intermediate, and advanced certificates, respectively. As mentioned before, the objective of the second part is to assess participants' comprehension of concepts and current standards outlined in the technical norm, and therefore, such knowledge constitutes occupation-specific skills.[21]

3.2 PILA and Estimation Sample

To obtain the labor market histories, we use employer-employee-linked administrative data from the Unified Social Security Contributions Form (PILA, by its Spanish acronym). By law, all workers and firms in the formal sector must report to PILA their contributions to the social security system. PILA provides monthly information on wages, payroll-tax payments, employment type (salaried work or self-employment), and firm and job characteristics. We also observe workers' transitions between employers and in and out of PILA. However, we lack information on individuals working in the informal sector.

We can only match personal identifier numbers between PILA and SENA data for the subsample of program participants who reported to PILA at any point during 2010.[22] This implies that for individuals who did not report to PILA in 2010, we cannot observe their labor market outcomes at

21. For instance, while all plumbers likely possess the capability to install and repair drinking water and drainage networks, only the most skilled and up-to-date individuals are familiar with the design principles of the network that allows them to determine the minimum pipe diameter required for the different devices in the restroom according to the current norms and standards. For example, according to the technical norm, a Toilet with a flush tank requires a minimum pipe diameter of 1/2 inch, while a toilet with a Toilet flush valve requires 1 inch, and a urinal with a flushometer requires 3/4 inch. Therefore, approving the exam with a score above 90 points indicates that a plumber, in fact, knows the differences between toilet types and can choose the right pipe diameter to install them successfully.

22. Law 1581 of 2012 is the general legal framework applicable to managing and protecting personal data. Because of the restrictions imposed by the law, individual identification numbers were part of PILA only in 2010.

any point in time. In the third column of Table 1, we report descriptive statistics for the matched sample of men. Our estimation sample is the matched sample of men. Section 5.3 presents additional results for the matched sample of men and women.

The matched sample contains 39% of individuals from the entire sample of men. There are significant differences between the matched and unmatched samples. Nevertheless, the magnitude of such differences is, in most cases, subtle. First, the matched sample is older than the unmatched one. This difference is not surprising since matched individuals reported to PILA in 2010. Hence, younger individuals, who are less likely to have worked in 2010 (seven to nine years before certification), are less likely to be matched. Second, unemployment is less prevalent in the matched sample. This fact is also expected since the matched sample contains individuals already employed at a younger age. Notably, all 912 technical norms are present in the matched sample and individuals in the estimation sample are as likely to obtain a basic, intermediate, or advanced certificate as in the full sample.[23]

We aggregate PILA information at the quarterly level in the following way.[24] First, our measure of income is the average monthly reported income. Second, we classify an individual as employed if he appeared in PILA at least one month in the quarter. Third, if an individual does not report to PILA in any month during the quarter, we classify him as not being employed. Given our data on labor market outcomes, we cannot distinguish unemployment from employment in the informal sector, in which reporting to PILA is not mandatory. Nevertheless, taking advantage of the self-reported data on employment from SENA and comparing it against the employment data on PILA at the time of certification, we can infer the relevance of the informal sector in our sample of participants. While the measure of employment in SENA data is likely more comprehensive than

23. Table OA1 in online Appendix A displays the top 10 technical norms in the matched and unmatched samples. There is a fair degree of overlap in the more prevalent norms between the two samples, with only four norms in the top 10 for the matched sample and not appearing in the top 10 for the unmatched sample.

24. We opt to aggregate the data from PILA, which is available at a monthly frequency, to quarterly intervals for enhanced computational efficiency.

the one from PILA, the employment rate in both samples is remarkably similar. In both data sets, despite the slight differences in composition, the overall employment rate at the time of certification is around 92%, suggesting that the informal sector is not as relevant for our sample as it may be in the general population of Colombian workers.

Each month, workers must classify their occupational status using PILA's categories. We classify individuals as salaried workers if they are categorized as dependents or belong to any other category in which their employers make contributions to the social security system on their behalf. Conversely, individuals are classified as self-employed if they report being independent workers or belong to any other category in which they have to pay their entire contribution to the social security system.

Regarding certification, workers are allowed to be certified in multiple norms and 23% of them have more than one certification. In our preferred specification, we focus on the returns to the first certificate. As we show in Section 5.3, our conclusions remain if we restrict the sample to include those with only one certificate between 2017 and 2019. Lastly, we look at outcomes up to two years after certification, when the certificates remain valid.[25]

25. SENA certificates are valid for three years. However, we choose to look at outcomes up to two years out because we lack data beyond the third quarter of 2021 and because we want to get a balanced sample of individuals applying for a certificate between 2017 and 2019.

Table 1: Descriptive Statistics

	SENA data		Estimation Sample
	Full Sample	Men Only	(Men)
	A. Demographic Characteristics (SENA)		
Demographic Characteristics (Mean)			
Age	38.24	38.53	45.03 (0.00)
Less Than High School	0.19	0.22	0.20 (0.00)
High School	0.41	0.46	0.46 (0.07)
Some College	0.37	0.30	0.30 0.00)
College or More	0.04	0.02	0.04 (0.00)
Employment Status (Mean)			
Salaried Worker	0.78	0.80	0.87 (0.00)
Self-Employed	0.05	0.05	0.05 (0.00)
	B. Certification Program (SENA)		
Skills Certified			
Technical Norms	912	912	912
Industry Skill Councils	74	74	74
Certification Level (Mean)			
Basic	0.13	0.13	0.13 (0.02)
Intermediate	0.40	0.39	0.39 (0.00)
Advanced	0.47	0.48	0.47 (0.00)
Certification Two-Part Exam (Mean)			
Knowledge	81.97	82.11	82.02 (0.00)
Competence	99.15	98.91	99.02 (0.00)
Individuals	627,340	429,272	181,395
	C. Post Certification Labor Market Outcomes (PILA)		
Employment Status (Mean)			
Salaried Work at Certification	...	...	0.81
Self-Employment at Certification	...	...	0.09
Potential Experience at Certification	...	...	27.38
Salaried Work	...	...	0.77
Self-Employment	...	...	0.09
Job-to-Job Transition Probability	...	...	0.06
Dummy for Accumulated Job-to-Job Trans.	...	...	0.19
Income (Mean)	...	...	
Income	...	...	1,153,149
Ln of Income - Salaried Worker	...	...	13.97
Ln of Income - Self-Employed	...	...	13.90
Observations	...	...	1,434,061

Notes: This table reports descriptive statistics for the full sample of men and women applying to get SENA certificates between 2017 and 2019 (first column), the full sample of men (second column), and the matched sample of men (third column). The matched (estimation) sample corresponds to the subsample of men we could match with PILA. P-values of a difference-in-means test for the full and matched samples of men are reported in parenthesis adjacent to the corresponding means for the matched sample. The first panel reports demographic characteristics and employment information, calculated using SENA data only. The second panel reports information regarding the certification program. The last panel shows descriptive statistics at the time of certification, for selected variables, and for the two years following certification, using PILA data. Potential experience at the time of certification is calculated by subtracting years of education plus six years from the worker's age. A job-to-job transition is a worker's move from one firm to another in the subsequent quarter. The dummy variable for accumulated job-to-job transitions takes the value one if the individual has had at least one job-to-job transition after certification. The income variable contains zeros in periods when individuals are not salaried workers or self-employed.

In our panel, an observation is a worker-quarter pair. The last panel of Table 1 reports summary statistics on labor market outcomes for the estimation sample within two years of certification. The overall employment rate in this two-year period is 86%, with 77% of workers being salaried. On average, workers possess 27 years of potential experience, calculated by subtracting years of education plus six years from the individual's age. The average monthly income for our sample is 1,153 thousand Colombian pesos, which is equivalent to approximately USD 427 in 2018 dollars. This amount is slightly higher than the average minimum wage between 2017 and 2021, standing at 826 thousand Colombian pesos, suggesting that most of the people in our sample work in low-paying jobs that don't require formal education, such as a college degree.

4 Empirical Strategy

4.1 Research Design

This section describes the empirical strategy used to estimate the returns of obtaining a basic, intermediate, or advanced certificate. Given the nature of the SENA certification program, we use a sharp regression discontinuity (RD) design (Cattaneo et al. 2020; Lee and Lemieux 2010). In a typical RD design, all units receive a score, and the treatment is assigned to units with a score above a known cutoff. The key feature of the RD design is that, given the score, the probability of receiving treatment changes discontinuously at the cutoff. As long as units cannot sort around the known cutoff, which can be verified empirically, the abrupt change in the probability of receiving treatment is as good as random. Therefore, it can be used to learn about the local causal effect of the treatment.

Let $T_{it}^{c} = \mathbf{1}(score_{it} > c)$ be an indicator variable that takes the value of 1 if individual i, taking the exam in year t, obtains a certification score, $score_{it}$, above the threshold c. As noted in Section 3.1, we consider three thresholds: 30, 60, and 90, which correspond to obtaining a basic, intermediate, or advanced certificate, respectively. The standard local linear estimator of the RD treatment is implemented by running the following weighted least squares regression:

$$Y_{is} = \alpha + \beta score_{it} + \delta^c_{RD} T^c_{it} + \tau score_{it} \times T^c_{it} + \gamma Z'_i + \varepsilon_{is}, \tag{1}$$

where, Z_i are predetermined covariates and Y_{is} represents the labor market outcome of interest $s > 0$ quarters after certification. Equation (1) is estimated with only individuals with scores within a chosen bandwidth h, such that $score_{it} \in [c-h, c+h]$, and with weights applied according to some kernel function. The main parameter of interest, δ^c_{RD}, is estimated as

$$\delta^c_{RD} = \lim_{score_{it} \downarrow c} E[Y_{is}|score_{it}, Z'_i] - \lim_{score_{it} \uparrow c} E[Y_{is}|score_{it}, Z'_i]. \tag{2}$$

Our primary outcome of interest is the natural logarithm of income, which includes earnings from salaried work and self-employment.[26] It is important to note that PILA data does not capture earnings in the informal sector. Thus, our findings should be interpreted within the context of returns to the certificate in the formal sector.

As mentioned in Section 3.2, we look at outcomes up to eight quarters after certification (that is, $s \in [1, 8]$). The predetermined covariates, Z_i, include age and education dummies. We also include industry skill councils' fixed effects and year-of-certification fixed effects.[27] Therefore, we estimate the

26. By employing log income as the outcome measure, we exclude individuals reporting zero earnings. This approach helps to avoid potential confounding effects arising from the impact of signaling on employment. For example, if signaling negatively affects overall employment, we would observe an increase in zero-income cases, potentially attenuating the estimated effect on income. A detailed discussion of the effects on employment can be found in Section 6.

27. Ideally, we would like to include technical norm fixed effects. However, given the large number of technical norms (912), we instead choose to include industry skill councils' fixed effects (74), which can be regarded as industry fixed effects. In addition, while it would be interesting to add firm fixed effects, which would allow us to estimate the returns to the certificate within the firm, there is not enough variation in the sample to perform such an exercise. As a matter of fact, the median proportion of workers participating in the certification program between 2017 and 2019 is 4% of firms' total workers.

returns to the certificate by exploiting variation within age, education, year of certification, and industry groups. Following Cattaneo et al. (2020), we use a triangular kernel, a first-order polynomial, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator.[28] We report RD point estimators with robust bias-corrected confidence intervals (Cattaneo et al. 2020). Lastly, standard errors are clustered at the technical-norm level to adjust for the correlations induced by industry- and occupation-specific unobserved components.

4.2 Validity of the Design

The main threat to identification in an RD design is the possibility that program participants actively manipulate their score around the threshold of interest, implying that individuals just above the threshold are systematically different from individuals just below it. To mitigate this concern, we perform two falsification tests that support the validity of the RD design. First, we examine the density of the running variable, $score_{it}$, around each threshold. Second, we investigate whether treated individuals are similar around each threshold. The intuition for these two falsification tests is that if individuals cannot manipulate their score, the number of observations just above the threshold should be similar to the number of observations just below the threshold, and there should be no systematic differences across groups.

Manipulation of the score seems unlikely in our context for several reasons. As discussed in Section 2, the test format is multiple choice, and the grading is performed (by a computer) in a location different from the testing location, reducing the chances of manipulation. Furthermore, the underlying score is not revealed to participants or employers, who only get to see the certification level. Figure 1 displays the distribution of the scores.[29]

28. In Section 5.3, we show that our results are robust to the inclusion of additional controls (year and location fixed effects or no controls at all), using alternative methodologies to choose the bandwidth, using fixed bandwidths, using non-bias-corrected RD estimates, and not adjusting for the presence of mass points during estimation.

29. In the histogram in Figure 1, we exclude the highest score, 100, since it represents a significant mass point, denying a straightforward exploration of continuity. In Figure OA2 in online Appendix A, we display the complete histogram.

Visual inspection of the histogram shows no apparent discontinuities in the scores around the thresholds of interest: 30, 60, and 90. We formally test for the presence of manipulation of the score around each threshold using the test proposed by Frandsen (2017). Frandsen (2017) is the adequate manipulation test in our context since the running variable has mass points at integer values. The critical parameter in the manipulation test is k, which dictates the maximum degree of nonlinearity in the probability mass function that is still considered compatible with the absence of manipulation.[30] The results of the manipulation test around all three thresholds lead us to fail to reject the null hypothesis of absence of manipulation (p-value = 1).

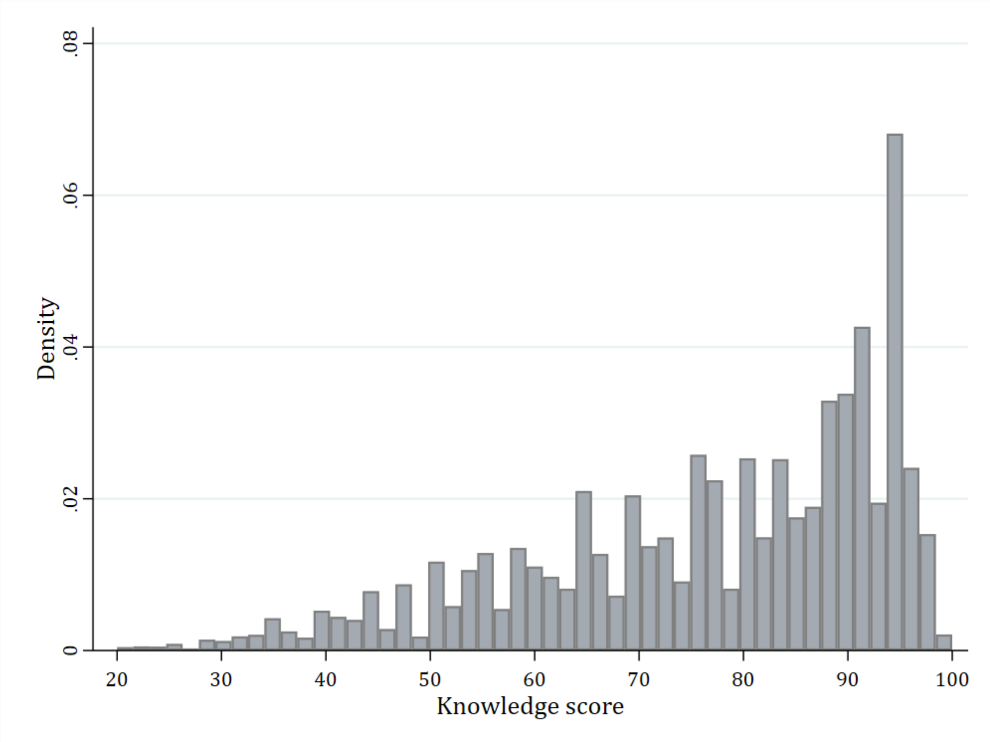
To perform the falsification analysis on predetermined characteristics, we estimate Equation (1), using each characteristic as the outcome variable. We analyze the set of predetermined covariates used in the primary analysis, Z_i, and income at the time of certification (that is, $s = 0$). The results are presented in Table 2. Our analysis shows that, at the moment of certification, individuals just below the threshold for receiving a basic certificate are not statistically different from individuals just above the threshold in terms of age or schooling. In addition, there are no observed differences regarding the reported income at the time of certification. We reach the same conclusion for individuals around the intermediate and advanced thresholds. In all, our tests show a smooth evolution through the different thresholds, confirming that participants just above and below the respective cutoffs are very similar.

5 Results

In this section, we present the core results. We use Equation (1) to estimate the returns from obtaining a given certification level. As mentioned before, our primary outcome of interest is the natural logarithm of income. We begin by examining the returns from the basic and intermediate certificates, separately. Subsequently, we present the estimates for the advanced

30. A smaller k means even tiny deviations from linearity will lead the test to reject the null of no manipulation with high probability (Frandsen 2017). We choose k using the entire distribution of the running variable, not just around the thresholds. Given our sample, the maximum suggested value for k is 0.001.

Figure 1: Distribution of Scores



Notes: This figure displays the distribution of scores in the second part of the certification exam (knowledge test) for the matched sample of men. The histogram excludes the highest score, 100, since it represents a significant mass point, denying a straightforward exploration of continuity. In Figure OA2 in online Appendix A, we display the complete histogram.

certificate. These results allow us to directly investigate the distributional effects associated with the content of the signal.

5.1 Effects of Obtaining a Basic or Intermediate Certificate

With regard to the basic certificate, the first panel of Table 3 displays the results on the log of income for quarters one to eight after certification. Figure 2 presents a visual depiction of the effects one, four, and eight quarters after certification. Following Equation (2), the effect of obtaining a basic certificate is measured by the discontinuity observed between individuals who score just below 30 points and those who score just above 30 points.

Table 2: Covariate Balance Check

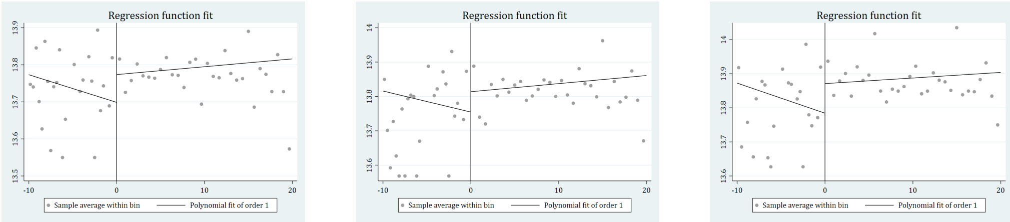
	(1) Threshold 30	(2) Threshold 60	(3) Threshold 90
Age	1.204	-0.142	-0.105
	(0.959)	(0.342)	(0.734)
	[48.255]	[45.369]	[44.739]
High School	0.052	-0.049	-0.050
	(0.054)	(0.019)	(0.032)
	[0.475]	[0.506]	[0.483]
Some College	-0.014	-0.001	-0.031
	(0.061)	(0.023)	(0.056)
	[0.200]	[0.265]	[0.304]
More Than College	0.017	0.006	0.001
	(0.007)	(0.004)	(0.014)
	[0.015]	[0.035]	[0.042]
Income at Certification (1000s)	36.989	-31.001	91.652
	(50.301)	(29.250)	(79.819)
	[863.888]	[1,024.739]	[1,121.895]
Number of Observations	181,395	181,395	181,395
Effective # of Control Observations	774	11,141	8,819
Effective # of Treatment Observations	2,894	17,158	19,950
Bandwidth	8.600	9.900	3.300

Notes: Standard errors are reported below the point estimates in parentheses. Standard errors are clustered at the technical norm level. The sample mean for the control group is displayed below the standard error in squared brackets. For each threshold, the analysis uses a fixed bandwidth that is the average of the optimal bandwidths in Table 3. Bandwidths are displayed below the effective number of observations.

Our estimates generally reveal no discernible effect on income within the first two years following certification. Specifically, for individuals with a basic certificate, income remains unchanged even after eight quarters, relative to marginal individuals without a certificate. This result is not entirely unexpected, considering the narrow sample size around the threshold for basic certificates, which could result in imprecise estimates.

Turning to the effects of acquiring an intermediate certificate, the second panel of Table 3 presents the results on the log of income one to eight quarters after certification. The effect is measured by the discontinuity observed between individuals who score just below 60 points and those who score just above 60 points. Figure 3 presents a visual depiction of the effects one, four, and eight quarters after certification. Our analysis indicates no effect on income for individuals obtaining an intermediate certificate relative to marginal individuals who obtain a basic certificate.

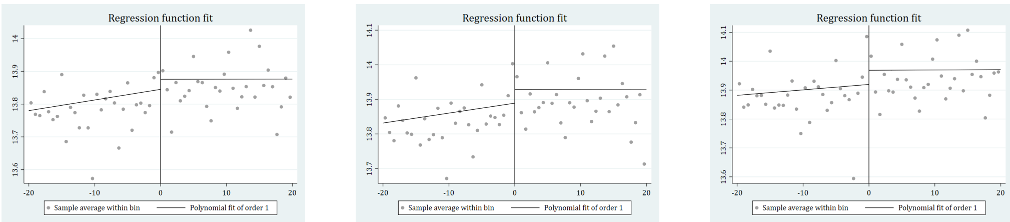
Figure 2: Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining a Basic Certificate on Log of Income



(a) Quarter One (b) Quarter Four (c) Quarter Eight

Notes: The three figures summarize the estimated results of Equation (1), one, four, and eight quarters after certification, using the log of income as the main outcome. The running variable is the exam score, and the discontinuity threshold is 30. The regressions include the controls described in Section 4.

Figure 3: Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Intermediate Certificate on Log of Income



(a) Quarter One (b) Quarter Four (c) Quarter Eight

Notes: The three figures summarize the estimated results of Equation (1), one, four, and eight quarters after certification, using the log of income as the main outcome. The running variable is the exam score, and the discontinuity threshold is 60. The regressions include the controls described in Section 4.

Two plausible explanations can account for the absence of returns from obtaining either a basic or an intermediate certificate. First, the basic or intermediate certificates may not significantly enhance workers' prospects for transitioning to other firms (for salaried workers, unemployed, or self-employed individuals). Potential employers likely do not want to incur the costs of poaching average workers and, consequently, there is no incentive for current employers to increase wages in response. Second, it is possible that the basic and intermediate certificates do not provide new information about workers' productivity, thus leading to minimal revisions in employers' priors and, consequently, earnings.[31]

Both explanations are foreseeable in our context given that 47% of the population applying to be certified gets an advanced certificate. Therefore, obtaining a basic or intermediate certificate does not lead to signaling valuable skills outside the incumbent firms or to adjusting priors about productivity. This outcome further aligns with predictions of the basic signaling models (e.g., Spence 1973, 1974; Weiss 1995). In these models, firms operate within a pooling equilibrium, wherein they pay wages based on average productivity. Consequently, only workers capable of signaling productivity levels above the average (e.g., advanced) are likely to experience wage adjustments.

5.2 Effects of Obtaining an Advanced Certificate

For the advanced certificate, the results for all eight quarters are displayed in the third panel of Table 3. Figure 4 presents a visual depiction of the effects on the log of income one, four, and eight quarters after certification. For all quarters, obtaining an advanced certificate has a substantial effect on income. The estimated effect is relatively stable over time, ranging between 8.7% and 12.7%.

31. One may be worried that employers pay lower wages when the certificate is not as expected (e.g., basic certificate). However, this is likely not the case. In the Colombian labor market, wages are characterized as downward rigid (Agudelo and Sala 2017). Likewise, it is unlikely that workers would be dismissed with cause for not reaching a given certification level, as this would not constitute a breach of the employment contract nor a case for termination with cause.

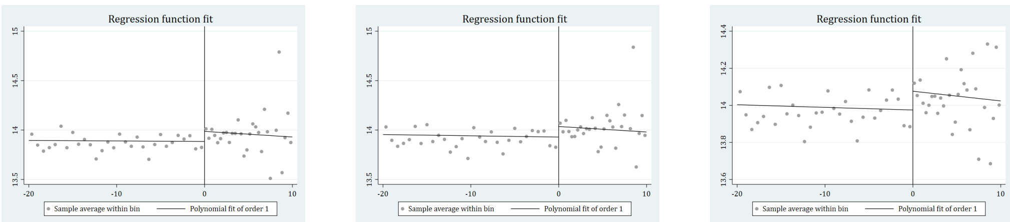
Table 3: Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining a Basic, Intermediate, and Advanced Certificate on Log of Income

	(1) Quarter 1	**(2) Quarter 2**	**(3) Quarter 3**	**(4) Quarter 4**	**(5) Quarter 5**	**(6) Quarter 6**	**(7) Quarter 7**	**(8) Quarter 8**
Basic Certificate	0.019	0.028	0.002	-0.009	0.027	0.049	0.039	0.062
	(0.030)	(0.037)	(0.037)	(0.040)	(0.034)	(0.043)	(0.031)	(0.033)
# of Observations	164,242	162,247	160,912	159,819	158,344	156,895	155,954	140,679
Eff. # of Control Obs.	756	633	698	713	617	680	611	641
Eff. # of Treatment Obs.	3,617	2,237	2,743	3,510	2,188	2,648	2,139	2,182
Bandwidth	10.14	7.738	9.994	10.47	7.661	9.038	7.203	8.306
Mean	13.726	13.738	13.751	13.777	13.775	13.777	13.805	13.814
Intermediate Certificate	-0.010	-0.002	-0.001	-0.013	-0.006	0.009	0.017	0.008
	(0.013)	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.018)	(0.018)
# of Observations	164,242	162,247	160,912	159,819	158,344	156,895	155,954	140,679
Eff. # of Control Obs.	9,611	9,921	9,808	9,319	11,296	11,248	11,393	10,147
Eff. # of Treatment Obs.	13,679	15,196	14,987	13,323	17,176	17,302	17,182	15,226
Bandwidth	8.798	9.714	9.357	8.753	10.30	10.79	11.00	10.41
Mean	13.829	13.840	13.863	13.873	13.878	13.892	13.909	13.908
Advanced Certificate	0.087	0.087	0.082	0.127	0.104	0.094	0.099	0.099
	(0.028)	(0.031)	(0.034)	(0.029)	(0.029)	(0.027)	(0.032)	(0.032)
# of Observations	164,242	162,247	160,912	159,819	158,344	156,895	155,954	140,679
Eff. # of Control Obs.	8,322	8,009	6,843	7,986	7,901	10,235	7,619	6,929
Eff. # of Treatment Obs.	18,098	17,852	14,410	17,669	17,400	23,044	16,776	14,754
Bandwidth	3.955	3.548	2.981	3.684	3.625	4.113	3.082	3.013
Mean	13.885	13.901	13.913	13.927	13.937	13.956	13.970	13.971

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1), one to eight quarters after certification, for each discontinuity threshold. The outcome is the log of income. The running variable is the exam score, and the three discontinuity thresholds are 30 (first panel), 60 (second panel), and 90 (third panel). All regressions include the controls described in Section 4, use a triangular kernel, and use the bandwidth that minimizes the mean squared error of the local polynomial regression discontinuity estimator. The total number of observations changes across quarters given variation in the number of individuals with positive earnings; it further drops in quarter 8 due to missing information in the last quarter for individuals that certified in the last quarter of 2019. The effective number of observations changes across quarters given variation in the optimal bandwidth. Robust bias-corrected standard errors are reported below the point estimates in parentheses. Standard errors are clustered at the technical-norm level. The sample mean for the control group is displayed below the optimal bandwidth.

The sizable returns associated with acquiring an advanced certificate suggest that it provides new and reliable information to employers. Workers with advanced certificates can distinguish themselves from average workers and experience wage growth. For instance, an advanced certificate can serve as a signal of occupation-specific skills to prospective employers, potentially leading to income adjustments. These adjustments may result from new employers seeking to attract the most productive workers or from incumbent employers aiming to retain their talented workforce. Therefore, obtaining an advanced certificate can contribute to wage growth within the firm, even when the current employer accurately knows the worker's productivity. In Section 6, we argue that the ability to signal occupation-specific skills to prospective employers emerges as the main mechanism behind our core results. Furthermore, we posit that, considering the predominance of experienced individuals in our sample, many of whom have held significant tenures in their current firms, our results are unlikely to be explained by the certificate's potential to (i) signal skills to incumbent employers, (ii) function as a screening tool for justifying promotions, or (iii) attenuate workers' uncertainties regarding their skills.

Figure 4: Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Advanced Certificate on Log of Income



(a) Quarter One (b) Quarter Four (c) Quarter Eight

Notes: The three figures summarize the estimated results of Equation (1), one, four, and eight quarters after certification, using the log of income as the main outcome. The running variable is the exam score, and the discontinuity threshold is 90. The regressions include the controls described in Section 4.

There are two additional considerations to highlight. First, our returns for the advanced certificate are within the range of estimated returns to certification in developed economies (Albert 2017; Kleiner and Krueger

2013; Kleiner and Vorotnikov 2017). Second, our estimated returns to signaling advanced occupation-specific skills are comparable to spending an additional year at school in Colombia (Garcıa-Suaza et al. 2014; Herrera-Idárraga et al. 2015; Morales et al. 2021). In that sense, the certificate seems to transfer information about a worker's productivity that is as valuable as that coming from schooling. Such a conclusion is important for individuals with characteristics similar to our estimation sample—namely, less educated workers in their forties who have finished school and likely have limited opportunities for wage growth.

5.3 Robustness Checks

We consider several alternative specifications to evaluate the robustness of our findings. The complete set of results is presented in online Appendix B. Upon examination of the estimates, it becomes evident that our main conclusions remain robust across various specifications and samples.

In Figure OA3 in online Appendix B, we show that our main conclusions are robust to using different specifications to evaluate the effects of the certificate.[32] For instance, our core findings are robust to including year and location fixed effects, excluding controls, using an optimal bandwidth that minimizes the coverage error, using a fixed bandwidth, employing both a fixed bandwidth and a sample reporting earnings in all eight periods considered (leading to a fixed number of total and effective observations over time), using non-bias-corrected RD estimates (Calonico et al. 2014), and not adjusting for the presence of mass points during estimation. The magnitude and significance of the returns to signaling occupation-specific skills remain in all specifications. The most notable deviation arises when employing a fixed bandwidth to evaluate the effects of obtaining an advanced certificate. However, even in this case, the estimates consistently confirm the existence of positive and significant returns. On average, these returns amount to 80% of the baseline estimates.

32. The complete set of results, with detailed information on standard errors, number of observations, and bandwidth, are presented in Tables OA3 to OA5 in online Appendix B.

In addition, in Tables OA6 to OA8 in online Appendix B, we show that our main conclusions are robust to using different samples.[33] First, our primary findings remain largely unchanged when utilizing a sample comprising both men and women.[34] In this scenario, acquiring either a basic or intermediate certificate yields no returns, whereas obtaining an advanced certificate leads to positive, significant, and permanent returns. Compared to the baseline results for the advanced certificate, the returns in the full sample are larger and more precisely estimated for all quarters. This observation suggests that women face larger returns to signaling occupation-specific skills, which aligns with traditional models of discrimination. According to these models, either employers prefer to work with males or possess prior beliefs that women have lower productivity than men, resulting in differential compensation (Aigner and Cain 1977; Lang and Spitzer 2020). The presence of an advanced certificate likely corrects these prior beliefs by providing evidence that both men and women possess equivalent occupation-specific skills. Consequently, in line with our findings, the proportional increase in returns for women should be greater.[35]

Second, our main conclusions remain mostly unchanged when we restrict the sample to include only men who applied for just one certificate in 2017, 2018, and 2019. For the advanced certificate, the results are slightly smaller in magnitude and less precisely estimated, suggesting that the marginal value of signaling more than one occupation-specific skill within an industry is somewhat important. Therefore, our results may be partly driven by the presence of multiple certificates or the existence of complementarities between certificates.

Third, to account for the fact that our measure of income may be subject to underreporting, we analyze two subsamples to evaluate the robustness of our results.[36] First, we estimate Equation (1) excluding self-employed

33. The complete set of results for alternative samples, with detailed information on standard errors, number of observations, and bandwidth, are presented in Tables OA6 to OA8 in online Appendix B.

34. Table OA2 in online Appendix A provides descriptive statistics for the estimation sample of men and women.

35. This is an interesting finding that deserves closer examination in future research.

36. In Colombia, the monthly contribution to social security includes three categories: pension, health insurance, and insurance to cover occupational hazards. Since the cover-

individuals, who are more likely to underreport earnings. Second, we use a more restricted sample consisting of those individuals who only worked as salaried employees within the two years following certification. Overall, the conclusions for all three certificates remain robust, suggesting that underreporting does not significantly influence our main results.

To further validate our results, we perform a falsification test to look at placebo thresholds, that is, thresholds other than the real thresholds determining the treatment assignment (Cattaneo et al. 2020). The intuition behind this falsification test is that the probability of receiving treatment should change abruptly only at the true thresholds. Hence, we should not observe abrupt changes in log income at artificial thresholds. We perform the falsification tests by estimating Equation (1) using six placebo thresholds: 25, 35, 55, 65, 85, and 95. The results are summarized in Figure OA7 in online Appendix B.[37] We find no effect on log income for any of the alternative thresholds, which further validates our research design.

The evidence in this section suggests that our dataset satisfies the critical assumptions for sharp RD estimation. Furthermore, our core findings are not driven by a specific bandwidth choice or specific controls and are not affected by underreported income. Moreover, we provide evidence that our key insights are not sample-specific.

6 Mechanisms

Our baseline estimates suggest that obtaining an advanced certificate has a large positive effect on income. Nonetheless, there are no effects for the intermediate and basic certificates. In this section, we focus on the advanced certificate to discuss potential mechanisms explaining positive returns. We start our analysis by examining a pivotal theoretical mechanism that can

age does not depend on the contribution for health and occupational hazards, individuals have incentives to underreport earnings obtained from self-employment or working in the informal sector. Such an incentive does not exist for salaried workers since the employer makes the payments, which count as labor expenses toward tax returns.

37. The complete set of results for placebo thresholds, with detailed information on standard errors, number of observations, and bandwidth, are presented in Table OA9 in online Appendix B.

help elucidate our results. We propose that the certificate reveals valuable information about productivity to prospective employers, suggesting that the underlying force behind the documented returns is largely compatible with signaling.

Subsequently, we employ our data to investigate whether responses provide empirical support to the proposed mechanism. We further use the empirical analysis to discuss some alternative explanations that are likely less prevalent in our context. In particular, based on the characteristics of our sample and the substantial returns observed among experienced employees, we posit that our results are unlikely to be explained by the certificate's potential to (i) signal skills to incumbent employers, (ii) function as a screening tool for justifying promotions, or (iii) attenuate workers' uncertainties regarding their own skills.

6.1 Conceptual Framework: Signaling Occupation-Specific Skills to Potential Employers

From the perspective of traditional signaling models (Spence 1973, 1974; Weiss 1995), the returns of the advanced certificate can be explained by its ability to transfer valuable information about the worker's potential productivity to prospective employers and alter their information set. Under this possibility, the certificate's significance lies in its ability to convey essential information that may not be readily discernible from resumes or other publicly observable attributes. This includes pertinent details on whether the individual possesses up-to-date skills aligned with the constantly evolving and prevailing occupation-specific standards. As such, employers seeking workers equipped with the latest skills can use the certificate to screen candidates, reassess their expectations about candidates' productivity, and adjust wages accordingly.

In this context, the certificate is a valuable tool for individuals not currently employed in salaried positions - such as the unemployed or self-employed - to facilitate a transition to salaried employment. By providing crucial insights into occupation-specific skills to prospective employers, the certificate will likely be instrumental in this transitional process (Abebe et al. 2021; Bassi and Nansamba 2022; Carranza et al. 2022; Groh et al. 2015).

The certificate can also be a valuable tool for salaried workers, enabling them to convey skill-related information to potential employers. Such a mechanism becomes crucial in the context of asymmetric information, where incumbent employers possess more knowledge about workers' occupation-specific skills than potential employers do (Kahn 2013; Pinkston 2009). Accurately assessing these skills and determining whether workers meet current occupational standards can present a significant challenge for external firms lacking insider information. This challenge underscores the certificate's pivotal role in bridging the information gap.

Consequently, the certificate has the potential to trigger outside offers from potential employers (i.e., *direct* response), yielding two possible outcomes. First, salaried workers may opt to transition to a new firm in the absence of a counteroffer from the incumbent employer or if the counteroffer is not attractive enough. Second, the incumbent employer may respond by adjusting wages to retain valuable workers (Postel–Vinay and Robin 2002; Postel-Vinay and Robin 2002).[38] According to this possibility, by signaling occupation-specific skills to potential employers, *indirect* responses (as they are not directly coming from acquiring new information about the worker's productivity) from incumbent employers can also generate positive returns even though learning about productivity has already occurred in the workplace.

Importantly, since information about the individual's alignment with current occupational standards is not perfectly correlated with experience, the proposed mechanism can remain pertinent even among experienced workers. In essence, the certificate provides unique value to potential employers by offering information that transcends the scope of traditional work experience metrics.

38. In frictional labor markets marked by information asymmetry, such a response is probable. Within those environments, a wedge often emerges between workers' marginal products and their wages, presenting opportunities for wage adjustments. In contrast, within perfectly competitive markets, firms pay wages in accordance with the worker's marginal product and, therefore, the incumbent employer would be less likely to respond to counteroffers.

In Section 6.3, we examine the possibility of incumbent firms *directly* responding to the information provided by the certificate, among other alternative mechanisms. This response typically involves the reassessment of productivity expectations, leading to potential adjustments in wages, and is likely to be prevalent among individuals with lower tenure, as the incumbent is still learning their productivity. Considering the tenure composition of our sample, we posit that this alternative mechanism is unlikely to be the primary driver behind our observed results.

6.2 Evidence on Mechanisms

6.2.1 The Value of Signaling to Potential Employers: Evidence from the Self-Employed and the Unemployed

We start by evaluating whether signaling occupation-specific skills to potential employers can explain some of the returns of the advanced certificate. We do so by exploring the effects on income and employment outcomes based on the individual's employment status at the time of certification.[39] Our initial emphasis is on participants who are not engaged in an employer-employee relationship at the time of certification, specifically those who are self-employed or unemployed. This focus aims to ensure that incumbent employers do not influence responses from potential employers. In the next subsection, we shift focus to salaried workers, for whom the certificate may generate responses from both incumbent and potential employers.

To the extent that the certificate allows self-employed and unemployed individuals to provide critical information about productivity to potential employers, we should observe transitions into salaried work after certification accompanied by increases in income. Nonetheless, we do not necessarily expect such transitions to happen immediately after certification due to frictions in the labor market (Lain 2019; Narita 2020).

We begin the analysis by discussing the results for self-employed individuals at the time of certification. Figure 5 presents the estimates for the

39. As mentioned before, employment status at the time of certification was collected by SENA in three different categories: self-employed, unemployed, and salaried individuals.

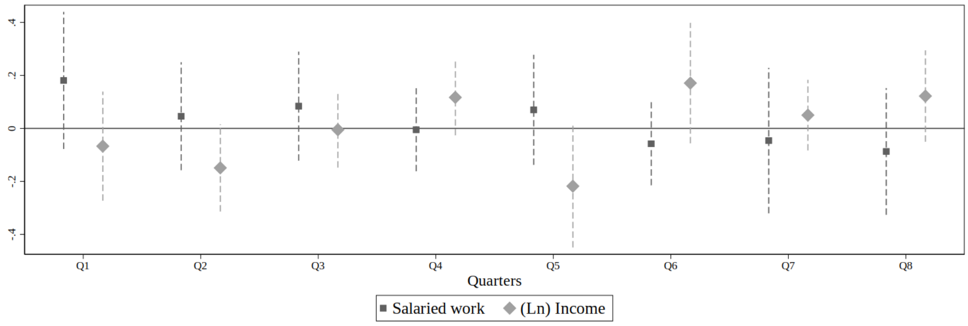
effect of obtaining an advanced certificate on income and employment outcomes.[40] Our estimates reveal a positive and statistically significant increase in salaried work, 16.4 percentage points on average, albeit with a delayed manifestation evident three calendar quarters after certification. Such an increase in salaried work is accompanied, as expected, by increases in income. Our estimates show an average increase of 15.5% between quarters four and eight. Our results indicate that potential employers significantly react to information shocks, underscoring the distinctive signaling value of the certificate.

The previous conclusion does not apply to those unemployed at the time of certification. For this group, we find no evidence of increases in either salaried work (Figure 5) or self-employment (Table OA11) and, as expected, no consequential effects on income. One possible reason for the conflicting outcomes between unemployed and self-employed individuals is that their employment status significantly impacts the employers' productivity priors beyond the certificate's positive information regarding their skills. All else being equal, unemployed individuals face the disadvantage of not being attached to the labor market despite possessing advanced skills. In such a case, negative information from employment status counteracts positive information regarding skills.[41] Conversely, it is possible that individuals attached to the labor market, such as the self-employed individuals, are better at finding suitable jobs that they accept, relative to the unemployed (Blau and Robins 1990; Faberman et al. 2022). Regardless, the evidence suggests that providing information about occupation-specific skills may not be sufficient to take participants out of unemployment and generate income increases.

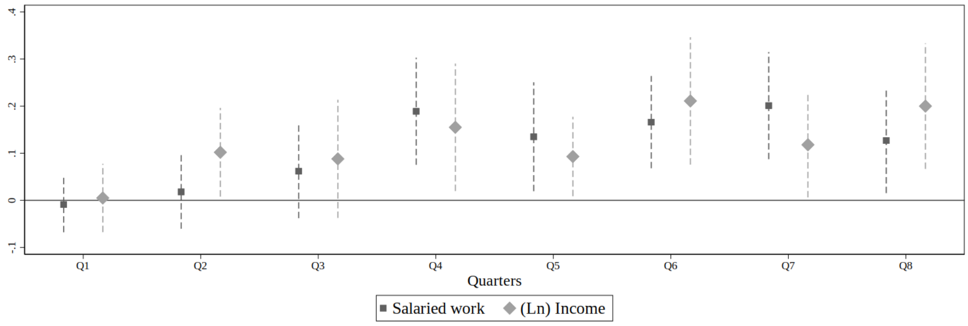
40. The complete set of results, with detailed information on standard errors, number of observations, and bandwidth, are displayed in Table OA11 in online Appendix C. For completeness, Table OA10 in online Appendix C presents the estimates for the effects of obtaining an advanced certificate on income and employment outcomes for the whole sample of men, without subdividing by initial employment status.

41. This explanation aligns with previous literature suggesting that, all else equal, employers are more inclined to hire individuals who are currently employed to mitigate the risk of hiring subpar candidates, known as lemons (Kugler and Saint-Paul 2004).

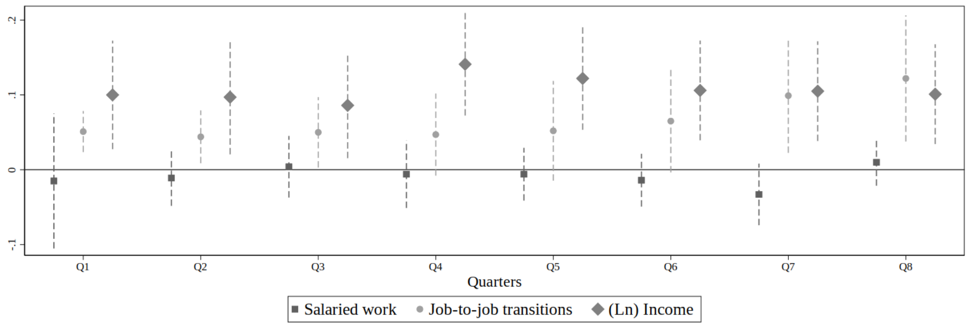
Figure 5: Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Advanced Certificate by Initial Employment Status



(a) Initial Status: Unemployed



(b) Initial Status: Self-employed



(c) Initial Status: Salaried Work

Notes: Each plot displays the estimate for the main coefficient of interest in Equation (1) and its 95% confidence interval, one to eight quarters after certification, for three outcomes based on employment status at certification: unemployed, self-employed, or salaried worker. The three outcomes are salaried work, log of income, and the probability of having changed jobs after certification (for salaried workers only). The running variable is the exam score, and the discontinuity threshold is 90. All regressions include controls described in Section 4, use a triangular kernel, and use the bandwidth that minimizes the mean squared error of the local polynomial regression discontinuity estimator. Standard errors used to compute the 95% confidence intervals are clustered at the technical-norm level. Detailed results are displayed in Table OA11 in online Appendix C.

6.2.2 The Value of Signaling to Incumbent and Potential Employers: Evidence from Salaried Workers

In this section, we discuss the certificate's signaling value among salaried workers. The certificate allows workers to signal their skills outside of the current firm, reducing the informational gap between incumbent and potential employers. This mechanism can generate *direct* responses from potential employers (i.e., outside offers) and *indirect* responses from incumbent employers (i.e., counteroffers).

We begin by presenting evidence of returns for salaried workers at certification and subsequently discuss, to the extent that our data allows, whether responses are coming from potential or incumbent employers. Figure 5 displays the effects on income and employment outcomes up to eight quarters after certification for salaried workers at the time of certification. For all quarters, we observe positive and significant effects on income ranging from 8.6% to 14.1%, with an average increase of 10.7%. Moreover, we find no significant changes in either salaried work or self-employment within the same period (see Table OA11). Figure 5 further uncovers a positive effect on the probability of switching jobs after certification. Our findings show that the probability of changing jobs (at least once) after certification increases by 6.6 percentage points (46.8%), on average, within the two years after certification. This result suggests that the estimated effects may be attributed to the possibility of signaling skills to potential employers, which triggers transitions to new firms. However, it does not eliminate the possibility of the certificate prompting responses from incumbent employers.

To explore responses from incumbent employers, Table 4 divides the sample of salaried workers based on whether they had a job-to-job transition within 3, 12, and 24 months following certification. Estimates show returns ranging between 9.1% and 15.4% among workers who stayed in the same firm upon certification. While these estimates may be subject to selection, given that estimation requires splitting the sample by an outcome realized after treatment, the magnitude of the effect provides suggestive evidence that incumbent employers are also reacting to the advanced certificate.

Table 4: Sharp Regression Discontinuity Estimates of the Effects of Obtaining an Advanced Certificate: Salaried Workers Without Job-to-Job Transitions

Outcome	**(1) Quarter 1**	**(2) Quarter 4**	**(3) Quarter 8**
Ln (Income)	0.111	0.154	0.091
	(0.038)	(0.036)	(0.032)
Observations	125,524	110,886	87,052
Control Obs.	5,653	5,009	4,594
Treat. Obs.	10,916	9,639	9,294
Bandwidth	2.921	2.965	3.652

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1). The outcomes are the log of income after one quarter, one year, and two years following certification, respectively, for individuals who did not switch jobs up to the corresponding periods. For instance, in column 2, we focus on individuals who did not undergo a job-to-job transition within the first year following certification. All estimates are based on the sample of salaried workers at certification. The running variable is the exam score, and the discontinuity threshold is 90. All regressions include controls described in Section 4, use a triangular kernel, and use the bandwidth that minimizes the mean squared error of the local polynomial regression discontinuity estimator. We report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical-norm level.

As mentioned in Section 6.1, in the context of asymmetric information between employers, both experienced and inexperienced workers may benefit from signaling occupation-specific skills to potential employers. Hence, analyzing effects based on experience provides valuable insights. Figure 6 examines the effects on the probability of changing jobs and income among salaried workers at certification, based on their potential experience.[42] We consider three different subsamples and estimate the returns for each one: (i) workers with 15 years or less, (ii) workers with more than 15 years but less than 30, and (iii) workers with more than 30 years.

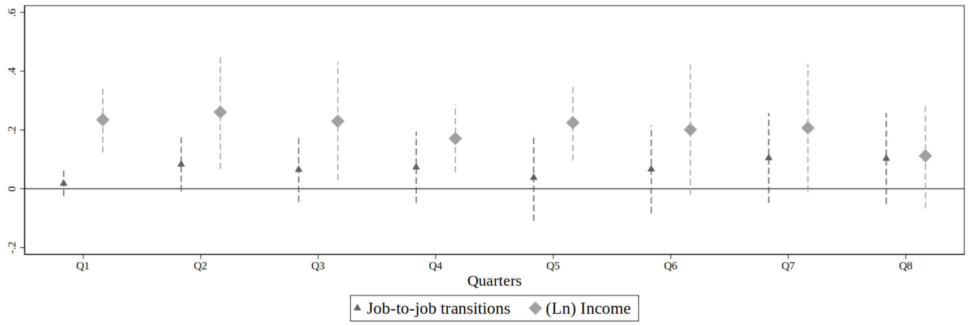
On the one hand, we find sizable effects on income among less experienced workers. For instance, we estimate an average increase in income of 20.5% for salaried workers with less than 15 years of potential experience. Interestingly, there is no discernible evidence of job mobility, suggesting that wage adjustments may originate within the incumbent firm. On the

42. Potential experience is calculated by subtracting years of education plus six years from age. Average potential experience in the sample is 27 years (see Table 1).

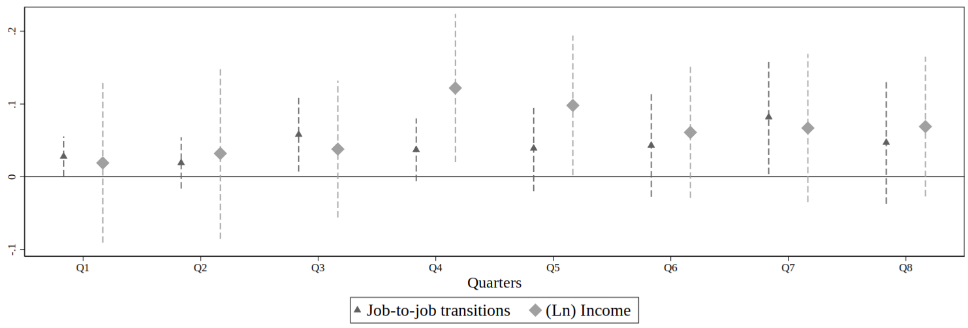
other hand, while we estimate sizable effects on income among more experienced workers, there is also some evidence of increases in the probability of changing jobs after certification. For example, individuals with 15 to 30 years of potential experience exhibit an average income increase of 6.3%, as well as an average increase in the probability of switching jobs of 4.4 percentage points (28.6%). These results reinforce the notion that potential employers react to the information about productivity conveyed by the certificate. Importantly, returns for all experience groups are statistically indistinguishable from each other.

Our results suggest that the observed returns from the certificate among salaried workers are compatible with the possibility of signaling occupation-specific skills to potential employers. Our evidence shows that the certificate (i) triggers *direct* responses from prospective employers, with the aim of attracting valuable workers, and, in some cases, (ii) triggers *indirect* responses from incumbent employers, who adjust wages to stop potential employers from poaching their talented workforce. Our results further confirm that incumbent employers face an increasing probability of workers with advanced skills leaving the firm. In such a way, documented responses from incumbent employers are compatible with the idea of firms aiming to retain valuable employees rather than being attributed to shifts in priors regarding their own workers' productivity, as we discuss in the next section (Section 6.3). Lastly, the similarity of estimates for salaried workers across experience groups indicates that, in the context of asymmetric information regarding occupation-specific skills, even experienced workers can capture sizable returns.

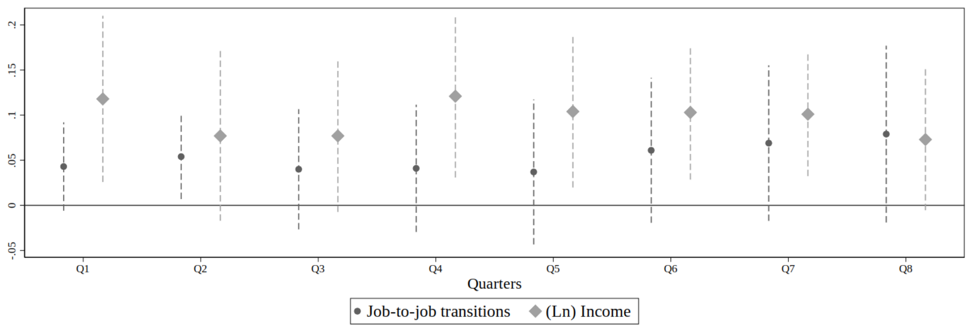
Figure 6: Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Advanced Certificate for Salaried Workers by Potential Experience



(a) Less than 15 years of potential experience



(b) Between 15 and 30 years of potential experience



(c) More than 30 years of potential experience

Notes: Each plot displays the estimate for the main coefficient of interest in Equation (1) and its 95% confidence interval, one to eight quarters after certification, for two outcomes by potential experience: workers with 15 years or less, workers with more than 15 years but less than 30, and workers with more than 30 years. All estimates are based on the sample of salaried workers at certification. The outcomes are log of income and the probability of having changed jobs after certification. The running variable is the exam score, and the discontinuity threshold is 90. All regressions include controls described in Section 4, use a triangular kernel, and use the bandwidth that minimizes the mean squared error of the local polynomial regression discontinuity estimator. Standard errors used to compute the 95% confidence intervals are clustered at the technical-norm level. Detailed results are displayed in Table OA12 in online Appendix C.

6.3 Alternative Explanations

6.3.1 Signaling Occupation-Specific Skills to Incumbent Employers.

An alternative mechanism that could explain the documented increases in income among salaried workers pertains to the certificate's role in providing an avenue for showcasing skills to incumbent employers. In such a way, it is possible to attribute returns originating within the firm to the certificate's ability to affect the information set of incumbent employers who reassess productivity expectations and adjust wages accordingly. This mechanism is likely more pronounced among low-tenured workers as incumbent firms may not have had ample time to gauge the workers' productivity, assess the currency of workers' skills, and update their expectations (Altonji 2005; Farber and Gibbons 1996; Jovanovic 1979; Lange 2007). In contrast, this mechanism is potentially irrelevant among high-tenured workers, given that incumbent firms have gained enough knowledge over time to assess skills and adjust expectations accordingly.

We posit that, in our context, this mechanism is unlikely to function as a determinant of returns among salaried workers for several reasons. For the advanced certificate, our sample includes workers with an average tenure of 4.3 years. Additionally, over 65% of salaried workers near the threshold for obtaining an advanced certificate have worked in the firm for over five years. Previous research suggests that incumbent employers learn quickly, with most learning occurring within three years of tenure (Lange 2007). Therefore, it is improbable that incumbent employers would significantly update their expectations upon observing the certificate. Additionally, the skills under consideration primarily pertain to low-paid jobs, making the evaluation of those skills even more likely to occur during the initial years on the job. Nonetheless, as previously mentioned, incumbent employers may still react to the threat of outside offers if they are underpaying workers.[43] Consequently, we conclude that the evidence presented in Section 6.2.2 regarding incumbent firms' responses is mostly compatible with *indirect* responses (i.e., counteroffers) aimed at retaining valuable workers and

43. This idea is compatible with some of the results in Adhvaryu et al. (2023).

preventing their loss to competing firms.

Relatedly, it is also plausible that the certificate may provide incumbent firms an objective criterion for awarding promotions.[44] Once again, considering that the certified skills are developed on the job and can be evaluated over the years, combined with the fact that workers in our sample are experienced, it is likely that their current employers possess accurate information regarding the extent of their occupation-specific skills and whether those skills are up-to-date. Therefore, when identifying the most skilled workers, the certificate may be redundant. In this context, it makes little sense to think that a certificate provides definitive criteria for permanently increasing salaries by 10%, especially among the most experienced.[45]

6.3.2 Attenuating Workers' Uncertainty About Their Own Skills.

An alternative explanation for the observed increases in income is based on the hypothesis that workers are uncertain about their level of skills.[46] According to this explanation, when workers receive an advanced certificate, they learn about their abilities and realize their true prospects in the labor market. On the one hand, individuals who receive the certificate may tend to proactively intensify their job search efforts, leading to an upswing in secured employment opportunities (Carranza et al. 2022; Falk et al. 2006; Mueller et al. 2021). Conversely, possessing an advanced certification and learning about own skills may instill a heightened sense of confidence, fostering the belief in one's capacity to thrive as an entrepreneur and prompting a transition towards self-employment (Asoni 2011; Hamilton et al. 2019; Levine and Rubinstein 2017).

44. Benson et al. (2019) discusses the importance of establishing criteria for promotion that do not lead to perceptions of favoritism, unfairness, or the impression that effort in one's job goes unrewarded.

45. Furthermore, while we have firm identifiers in the PILA, we do not have sufficient variation within firms to convincingly compare workers with and without advanced certificates of the same kind and explore earnings differentials. In addition, we do not have occupation information, which would be required to formally explore the possibility of using the certificate to justify promotions.

46. For papers using an experimental approach to prove evidence about this channel, see Falk et al. (2006). For papers adopting non-experimental approaches, see, for example, Antonovics and Golan (2012), Golan and Sanders (2019), and Sanders (2014).

While it is plausible that workers' uncertainty about their own skills explains part of the effects, we think it is unlikely that this is the main driver for at least two reasons. First, under this explanation, the knowledge gained regarding one's own skills and the boost in self-confidence instilled by the certificate unequivocally contribute to reduced unemployment through transitions to self-employment or salaried work. However, our results provide no evidence of a reduction in unemployment or an increase in self-employment among unemployed individuals at the time of certification (see Table OA11). Second, the critical assumption behind this mechanism is that workers are unaware of their potential, so moving across occupations helps them to realize their relative advantage. Usually, studies in this stream of literature focus on transitions between occupations that happen early in workers' careers. The findings suggest that most of the learning about one's skills happens early and that experimentation ceases to explain transitions between jobs after a few periods of accumulating job experience.[47] Therefore, it is not easy to reconcile such evidence with the fact that workers in our sample have an average of 27 years of potential experience. Since most of the learning about their skills probably happened before they decided to apply for the certificate, it is unlikely the certificate adds critical new information to the worker's own information set.

7 Conclusion

In this paper, we provide causal evidence of the effect of signaling occupation-specific skills on income. We take advantage of a novel program in Colombia that certifies workers' occupation-specific skills. Our study context is unique in that it allows us to directly evaluate the effect of the signal's content, as the certification program offers three levels of certification, which are entirely determined by sharp thresholds: basic, intermediate, and advanced. Using a regression discontinuity design, we estimate returns on earnings up to two years after certification and find that the effects vary significantly with the signal content.

47. For example, Antonovics and Golan (2012) find that much of the learning takes place in the first seven years.

On the one hand, workers with a basic or intermediate certificate have no returns on earnings within two years. On the other hand, there is a sizable and permanent effect on average earnings (9.7%) for individuals with advanced certificates. We argue that obtaining an advanced certificate mainly impacts earnings by allowing individuals to effectively signal their occupation-specific skills to potential employers, increasing their likelihood of receiving outside offers. Although such a mechanism is particularly prevalent among self-employed individuals, we also find evidence among salaried workers, including the most experienced ones. For salaried workers, results suggest that returns are not only coming from prospective employers but also from incumbent employers, who react to the possibility of losing valuable workers.

Our results provide compelling evidence that certification programs can stimulate post-schooling wage growth among low-educated, experienced workers. The certificate serves as a reliable indicator of productivity, particularly in cases where traditional signals of academic ability are not informative about specific aspects of human capital, such as occupation-specific skills. Additionally, the certificate is valuable when job market history fails to demonstrate the worker's current alignment with constantly evolving occupation-specific standards.

It is important to acknowledge one caveat when interpreting our findings. Our sample is confined to Colombia, which implies that our results primarily pertain to labor markets characterized by significant information frictions. In this sense, our findings hold broader implications for developing countries sharing similar labor market characteristics.

In all, our findings suggest the existence of information asymmetries among employers even after workers have accumulated considerable labor market experience and the certificate partially corrects them. A key takeaway from our research is that implementing policy measures designed to disclose information pertaining to previously acquired skills, thereby reducing the informational gap between incumbent and potential employers, holds the potential for substantial efficiency gains by facilitating the reallocation of workers. Due to the rapid evolution of skills demanded in the labor market, policymakers often emphasize the importance of continued development of occupation-specific skills for this particular segment of the workforce. Nonetheless, according to our findings, another set of effective policy measures involves the design of mechanisms for revealing information about already acquired skills on the job. Moreover, such mechanisms can also incentivize individuals to maintain their skills up-to-date.

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Online Appendix A. Additional Figures and Tables

Figure OA1: Example of an Advanced Certificate

Libertad y orden
RÉPUBLICA DE COLOMBIA

El Servicio Nacional de Aprendizaje SENA

En Cumplimiento del Decreto 933 de 2003
otorga
Certificado de Competencia Laboral a

[redacted]

Con CÉDULA DE CIUDADANÍA No. [redacted]

Quien demostró su Competencia Laboral en la Norma

LEVEL OF CERTIFICATE

NIVEL AVANZADO

TECHNICAL NORM

Transportar usuarios en los vehículos automotores de servicio especial de acuerdo a normatividad vigente.

Código: 280601013

En testimonio de lo anterior, se firma el presente en CHÍA, A los veintiuno (21) días del mes de Junio de dos mil diecisiete (2017)

DATE

Firmado Digitalmente por

[redacted]

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VIGENCIA
21 de Junio de 2020

La autenticidad de este documento puede ser verificada en el registro electrónico que se encuentra en la página web http://certificados.sena.edu.co, bajo el número 951300280601013CC11435671C.

Table OA1: Top 10 Technical Norms: Matched and Unmatched Samples

Matched Sample

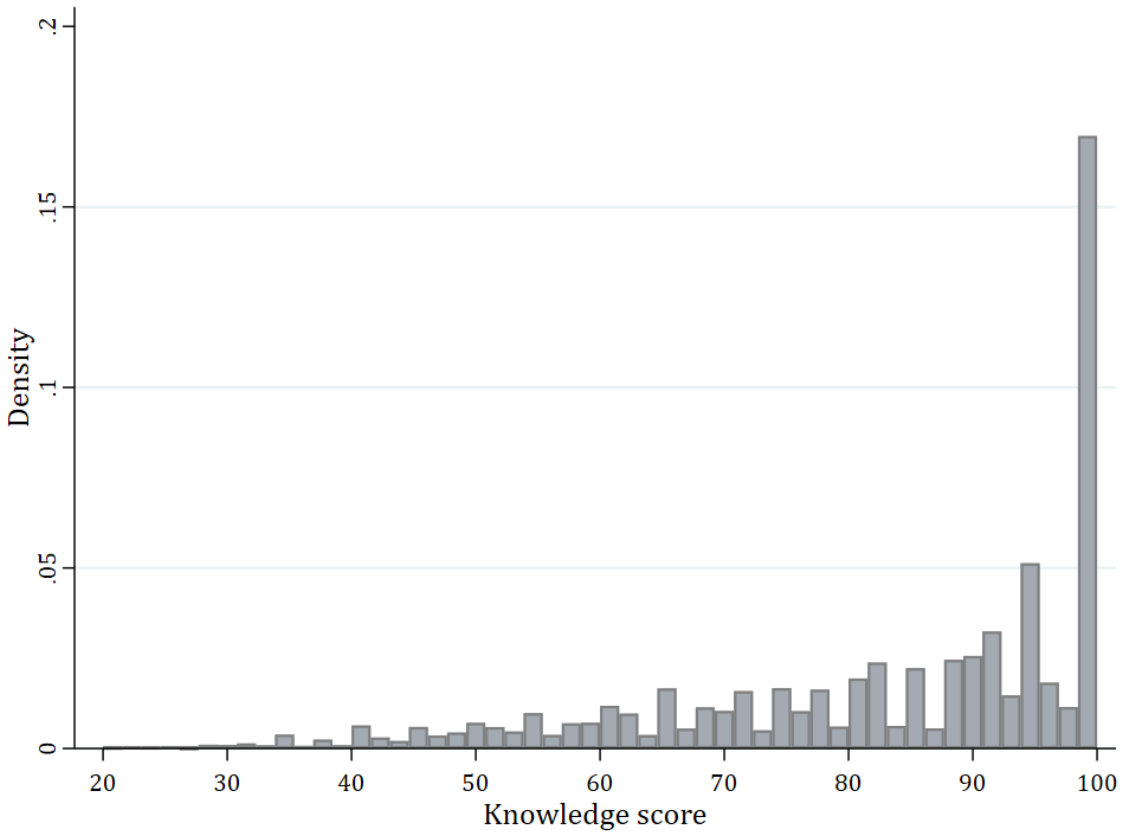
Ranking in Matched	Name	Share of Participants	Ranking in Unmatched
1	Serve customers in accordance with service procedures and regulations.	0.10	1
2	To guide classroom training in accordance with technical procedures and regulations.	0.05	3
3	Control access in accordance with private security regulations.	0.04	5
4	Operate forklifts according to the technical manual.	0.04	23
5	Handle food according to current standards.	0.02	2
6	Operate the hydraulic excavator according to the technical manual.	0.02	17
7	Drive light vehicles according to technical procedures and traffic and transportation regulations.	0.02	7
8	Prevent security and surveillance incidents by technical regulations.	0.02	15
9	Prepare light vehicles in accordance with legal and technical regulations.	0.02	9
10	To drive inter-municipal or special passenger service motor vehicles, category c2, by the regulations in force.	0.02	30

Un-Matched Sample

Ranking in Unmacthed	Name	Share of Participants	Ranking in Matched
1	Serve customers in accordance with service procedures and regulations.	0.21	1
2	Handle food according to current standards.	0.07	5
3	To guide classroom training in accordance with technical procedures and regulations.	0.07	2
4	Administer immunobiological according to delegation and health regulations.	0.05	76
5	Control access in accordance with private security regulations.	0.04	3
6	Orient people according to health standards.	0.03	65
7	Drive light vehicles according to technical procedures and traffic and transportation regulations.	0.03	7
8	Collect potentially recyclable solid waste according to established procedures and current regulations.	0.02	110
9	Prepare light vehicles in accordance with legal and technical regulations.	0.02	9
10	Transfer users in accordance with coexistence, transit, and land transportation regulations.	0.02	12

Notes: This table displays the top 10 technical norms in the matched (estimation) and unmatched samples of men.

Figure OA2: Distribution of Scores



Notes: This figure displays the distribution of scores in the second part of the certification exam (knowledge test) for the matched sample of men.

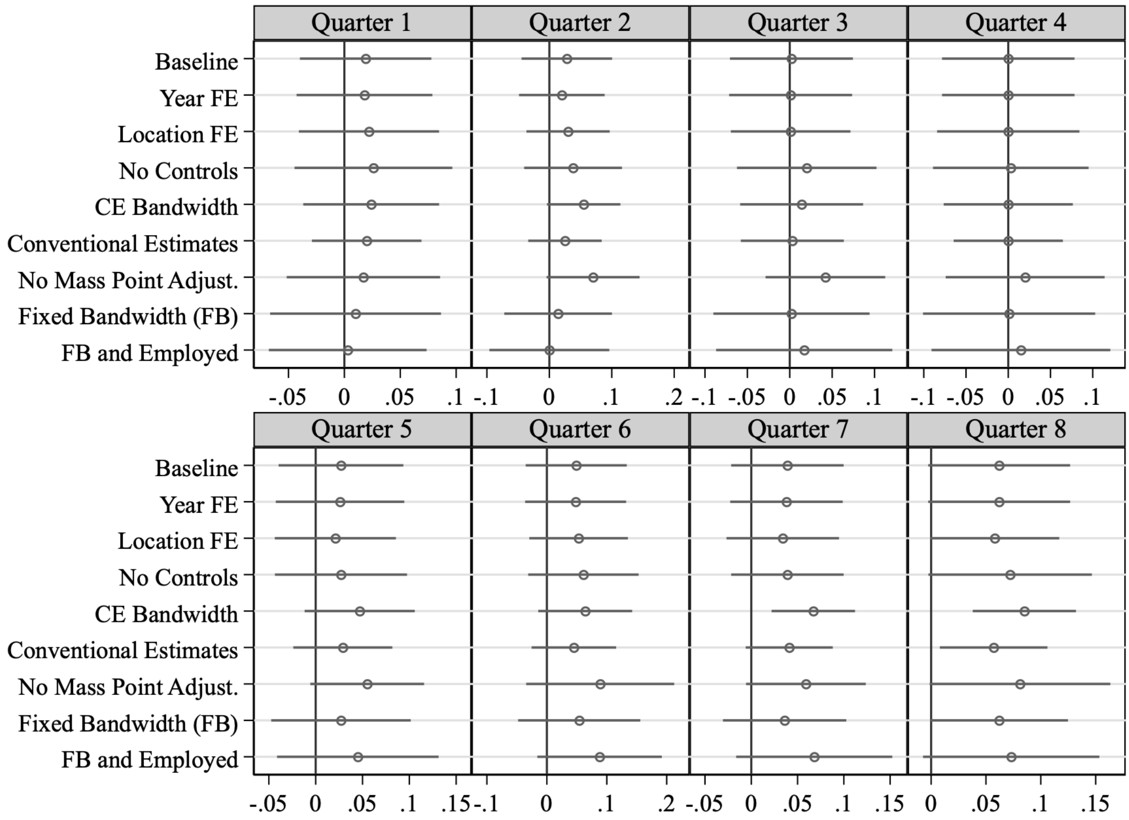
Table OA2: Descriptive Statistics: Estimation Sample of Men and Women

Variable	**# Observations**	**Mean**	**Std. dev.**
Employed	2,043,639	0.88	0.32
Income	2,043,639	1,186,950	983,688
Salaried Work	2,043,639	0.74	0.44
Self-employment	2,043,639	0.12	0.32
Ln of Income	1,800,266	13.97	0.56
Ln of Income - Salaried Worker	1,503,237	13.99	0.55
Ln of Income - Self-Employed	237,918	13.90	0.35

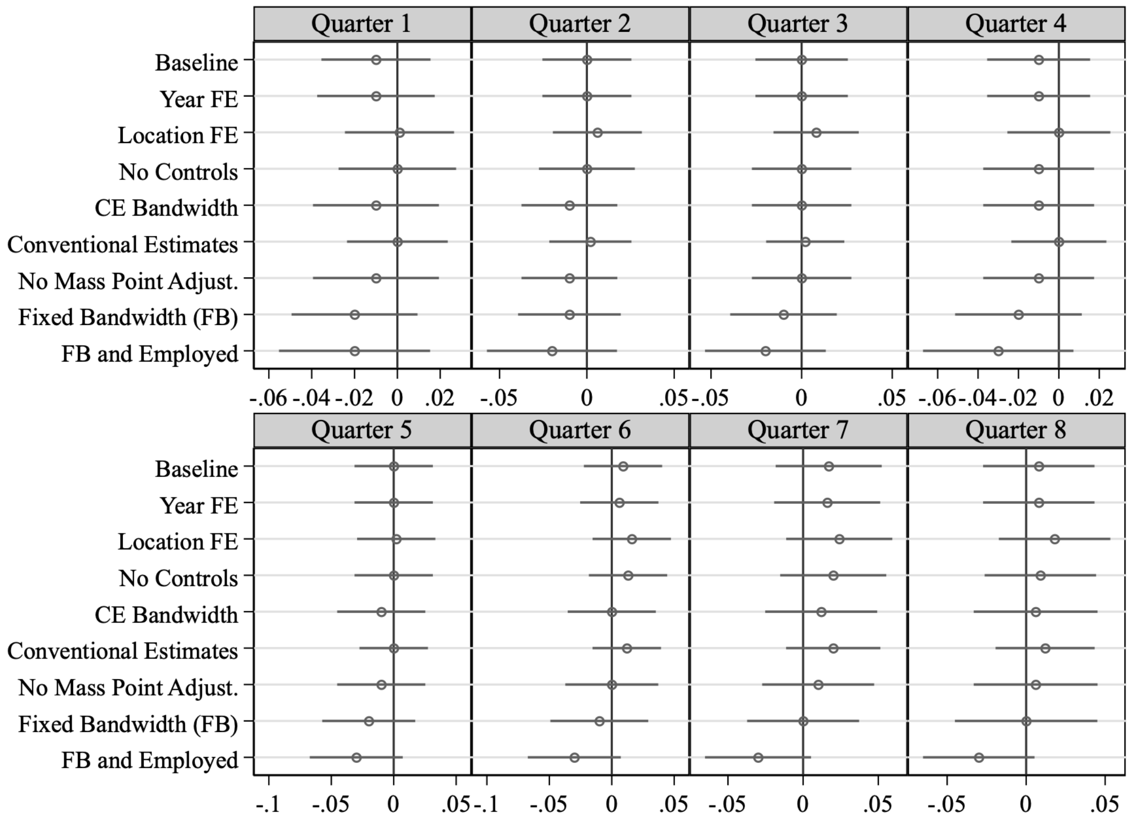
Notes: The table shows descriptive statistics for the panel of men and women two years after certification. Employment and income information are calculated using PILA data. Individuals are classified as employed if they are categorized as salaried workers, self-employed, or if they are assigned to any other category in which employers make contributions to the social security system on their behalf. Therefore, the employment rate is larger than the sum of self-employment and salaried work. The income variable contains zeros in periods when individuals are not employed.

Online Appendix B. Robustness Checks

Figure OA3: Sharp Regression Discontinuity Estimates of the Effects of Obtaining a Certificate on Log of Income: Robustness Checks

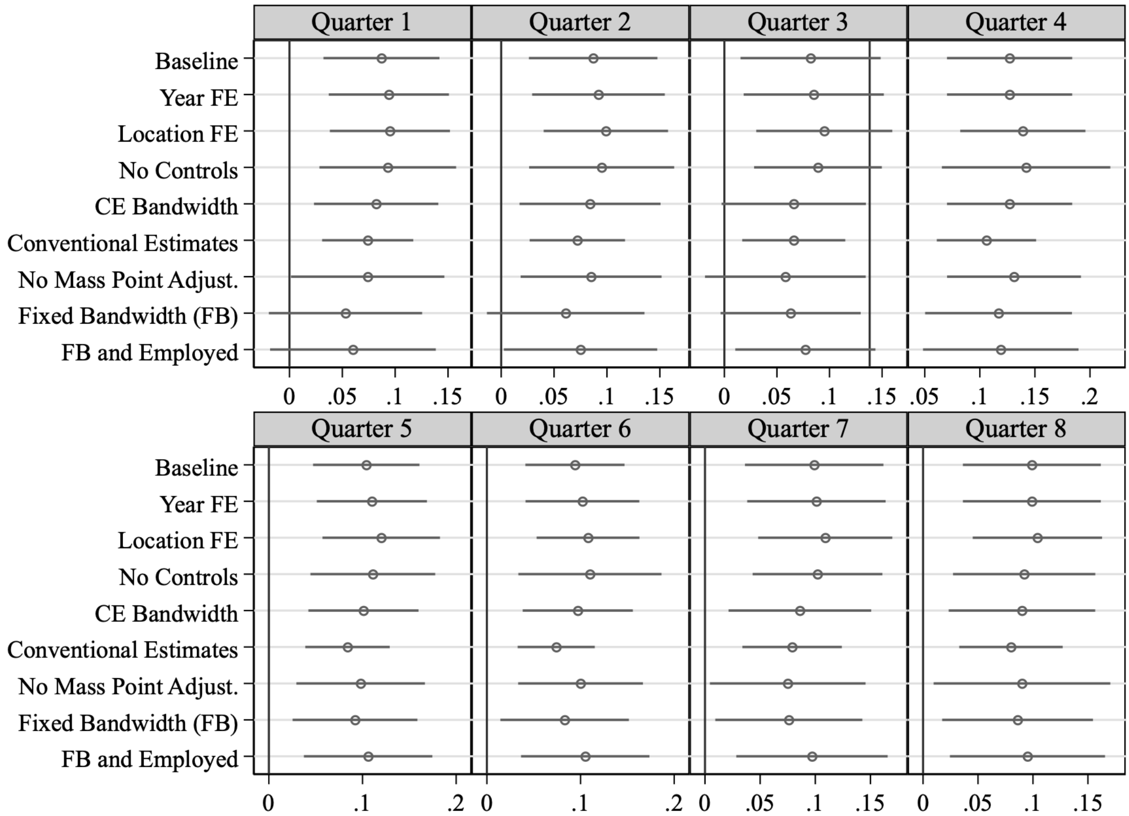


(a) Basic



(b) Intermediate

Figure OA3 Continued. Sharp Regression Discontinuity Estimates of the Effects of Obtaining a Certificate on Log of Income: Robustness Checks



(c) Advanced

Notes: Each plot displays the estimate for the main coefficient of interest in Equation (1) and its 95% confidence interval, one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score, and the discontinuity threshold is 30 for the basic certificate (panel a), 60 for the intermediate certificate (panel b), and 90 for the advanced certificate (panel c). In each plot, row 1 displays the baseline results from Table 3. Rows 2 and 3 show the results when we add year and location fixed effects (FE), respectively. Row 4 excludes controls. Row 5 uses the bandwidth that minimizes the coverage error (CE) of the local polynomial regression discontinuity estimator. Row 6 reports non-bias-corrected estimates. Row 7 does not adjust for the presence of mass points. Row 8 uses a fixed bandwidth. Row 9 uses a fixed bandwidth and restricts attention to individuals who are employed in all eight quarters. All specifications include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator, except for rows 5, 8, and 9. Standard errors used to compute 95% confidence intervals are clustered at the technical-norm level. Detailed results for all three certificates are displayed in Tables OA3, OA4, and OA5.

Table OA3: Sharp Regression Discontinuity Estimates of the Effects of Obtaining a Basic Certificate on Log of Income: Robustness Checks

	(1) Quarter 1	**(2) Quarter 2**	**(3) Quarter 3**	**(4) Quarter 4**	**(5) Quarter 5**	**(6) Quarter 6**	**(7) Quarter 7**	**(8) Quarter 8**
1. Baseline	0.019	0.028	0.002	-0.009	0.027	0.049	0.039	0.062
	(0.030)	(0.037)	(0.037)	(0.040)	(0.034)	(0.043)	(0.031)	(0.033)
Eff. # of Control Obs.	756	633	698	713	617	680	611	641
Eff. # of Treatment Obs.	3,617	2,237	2,743	3,510	2,188	2,648	2,139	2,182
Bandwidth	10.140	7.738	9.994	10.470	7.661	9.038	7.203	8.306
2. Year FE	0.018	0.020	0.001	-0.009	0.026	0.048	0.038	0.062
	(0.031)	(0.035)	(0.037)	(0.040)	(0.035)	(0.043)	(0.031)	(0.033)
Eff. # of Control Obs.	715	704	739	713	616	681	610	641
Eff. # of Treatment Obs.	2,821	2,760	3,511	3,510	2,174	2,660	2,126	2,182
Bandwidth	9.937	9.359	10.200	10.470	7.432	9.223	7.138	8.306
3. Location FE	0.022	0.030	0.001	-0.003	0.021	0.053	0.034	0.058
	(0.032)	(0.034)	(0.036)	(0.043)	(0.033)	(0.042)	(0.031)	(0.030)
Eff. # of Control Obs.	644	676	672	648	615	680	612	600
Eff. # of Treatment Obs.	2,294	2,523	2,510	2,504	2,173	2,456	2,140	1,935
Bandwidth	7.584	8.109	8.188	8.086	7.214	9.005	7.296	7.853
4. No Controls	0.026	0.038	0.020	0.003	0.027	0.061	0.039	0.072
	(0.036)	(0.040)	(0.042)	(0.047)	(0.036)	(0.047)	(0.031)	(0.038)
Eff. # of Control Obs.	645	574	628	648	682	657	656	599
Eff. # of Treatment Obs.	2,295	1,934	2,224	2,504	2,708	2,439	2,453	1,918
Bandwidth	7.643	6.795	7.591	8.200	9.447	8.133	8.919	7.245
5. CE Bandwidth	0.024	0.055	0.014	-0.001	0.047	0.064	0.067	0.085
	(0.031)	(0.030)	(0.037)	(0.039)	(0.030)	(0.040)	(0.023)	(0.024)
Eff. # of Control Obs.	643	484	621	604	472	546	470	462
Eff. # of Treatment Obs.	2,277	1,758	2,191	2,198	1,709	1,854	1,658	1,503
Bandwidth	7.186	5.484	7.081	7.416	5.431	6.405	5.105	5.895

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Table OA3 Continued. Sharp Regression Discontinuity Estimates of the Effects of Obtaining a Basic Certificate on Log of Income: Robustness Checks

	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
6. Conventional Estimates	0.020	0.025	0.003	-0.007	0.029	0.045	0.041	0.057
	(0.025)	(0.030)	(0.031)	(0.033)	(0.027)	(0.036)	(0.024)	(0.025)
Eff. # of Control Obs.	756	633	698	713	617	680	611	641
Eff. # of Treatment Obs.	3,617	2,237	2,743	3,510	2,188	2,648	2,139	2,182
Bandwidth	10.140	7.738	9.994	10.470	7.661	9.038	7.203	8.306
7. No Mass Points Adjustment	0.017	0.070	0.042	0.020	0.055	0.089	0.059	0.081
	(0.035)	(0.038)	(0.036)	(0.048)	(0.031)	(0.063)	(0.033)	(0.042)
Eff. # of Control Obs.	326	321	410	298	413	311	309	302
Eff. # of Treatment Obs.	800	777	949	745	936	743	743	659
Bandwidth	3.689	3.514	4.077	3.029	4.398	3.704	3.618	3.060
8. Fixed Bandwidth	0.010	0.014	0.002	0.001	0.027	0.054	0.036	0.062
	(0.039)	(0.044)	(0.047)	(0.052)	(0.038)	(0.052)	(0.034)	(0.032)
Eff. # of Control Obs.	690	679	675	650	660	660	656	641
Eff. # of Treatment Obs.	2,592	2,527	2,515	2,508	2,483	2,444	2,441	2,187
Bandwidth	8.600	8.600	8.600	8.600	8.600	8.600	8.600	8.600
9. Fixed Bandwidth and	0.003	-0.001	0.017	0.015	0.045	0.088	0.068	0.073
Always Employed	(0.036)	(0.049)	(0.053)	(0.054)	(0.044)	(0.053)	(0.043)	(0.041)
Eff. # of Control Obs.	461	461	461	461	461	461	461	461
Eff. # of Treatment Obs.	1,557	1,557	1,557	1,557	1,557	1,557	1,557	1,557
Bandwidth	8.600	8.600	8.600	8.600	8.600	8.600	8.600	8.600

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1), one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score, and the discontinuity threshold is 30. Row 1 displays the baseline results from Table 3. Rows 2 and 3 show the results when we add year and location fixed effects (FE), respectively. Row 4 excludes controls. Row 5 uses the bandwidth that minimizes the coverage error (CE) of the local polynomial regression discontinuity estimator. Row 6 reports non-bias-corrected estimates. Row 7 does not adjust for the presence of mass points. Row 8 uses a fixed bandwidth. Row 9 also uses a fixed bandwidth and restricts attention to individuals that are employed in all eight quarters. All specifications include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator, except for rows 5, 8, and 9. In all specifications, except for row 7, we report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical-norm level. Bandwidths are displayed below the effective number of observations. The effective number of observations changes across quarters given variation in the number of individuals with positive earnings and the optimal bandwidth.

Table OA4: Sharp Regression Discontinuity Estimates of the Effects of Obtaining an Intermediate Certificate on Log of Income: Robustness Checks

	(1) Quarter 1	**(2) Quarter 2**	**(3) Quarter 3**	**(4) Quarter 4**	**(5) Quarter 5**	**(6) Quarter 6**	**(7) Quarter 7**	**(8) Quarter 8**
1. Baseline	-0.010	-0.002	-0.001	-0.013	-0.006	0.009	0.017	0.008
	(0.013)	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.018)	(0.018)
Eff. # of Control Obs.	9,611	9,921	9,808	9,319	11,296	11,248	11,393	10,147
Eff. # of Treatment Obs.	13,679	15,196	14,987	13,323	17,176	17,302	17,182	15,226
Bandwidth	8.798	9.714	9.357	8.753	10.300	10.790	11.000	10.410
2. Year FE	-0.012	-0.006	-0.003	-0.013	-0.008	0.006	0.016	0.008
	(0.014)	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.018)	(0.018)
Eff. # of Control Obs.	9,608	9,913	9,808	9,319	11,295	11,248	11,128	10,147
Eff. # of Treatment Obs.	13,645	15,163	14,983	13,323	17,176	17,071	17,179	15,226
Bandwidth	8.653	9.544	9.272	8.753	10.200	10.540	10.910	10.410
3. Location FE	0.001	0.006	0.008	-0.005	0.002	0.016	0.024	0.018
	(0.013)	(0.013)	(0.012)	(0.013)	(0.016)	(0.016)	(0.018)	(0.018)
Eff. # of Control Obs.	10,058	11,673	9,817	9,727	11,296	11,518	11,393	10,147
Eff. # of Treatment Obs.	15,270	17,688	15,031	14,856	17,197	19,505	19,365	15,452
Bandwidth	9.412	10.210	9.647	9.183	10.450	11.020	11.030	10.680
4. No Controls	-0.009	0.000	-0.000	-0.010	-0.005	0.013	0.020	0.009
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.018)	(0.018)
Eff. # of Control Obs.	9,611	11,673	9,808	9,727	11,296	11,518	11,128	10,147
Eff. # of Treatment Obs.	13,692	17,688	14,991	14,865	17,196	19,505	17,182	15,227
Bandwidth	8.851	10.160	9.465	9.213	10.380	11.030	10.990	10.540
5. CE Bandwidth	-0.018	-0.012	-0.009	-0.016	-0.013	-0.003	0.012	0.006
	(0.015)	(0.014)	(0.014)	(0.014)	(0.018)	(0.018)	(0.019)	(0.020)
Eff. # of Control Obs.	7,235	7,191	7,103	7,024	8,059	8,053	7,996	7,281
Eff. # of Treatment Obs.	10,890	10,911	10,675	10,595	11,819	11,751	11,680	10,510
Bandwidth	6.139	6.777	6.528	6.107	7.183	7.530	7.671	7.278

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Table OA4 Continued. Sharp Regression Discontinuity Estimates of the Effects of Obtaining an Intermediate Certificate on Log of Income: Robustness Checks

	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
6. Conventional Estimates	-0.004	0.002	0.002	-0.008	-0.003	0.012	0.020	0.012
	(0.012)	(0.012)	(0.011)	(0.012)	(0.014)	(0.014)	(0.016)	(0.016)
Eff. # of Control Obs.	9,611	9,921	9,808	9,319	11,296	11,248	11,393	10,147
Eff. # of Treatment Obs.	13,679	15,196	14,987	13,323	17,176	17,302	17,182	15,226
Bandwidth	8.798	9.714	9.357	8.753	10.300	10.790	11.000	10.410
7. No Mass Points Adjustment	-0.018	-0.012	-0.009	-0.016	-0.013	-0.005	0.010	0.006
	(0.015)	(0.014)	(0.014)	(0.014)	(0.018)	(0.019)	(0.019)	(0.020)
Eff. # of Control Obs.	7,232	7,167	7,099	7,036	6,918	8,040	7,971	7,281
Eff. # of Treatment Obs.	10,890	10,781	10,673	10,595	10,498	11,745	11,661	10,510
Bandwidth	6.028	6.328	6.428	6.204	6.531	7.222	7.202	7.207
8. Fixed Bandwidth	-0.023	-0.019	-0.014	-0.020	-0.020	-0.014	-0.001	-0.002
	(0.015)	(0.015)	(0.015)	(0.016)	(0.019)	(0.020)	(0.019)	(0.023)
Eff. # of Control Obs.	10,069	9,922	9,818	9,738	9,569	9,550	9,445	8,661
Eff. # of Treatment Obs.	15,316	15,197	15,037	14,936	14,753	14,648	14,528	13,107
Bandwidth	9.900	9.900	9.900	9.900	9.900	9.900	9.900	9.900
9. Fixed Bandwidth and	-0.022	-0.021	-0.026	-0.035	-0.033	-0.036	-0.033	-0.033
Always Employed	(0.018)	(0.019)	(0.017)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
Eff. # of Control Obs.	6,114	6,114	6,114	6,114	6,114	6,114	6,114	6,114
Eff. # of Treatment Obs.	9,244	9,244	9,244	9,244	9,244	9,244	9,244	9,244
Bandwidth	9.900	9.900	9.900	9.900	9.900	9.900	9.900	9.900

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1), one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score, and the discontinuity threshold is 60. Row 1 displays the baseline results from Table 3. Rows 2 and 3 show the results when we add year and location fixed effects (FE), respectively. Row 4 excludes controls. Row 5 uses the bandwidth that minimizes the coverage error (CE) of the local polynomial regression discontinuity estimator. Row 6 reports non-bias-corrected estimates. Row 7 does not adjust for the presence of mass points. Row 8 uses a fixed bandwidth. Row 9 also uses a fixed bandwidth and restricts attention to individuals that are employed in all eight quarters. All specifications include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator, except for rows 5, 8, and 9. In all specifications, except for row 7, we report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical-norm level. Bandwidths are displayed below the effective number of observations. The effective number of observations changes across quarters given variation in the number of individuals with positive earnings and the optimal bandwidth.

Table OA5: Sharp Regression Discontinuity Estimates of the Effects of Obtaining an Advanced Certificate on Log of Income: Robustness Checks

	(1) Quarter 1	**(2) Quarter 2**	**(3) Quarter 3**	**(4) Quarter 4**	**(5) Quarter 5**	**(6) Quarter 6**	**(7) Quarter 7**	**(8) Quarter 8**
1. Baseline	0.087	0.087	0.082	0.127	0.104	0.094	0.099	0.099
	(0.028)	(0.031)	(0.034)	(0.029)	(0.029)	(0.027)	(0.032)	(0.032)
Eff. # of Control Obs.	8,322	8,009	6,843	7,986	7,901	10,235	7,619	6,929
Eff. # of Treatment Obs.	18,098	17,852	14,410	17,669	17,400	23,044	16,776	14,754
Bandwidth	3.955	3.548	2.981	3.684	3.625	4.113	3.082	3.013
2. Year FE	0.094	0.092	0.085	0.127	0.110	0.102	0.101	0.099
	(0.029)	(0.032)	(0.034)	(0.029)	(0.030)	(0.031)	(0.032)	(0.032)
Eff. # of Control Obs.	8,313	7,998	6,843	7,986	7,884	7,937	7,619	6,929
Eff. # of Treatment Obs.	18,087	17,852	14,410	17,669	17,400	17,330	16,776	14,754
Bandwidth	3.845	3.542	2.981	3.684	3.589	3.798	3.076	3.013
3. Location FE	0.095	0.099	0.095	0.139	0.120	0.108	0.109	0.104
	(0.029)	(0.030)	(0.033)	(0.029)	(0.032)	(0.028)	(0.031)	(0.030)
Eff. # of Control Obs.	8,122	7,997	6,843	7,881	7,782	7,820	7,619	6,034
Eff. # of Treatment Obs.	18,020	17,849	14,410	17,609	16,980	17,283	16,776	12,363
Bandwidth	3.580	3.512	2.969	3.334	3.007	3.734	3.072	2.968
4. No Controls	0.093	0.095	0.089	0.142	0.111	0.110	0.102	0.092
	(0.033)	(0.035)	(0.031)	(0.039)	(0.034)	(0.039)	(0.030)	(0.033)
Eff. # of Control Obs.	8,098	7,983	8,027	6,803	7,857	6,669	7,864	7,021
Eff. # of Treatment Obs.	17,987	17,821	17,701	14,293	17,367	14,068	17,274	15,174
Bandwidth	3.478	3.406	3.736	2.793	3.474	2.959	3.811	3.595
5. CE Bandwidth	0.082	0.084	0.066	0.127	0.101	0.09	0.086	0.090
	(0.030)	(0.034)	(0.035)	(0.029)	(0.030)	(0.030)	(0.033)	(0.034)
Eff. # of Control Obs.	6,994	6,768	6,709	6,792	6,743	6,656	6,478	5,910
Eff. # of Treatment Obs.	14,625	14,389	14,143	14,238	14,054	14,004	13,750	12,101
Bandwidth	2.744	2.462	2.068	2.556	2.515	2.854	2.138	2.094

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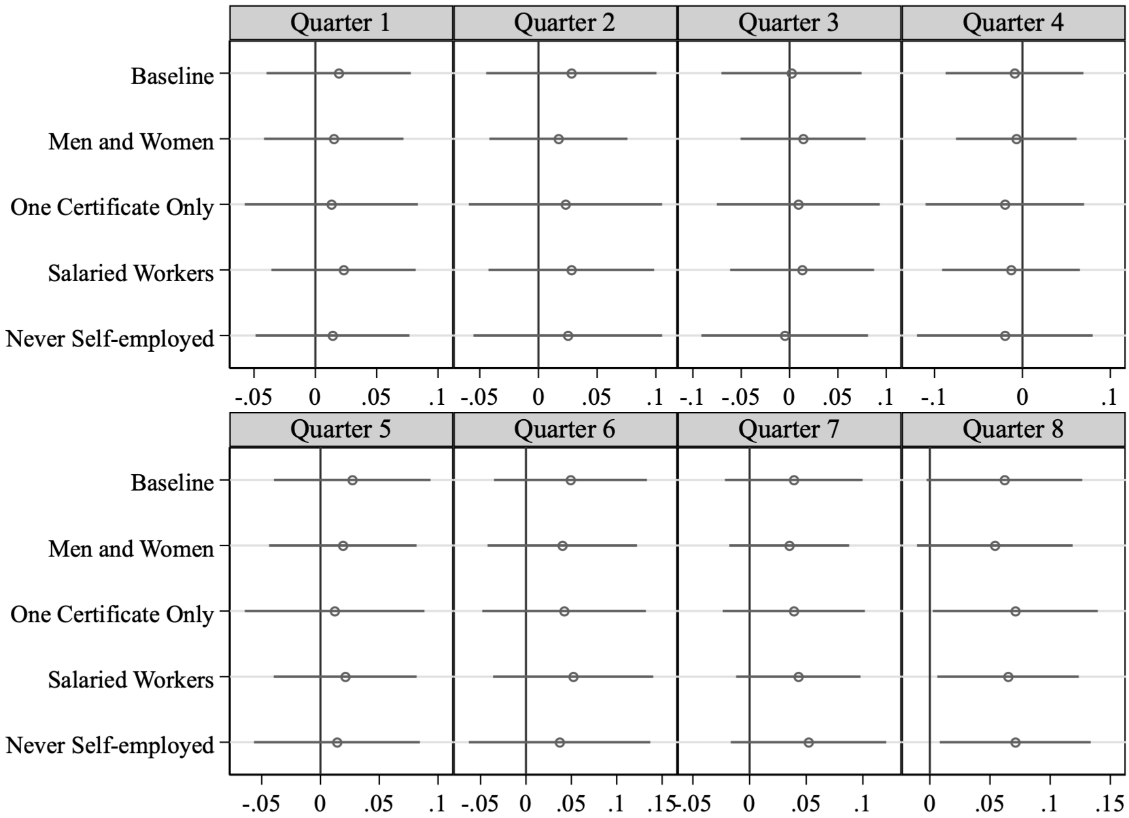
Table OA5 Continued. Sharp Regression Discontinuity Estimates of the Effects of Obtaining an Advanced Certificate on Log of Income: Robustness Checks

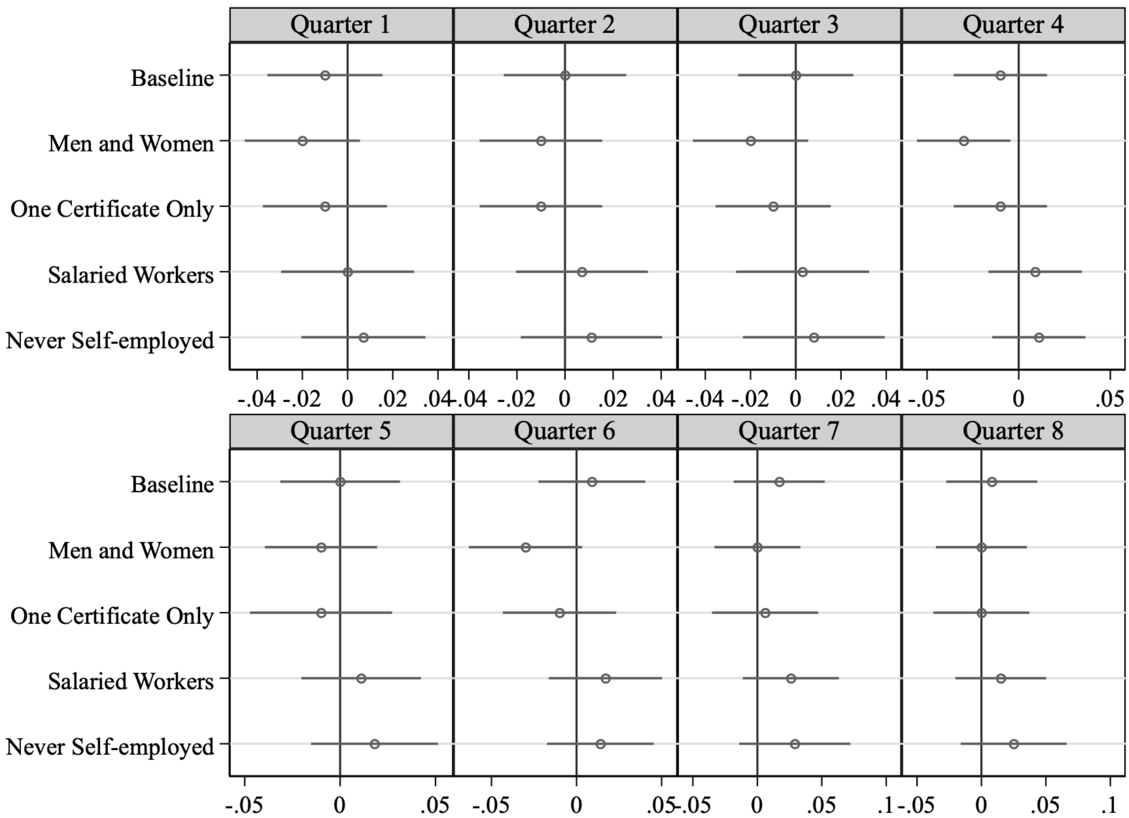
	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
6. Conventional Estimates	0.074	0.072	0.066	0.106	0.084	0.074	0.079	0.080
	(0.022)	(0.023)	(0.025)	(0.023)	(0.023)	(0.021)	(0.023)	(0.024)
Eff. # of Control Obs.	8,322	8,009	6,843	7,986	7,901	10,235	7,619	6,929
Eff. # of Treatment Obs.	18,098	17,852	14,410	17,669	17,400	23,044	16,776	14,754
Bandwidth	3.955	3.548	2.981	3.684	3.625	4.113	3.082	3.013
7. No Mass Points Adjustment	0.074	0.085	0.058	0.131	0.098	0.100	0.075	0.090
	(0.037)	(0.034)	(0.039)	(0.031)	(0.035)	(0.034)	(0.036)	(0.041)
Eff. # of Control Obs.	6,882	6,872	6,709	6,791	6,643	6,654	6,475	5,910
Eff. # of Treatment Obs.	14,495	14,479	14,143	14,238	13,927	13,989	13,750	12,101
Bandwidth	2.307	2.615	2.058	2.530	2.284	2.705	2.116	2.049
8. Fixed Bandwidth	0.053	0.061	0.063	0.117	0.092	0.083	0.076	0.086
	(0.037)	(0.038)	(0.034)	(0.034)	(0.034)	(0.035)	(0.034)	(0.035)
Eff. # of Control Obs.	8,073	7,960	7,907	7,877	7,832	7,712	7,635	6,975
Eff. # of Treatment Obs.	17,925	17,760	17,603	17,577	17,303	17,181	17,105	15,081
Bandwidth	3.300	3.300	3.300	3.300	3.300	3.300	3.300	3.300
9. Fixed Bandwidth and	0.060	0.075	0.077	0.119	0.106	0.105	0.097	0.095
Always Employed	(0.040)	(0.037)	(0.034)	(0.036)	(0.035)	(0.035)	(0.035)	(0.036)
Eff. # of Control Obs.	5,100	5,100	5,100	5,100	5,100	5,100	5,100	5,100
Eff. # of Treatment Obs.	10,825	10,825	10,825	10,825	10,825	10,825	10,825	10,825
Bandwidth	3.300	3.300	3.300	3.300	3.300	3.300	3.300	3.300

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1), one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score, and the discontinuity threshold is 90. Row 1 displays the baseline results from Table 3. Rows 2 and 3 show the results when we add year and location fixed effects (FE), respectively. Row 4 excludes controls. Row 5 uses the bandwidth that minimizes the coverage error (CE) of the local polynomial regression discontinuity estimator. Row 6 reports non-bias-corrected estimates. Row 7 does not adjust for the presence of mass points. Row 8 uses a fixed bandwidth. Row 9 also uses a fixed bandwidth and restricts attention to individuals that are employed in all eight quarters. All specifications include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator, except for rows 5, 8, and 9. In all specifications, except for row 7, we report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical-norm level. Bandwidths are displayed below the effective number of observations. The effective number of observations changes across quarters given variation in the number of individuals with positive earnings and the optimal bandwidth.

Figure OA5: Sharp Regression Discontinuity Estimates of the Effects of Obtaining a Certificate on Log of Income: Alternative Samples

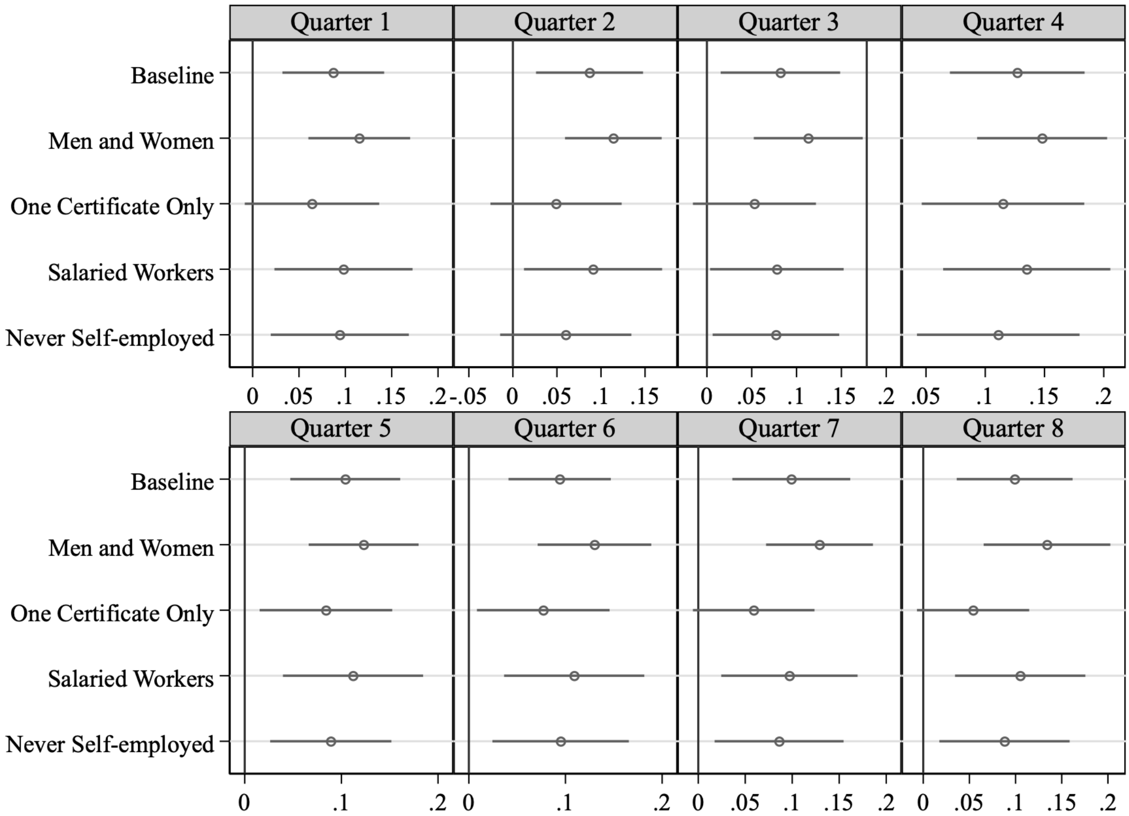


(a) Basic



(b) Intermediate

Figure OA5 Continued. Sharp Regression Discontinuity Estimates of the Effects of Obtaining a Certificate on Log of Income: Alternative Samples



(c) Advanced

Notes: Each plot displays the estimate for the main coefficient of interest in Equation (1) and its 95% confidence interval, one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score, and the discontinuity threshold is 30 for the basic certificate (panel a), 60 for the intermediate certificate (panel b), and 90 for the advanced certificate (panel c). In each plot, row 1 displays the baseline results from Table 3. Row 2 uses the full sample of men and women. Row 3 uses a sample of men who applied for only one certificate between 2017 and 2019. Row 4 uses a sample of salaried workers, while the fifth row further excludes individuals who are ever self-employed within two years of certification. All specifications include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator, except for rows 5, 8, and 9. Standard errors used to compute 95% confidence intervals are clustered at the technical-norm level. Detailed results for all three certificates are displayed in Tables OA6, OA7, and OA8.

Table OA6: Sharp Regression Discontinuity Estimates of the Effects of Obtaining a Basic Certificate on Log of Income: Alternative Samples

	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
1. Men and Women	0.015	0.017	0.014	-0.007	0.019	0.040	0.035	0.054
	(0.029)	(0.030)	(0.033)	(0.035)	(0.032)	(0.042)	(0.027)	(0.033)
# of Observations	235,346	231,969	229,967	228,652	226,496	224,094	222,619	201,123
Eff. # of Control Obs.	773	832	907	799	742	861	880	825
Eff. # of Treatment Obs.	2,666	2,988	3,627	2,939	2,517	3,288	3,548	2,951
Bandwidth	6.975	7.459	9.030	7.196	6.842	8.807	9.552	8.203
2. One Certificate Only	0.013	0.023	0.009	-0.020	0.012	0.042	0.039	0.071
	(0.036)	(0.042)	(0.043)	(0.046)	(0.039)	(0.046)	(0.032)	(0.035)
# of Observations	125,946	124,460	123,522	122,565	121,398	120,332	119,670	107,464
Eff. # of Control Obs.	500	537	527	509	482	608	483	510
Eff. # of Treatment Obs.	1,631	1,830	1,804	1,790	1,551	2,780	1,548	1,589
Bandwidth	6.810	7.333	7.649	7.161	6.651	10.26-	6.505	7.900
3. Salaried Worker	0.023	0.028	0.013	-0.013	0.021	0.052	0.043	0.065
	(0.030)	(0.036)	(0.038)	(0.040)	(0.031)	(0.045)	(0.028)	(0.030)
# of Observations	144,403	142,532	141,069	139,894	138,472	137,331	136,243	122,849
Eff. # of Control Obs.	661	615	633	653	600	591	579	535
Eff. # of Treatment Obs.	2,505	2,229	2,431	2,978	2,190	2,177	2,162	1,702
Bandwidth	9.410	8.173	9.158	10.46	8.613	8.886	8.361	7.977
4. Never Self-Employed	0.014	0.025	-0.005	-0.020	0.014	0.037	0.052	0.071
	(0.032)	(0.041)	(0.044)	(0.051)	(0.036)	(0.051)	(0.035)	(0.032)
# of Observations	125,383	123,881	123,040	122,412	121,235	120,425	119,612	107,859
Eff. # of Control Obs.	569	553	571	548	559	555	501	544
Eff. # of Treatment Obs.	1,997	1,944	2,117	2,106	2,092	2,088	1,662	1,821
Bandwidth	8.569	8.678	9.969	9.168	9.375	9.966	7.701	9.241

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1), one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score, and the discontinuity threshold is 30. Row 1 uses the full sample of men and women. Row 2 uses a sample of men who apply for only one certificate between 2017 and 2019. Row 3 uses a sample of salaried workers, while row 4 further excludes individuals who are ever self-employed within two years of certification. All specifications include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator. We report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical norm level. Bandwidths are displayed below the effective number of observations. The total number of observations changes across quarters given variation in the number of individuals with positive earnings; it further drops in quarter 8 due to missing information in the last quarter for individuals that certified in the last quarter of 2019. The effective number of observations changes across quarters given variation in the optimal bandwidth.

Table OA7: Sharp Regression Discontinuity Estimates of the Effects of Obtaining an Intermediate Certificate on Log of Income: Alternative Samples

	(1) Quarter 1	**(2) Quarter 2**	**(3) Quarter 3**	**(4) Quarter 4**	**(5) Quarter 5**	**(6) Quarter 6**	**(7) Quarter 7**	**(8) Quarter 8**
1. Men and Women	-0.021	-0.016	-0.028	-0.033	-0.014	-0.030	-0.009	-0.008
	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.017)	(0.017)	(0.018)
# of Observations	235,346	231,969	229,967	228,652	226,496	224,094	222,619	201,123
Eff. # of Control Obs.	12,060	11,949	9,896	9,814	12,655	9,636	11,354	10,343
Eff. # of Treatment Obs.	17,468	17,304	15,302	15,196	18,369	15,051	16,555	14,911
Bandwidth	7.209	7.768	6.584	6.326	8.095	6.828	7.739	7.667
2. One Certificate Only	-0.013	-0.010	-0.012	-0.018	-0.016	-0.011	0.006	-0.002
	(0.014)	(0.013)	(0.013)	(0.013)	(0.019)	(0.017)	(0.021)	(0.019)
# of Observations	125,946	124,460	123,522	122,565	121,398	120,332	119,670	107,464
Eff. # of Control Obs.	11,393	10,427	9,412	9,540	9,189	9,153	9,289	8,268
Eff. # of Treatment Obs.	18,774	17,868	13,990	15,897	13,897	13,631	15,501	12,310
Bandwidth	13.730	12.900	10.170	11.400	10.670	10.320	11.280	10.680
3. Salaried Worker	0.000	0.007	0.003	0.009	0.011	0.017	0.026	0.015
	(0.015)	(0.014)	(0.015)	(0.013)	(0.016)	(0.017)	(0.019)	(0.018)
# of Observations	144,403	142,532	141,069	139,894	138,472	137,331	136,243	122,849
Eff. # of Control Obs.	8,990	10,238	8,709	10,040	10,800	10,044	10,604	9,072
Eff. # of Treatment Obs.	13,060	14,730	12,787	14,361	17,906	16,330	17,678	14,624
Bandwidth	9.699	10.530	9.673	10.370	12.030	11.300	12.130	11.800
4. Never Self-Employed	0.007	0.011	0.008	0.011	0.018	0.014	0.029	0.025
	(0.014)	(0.015)	(0.016)	(0.013)	(0.017)	(0.016)	(0.022)	(0.021)
# of Observations	125,383	123,881	123,040	122,412	121,235	120,425	119,612	107,859
Eff. # of Control Obs.	8,894	9,617	8,650	8,865	10,118	8,664	9,212	8,424
Eff. # of Treatment Obs.	12,633	15,731	12,414	14,177	16,260	12,164	15,317	13,638
Bandwidth	10.730	12.160	10.930	11.430	13.020	11.000	12.800	12.320

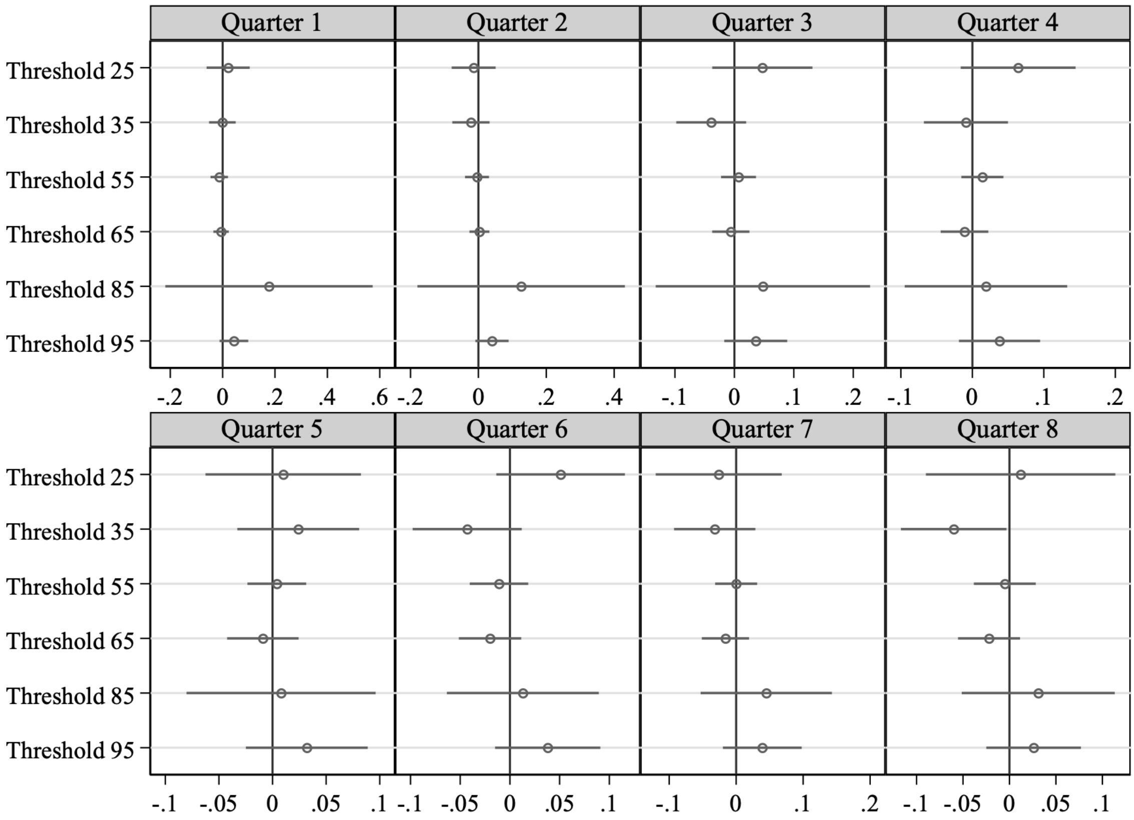
Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1), one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score, and the discontinuity threshold is 60. Row 1 uses the full sample of men and women. Row 2 uses a sample of men who apply for only one certificate between 2017 and 2019. Row 3 uses a sample of salaried workers, while row 4 further excludes individuals who are ever self-employed within two years of certification. All specifications include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator. We report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical norm level. Bandwidths are displayed below the effective number of observations. The total number of observations changes across quarters given variation in the number of individuals with positive earnings; it further drops in quarter 8 due to missing information in the last quarter for individuals that certified in the last quarter of 2019. The effective number of observations changes across quarters given variation in the optimal bandwidth.

Table OA8: Sharp Regression Discontinuity Estimates of the Effects of Obtaining an Advanced Certificate on Log of Income: Alternative Samples

	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
1. Men and Women	0.115	0.114	0.113	0.148	0.123	0.130	0.129	0.134
	(0.028)	(0.028)	(0.031)	(0.028)	(0.029)	(0.030)	(0.029)	(0.035)
# of Observations	235,346	231,969	229,967	228,652	226,496	224,094	222,619	201,123
Eff. # of Control Obs.	12,878	12,601	10,696	12,183	12,204	11,989	11,877	9,453
Eff. # of Treatment Obs.	24,914	24,688	20,115	24,147	24,011	23,787	23,630	17,351
Bandwidth	3.976	3.841	2.718	3.151	3.568	3.452	3.380	2.711
2. One Certificate Only	0.064	0.049	0.053	0.115	0.084	0.077	0.059	0.054
	(0.037)	(0.038)	(0.035)	(0.035)	(0.035)	(0.035)	(0.033)	(0.031)
# of Observations	125,946	124,460	123,522	122,565	121,398	120,332	119,670	107,464
Eff. # of Control Obs.	6,330	6,240	6,201	6,172	6,124	5,279	5,997	5,440
Eff. # of Treatment Obs.	13,671	13,298	13,191	13,206	12,980	10,669	12,829	11,237
Bandwidth	3.112	3.024	3.011	3.055	3.006	2.941	3.090	3.077
3. Salaried Worker	0.098	0.091	0.078	0.135	0.112	0.109	0.097	0.105
	(0.038)	(0.040)	(0.038)	(0.036)	(0.037)	(0.037)	(0.037)	(0.036)
# of Observations	144,403	142,532	141,069	139,894	138,472	137,331	136,243	122,849
Eff. # of Control Obs.	7,250	7,173	7,071	7,077	7,030	6,917	5,909	6,206
Eff. # of Treatment Obs.	15,470	15,352	15,138	15,076	14,852	15,080	12,060	12,892
Bandwidth	3.019	3.047	3.016	3.065	3.057	3.214	2.851	3.025
4. Never Self-Employed	0.094	0.060	0.077	0.111	0.089	0.095	0.086	0.088
	(0.038)	(0.038)	(0.036)	(0.035)	(0.032)	(0.036)	(0.035)	(0.036)
# of Observations	125,383	123,881	123,040	122,412	121,235	120,425	119,612	107,859
Eff. # of Control Obs.	6,337	6,241	6,216	6,219	6,257	6,087	5,191	5,463
Eff. # of Treatment Obs.	13,861	13,471	13,354	13,637	13,512	13,379	10,628	11,439
Bandwidth	3.182	3.051	3.095	3.155	3.740	3.237	2.811	3.019

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1), one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score, and the discontinuity threshold is 90. Row 1 uses the full sample of men and women. Row 2 uses a sample of men who apply for only one certificate between 2017 and 2019. Row 3 uses a sample of salaried workers, while row 4 further excludes individuals who are ever self-employed within two years of certification. All specifications include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator. We report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical norm level. Bandwidths are displayed below the effective number of observations. The total number of observations changes across quarters given variation in the number of individuals with positive earnings; it further drops in quarter 8 due to missing information in the last quarter for individuals that certified in the last quarter of 2019. The effective number of observations changes across quarters given variation in the optimal bandwidth.

Figure OA7: Sharp Regression Discontinuity Estimates of the Effects on Log of Income - Placebo Thresholds



Notes: Each plot displays the estimate for the main coefficient of interest in Equation (1) its 95% confidence interval, one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score, and the (placebo) thresholds of interest are 25, 35, 55, 65, 85, and 95. All specifications include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator. Standard errors used to compute 95% confidence intervals are clustered at the technical norm level. Detailed results for all placebo thresholds are displayed in Table OA9.

Table OA9: Sharp Regression Discontinuity Estimates of the Effects on Log of Income - Placebo Thresholds

	(1) Quarter 1	**(2) Quarter 2**	**(3) Quarter 3**	**(4) Quarter 4**	**(5) Quarter 5**	**(6) Quarter 6**	**(7) Quarter 7**	**(8) Quarter 8**
Threshold 25	0.021	-0.014	0.047	0.064	0.010	0.051	-0.026	0.012
	(0.042)	(0.033)	(0.043)	(0.041)	(0.037)	(0.033)	(0.048)	(0.052)
Eff. # of Control Obs.	260	358	256	272	246	311	246	236
Eff. # of Treatment Obs.	725	1,265	703	868	692	1,005	687	641
Bandwidth	5.331	8.912	5.093	6.277	5.437	7.770	5.266	5.233
Threshold 35	-0.001	-0.022	-0.039	-0.009	0.024	-0.043	-0.032	-0.060
	(0.026)	(0.028)	(0.030)	(0.030)	(0.029)	(0.028)	(0.031)	(0.029)
Eff. # of Control Obs.	1,446	1,473	1,263	1,277	1,273	1,252	1,255	1,171
Eff. # of Treatment Obs.	4,716	5,661	3,627	4,086	4,093	4,019	4,023	3,613
Bandwidth	9.549	10.060	7.265	8.724	8.097	8.285	8.347	8.911
Threshold 55	-0.013	-0.004	0.007	0.014	0.004	-0.011	-0.000	-0.005
	(0.017)	(0.018)	(0.015)	(0.015)	(0.014)	(0.015)	(0.016)	(0.017)
Eff. # of Control Obs.	9,707	9,556	10,190	8,901	10,027	8,695	9,521	7,824
Eff. # of Treatment Obs.	17,307	17,139	19,504	15,793	19,038	15,317	17,608	13,813
Bandwidth	11.950	11.740	13.490	10.990	13.380	10.230	12.420	10.250
Threshold 65	-0.006	0.003	-0.006	-0.011	-0.009	-0.020	-0.016	-0.022
	(0.015)	(0.015)	(0.016)	(0.017)	(0.017)	(0.016)	(0.018)	(0.017)
Eff. # of Control Obs.	18,541	15,985	18,131	16,243	16,005	15,902	13,198	13,046
Eff. # of Treatment Obs.	33,475	27,920	32,882	29,086	28,727	28,301	22,386	22,321
Bandwidth	15.240	13.140	15.600	14.802	14.910	14.170	11.170	12.150

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Table OA9 Continued. Sharp Regression Discontinuity Estimates of the Effects on Log of Income - Placebo Thresholds

	(1) Quarter 1	**(2) Quarter 2**	**(3) Quarter 3**	**(4) Quarter 4**	**(5) Quarter 5**	**(6) Quarter 6**	**(7) Quarter 7**	**(8) Quarter 8**
Threshold 85	0.177	0.126	0.048	0.019	0.008	0.013	0.045	0.031
	(0.202)	(0.156)	(0.092)	(0.058)	(0.045)	(0.039)	(0.050)	(0.042)
Eff. # of Control Obs.	4,945	5,086	5,388	7,651	7,689	7,554	7,552	6,723
Eff. # of Treatment Obs.	7,217	7,131	7,187	9,954	10,154	9,760	9,667	8,717
Bandwidth	2.126	2.376	2.651	3.050	3.280	3.065	3.121	3.163
Threshold 95	0.043	0.040	0.036	0.038	0.032	0.038	0.039	0.026
	(0.028)	(0.025)	(0.027)	(0.029)	(0.029)	(0.027)	(0.030)	(0.026)
Eff. # of Control Obs.	14,223	14,262	14,170	14,125	13,934	13,603	13,543	12,158
Eff. # of Treatment Obs.	13,838	13,735	13,595	13,541	13,417	13,268	13,192	11,454
Bandwidth	3.563	3.656	3.616	3.614	3.583	3.468	3.472	3.581

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1), one to eight quarters after certification. The outcome is the log of income. The running variable is the exam score and the (placebo) thresholds of interest are 25, 35, 55, 65, 85, and 95. All regressions include controls described in Section 4, use a triangular kernel, and choose the bandwidth to minimize the mean squared error (MSE) of the local polynomial RD estimator. We report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical norm level. Optimal bandwidths are displayed below the standard errors. The effective number of observations changes across quarters given variation in the number of individuals with positive earnings and the optimal bandwidth.

Online Appendix C. Mechanisms: Additional Results

Table OA10: Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Advanced Certificate: Additional Outcomes

	(1) Quarter 1	**(2) Quarter 2**	**(3) Quarter 3**	**(4) Quarter 4**	**(5) Quarter 5**	**(6) Quarter 6**	**(7) Quarter 7**	**(8) Quarter 8**
1. Overall Employment	0.008	-0.007	-0.015	-0.008	-0.010	0.011	-0.011	0.009
	(0.024)	(0.015)	(0.022)	(0.026)	(0.023)	(0.018)	(0.017)	(0.020)
Observations	181,395	181,395	181,395	181,395	181,395	181,395	181,395	164,296
Eff. # of Control Obs.	7,585	7,610	7,591	7,475	7,463	7,595	8,872	6,976
Eff. # of Treat. Obs.	16,237	16,375	16,287	16,078	16,061	16,288	20,057	14,358
Bandwidth	2.588	2.908	2.638	2.238	2.049	2.783	3.559	2.991
Mean	0.921	0.906	0.899	0.896	0.889	0.876	0.866	0.866
2. Salaried Work	-0.046	-0.039	-0.001	-0.028	-0.031	-0.000	-0.011	0.020
	(0.082)	(0.047)	(0.034)	(0.043)	(0.049)	(0.028)	(0.031)	(0.030)
Observations	181,395	181,395	181,395	181,395	181,395	181,395	181,395	164,296
Eff. # of Control Obs.	3,979	4,344	7,474	3,979	3,965	7,479	7,478	8,073
Eff. # of Treat. Obs.	12,090	12,177	16,065	12,090	12,007	16,181	16,181	17,499
Bandwidth	1.671	1.935	2.202	1.668	1.584	2.440	2.409	3.146
Mean	0.848	0.831	0.810	0.824	0.816	0.787	0.777	0.773
3. Self-Employment	-0.008	-0.016	-0.019	-0.022	-0.025	-0.014	-0.003	-0.012
	(0.040)	(0.040)	(0.033)	(0.041)	(0.028)	(0.032)	(0.039)	(0.037)
Observations	181,395	181,395	181,395	181,395	181,395	181,395	181,395	164,296
Eff. # of Control Obs.	3,813	3,935	3,969	3,826	4,340	4,340	3,813	3,633
Eff. # of Treat. Obs.	11,748	11,985	12,038	11,810	12,173	12,172	11,748	10,695
Bandwidth	1.369	1.439	1.623	1.410	1.858	1.805	1.390	1.721
Mean	0.044	0.045	0.049	0.048	0.057	0.055	0.050	0.050

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1) for the advanced certificate, one to eight quarters after certification. The three outcomes analyzed are overall employment, salaried work, and self-employment. The running variable is the exam score and the discontinuity threshold is 90. All regressions include the controls described in Section 4, use a triangular kernel, and use the bandwidth that minimizes the mean squared error of the local polynomial regression discontinuity estimator. We report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical-norm level. Optimal bandwidths are displayed below the standard errors. The total number of observations drops in quarter 8 due to missing information in the last quarter for individuals that certified in the last quarter of 2019. The effective number of observations changes across quarters given variation in the optimal bandwidth. The sample mean for the control group is displayed below the optimal bandwidth.

Table OA11: Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Advanced Certificate, by Initial Employment Status: Additional Outcomes

	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
1. Unemployed								
1a. Overall Employment	0.038	-0.019	-0.013	-0.050	0.000	-0.055	-0.043	-0.022
	(0.080)	(0.048)	(0.055)	(0.059)	(0.098)	(0.101)	(0.146)	(0.079)
Observations	14,851	14,851	14,851	14,851	14,851	14,851	14,851	13,485
Eff. # of Control Obs.	616	894	858	891	497	497	492	557
Eff. # of Treat. Obs.	1,837	2,321	2,266	2,316	1,515	1,514	1,486	1,597
Bandwidth	3.589	4.822	4.073	4.723	2.592	2.561	2.276	3.374
Mean	0.549	0.575	0.568	0.600	0.642	0.628	0.620	0.614
1b. Salaried Work	0.181	0.046	0.084	-0.005	0.070	-0.058	-0.046	-0.087
	(0.132)	(0.104)	(0.105)	(0.080)	(0.106)	(0.080)	(0.140)	(0.122)
Observations	14,851	14,851	14,851	14,851	14,851	14,851	14,851	13,485
Eff. # of Control Obs.	497	497	497	631	497	615	493	458
Eff. # of Treat. Obs.	1,515	1,519	1,518	1,851	1,514	1,837	1,499	1,314
Bandwidth	2.593	2.715	2.612	3.937	2.521	3.568	2.402	2.694
Mean	0.489	0.513	0.503	0.509	0.533	0.509	0.513	0.509
1c. Self-Employment	-0.059	-0.089	-0.043	-0.045	-0.046	-0.018	-0.013	0.007
	(0.060)	(0.048)	(0.041)	(0.052)	(0.051)	(0.051)	(0.035)	(0.040)
Observations	14,851	14,851	14,851	14,851	14,851	14,851	14,851	13,485
Eff. # of Control Obs.	271	494	610	606	606	497	894	784
Eff. # of Treat. Obs.	1,126	1,499	1,833	1,824	1,824	1,519	2,321	1,978
Bandwidth	1.975	2.458	3.444	3.149	3.147	2.714	4.963	4.182
Mean	0.063	0.059	0.061	0.073	0.091	0.078	0.089	0.098
1d. Ln (Income)	-0.067	-0.149	-0.005	0.117	-0.218	0.171	0.050	0.122
	(0.105)	(0.084)	(0.073)	(0.073)	(0.118)	(0.116)	(0.068)	(0.088)
Observations	7,676	8,156	8,378	8,521	8,800	8,936	8,967	8,158
Eff. # of Control Obs.	333	294	665	372	318	723	375	660
Eff. # of Treat. Obs.	915	841	1,643	1,038	875	1,733	1,094	1,576
Bandwidth	3.056	2.945	5.326	3.395	2.594	5.445	3.429	5.248
Mean	13.808	13.817	13.891	13.839	13.837	13.878	13.844	13.902
2. Self-Employed								
2a. Overall Employment	0.053	0.004	0.011	0.072	0.033	0.082	0.031	-0.009
	(0.055)	(0.068)	(0.049)	(0.048)	(0.037)	(0.063)	(0.072)	(0.086)
Observations	16,502	16,502	16,502	16,502	16,502	16,502	16,502	14,692
Eff. # of Control Obs.	503	495	586	582	764	495	495	434
Eff. # of Treat. Obs.	1,619	1,615	1,810	1,808	2,388	1,615	1,615	1,414
Bandwidth	2.711	2.427	3.680	3.329	4.597	2.473	2.328	2.261
Mean	0.905	0.869	0.865	0.843	0.863	0.844	0.826	0.820

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Table OA11 Continued. Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Advanced Certificate, by Initial Employment Status: Additional Outcomes

	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
2. Self-Employed								
2b. Salaried Work	-0.009	0.018	0.062	0.189	0.135	0.166	0.201	0.127
	(0.030)	(0.040)	(0.051)	(0.058)	(0.059)	(0.050)	(0.058)	(0.057)
Observations	16,502	16,502	16,502	16,502	16,502	16,502	16,502	14,692
Eff. # of Control Obs.	581	581	494	223	224	503	494	513
Eff. # of Treat. Obs.	1,807	1,808	1,603	1,312	1,312	1,616	1,603	1,438
Bandwidth	3.162	3.251	2.057	1.816	1.936	2.583	2.059	3.001
Mean	0.041	0.086	0.122	0.112	0.112	0.141	0.156	0.154
2c. Self-Employment	0.049	-0.008	-0.070	-0.100	-0.057	-0.104	-0.326	-0.370
	(0.051)	(0.055)	(0.085)	(0.077)	(0.085)	(0.081)	(0.175)	(0.230)
Observations	16,502	16,502	16,502	16,502	16,502	16,502	16,502	14,692
Eff. # of Control Obs.	581	589	495	495	503	495	224	165
Eff. # of Treat. Obs.	1,805	1,817	1,603	1,603	1,616	1,603	1,312	1,154
Bandwidth	3.091	3.759	2.215	2.200	2.593	2.210	1.928	1.700
Mean	0.859	0.778	0.735	0.693	0.720	0.703	0.661	0.636
2d. Ln (Income)	0.005	0.102	0.088	0.155	0.093	0.211	0.118	0.200
	(0.037)	(0.048)	(0.064)	(0.069)	(0.043)	(0.069)	(0.057)	(0.068)
Observations	14,972	14,495	14,305	14,182	13,983	13,800	13,729	12,267
Eff. # of Control Obs.	1,383	511	502	415	640	418	487	424
Eff. # of Treat. Obs.	2,924	1,595	1,591	1,392	2,008	1,351	1,525	1,345
Bandwidth	5.965	3.904	3.133	2.287	4.034	2.266	3.703	3.085
Mean	13.902	13.891	13.948	13.985	13.944	13.991	14.017	14.033
3. Salaried Worker								
3a. Overall Employment	-0.002	-0.013	-0.010	-0.008	-0.010	0.006	-0.016	0.015
	(0.027)	(0.015)	(0.019)	(0.023)	(0.022)	(0.018)	(0.017)	(0.020)
Observations	146,215	146,215	146,215	146,215	146,215	146,215	146,215	132,529
Eff. # of Control Obs.	6,318	6,326	6,443	6,326	6,322	6,430	7,661	6,813
Eff. # of Treat. Obs.	12,684	12,696	12,925	12,692	12,684	12,889	16,139	13,716
Bandwidth	2.112	2.299	2.956	2.229	2.118	2.859	3.917	3.060
Mean	0.949	0.933	0.926	0.921	0.910	0.899	0.889	0.887
3b. Salaried Work	-0.015	-0.011	0.004	-0.006	-0.006	-0.014	-0.033	0.010
	(0.046)	(0.019)	(0.021)	(0.023)	(0.018)	(0.018)	(0.021)	(0.016)
Observations	146,215	146,215	146,215	146,215	146,215	146,215	146,215	132,529
Eff. # of Control Obs.	3,745	6,325	7,377	6,327	6,419	7,393	6,429	7,051
Eff. # of Treat. Obs.	9,512	12,684	15,645	12,770	12,800	15,645	12,851	14,205
Bandwidth	1.828	2.198	3.022	2.408	2.583	3.039	2.795	3.845
Mean	0.941	0.917	0.904	0.896	0.884	0.871	0.860	0.855

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Table OA11 Continued. Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Advanced Certificate, by Initial Employment Status: Additional Outcomes

	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
3. Salaried Worker								
3c. Self-Employment	-0.002	0.001	-0.008	-0.005	-0.008	0.007	0.003	-0.002
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
Observations	146,215	146,215	146,215	146,215	146,215	146,215	146,215	132,529
Eff. # of Control Obs.	3,302	6,325	6,325	7,453	6,432	6,424	6,430	5,918
Eff. # of Treat. Obs.	9,148	12,684	12,684	16,042	12,916	12,849	12,857	11,336
Bandwidth	1.341	2.169	2.155	3.458	2.875	2.630	2.806	2.979
Mean	0.002	0.009	0.012	0.014	0.016	0.019	0.018	0.019
3d. Acc. Job-to-Job Transitions	0.051	0.044	0.05	0.047	0.052	0.065	0.099	0.122
	(0.014)	(0.018)	(0.024)	(0.028)	(0.034)	(0.035)	(0.039)	(0.043)
Observations	146,215	146,215	146,215	146,215	146,215	146,215	146,215	132,529
Eff. # of Control Obs.	6,326	6,326	6,326	6,327	6,326	6,326	6,316	3,451
Eff. # of Treat. Obs.	12,692	12,757	12,758	12,770	12,692	12,692	12,680	8,368
Bandwidth	2.245	2.320	2.376	2.449	2.263	2.251	2.006	1.873
Mean	0.052	0.090	0.121	0.148	0.179	0.203	0.226	0.246
3e. Ln (Income)	0.100	0.097	0.086	0.141	0.122	0.106	0.105	0.101
	(0.037)	(0.039)	(0.036)	(0.035)	(0.035)	(0.034)	(0.034)	(0.034)
Observations	138,151	136,228	134,891	133,826	132,261	130,891	130,005	117,239
Eff. # of Control Obs.	6,984	6,009	5,964	6,790	6,741	6,671	6,594	6,038
Eff. # of Treat. Obs.	12,170	12,021	11,855	14,364	14,090	14,267	13,887	12,181
Bandwidth	3.003	2.978	2.990	3.011	3.037	3.182	3.056	3.071
Mean	13.894	13.900	13.917	13.930	13.944	13.964	13.978	13.978

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1) for the advanced certificate, one to eight quarters after certification, by initial employment status: unemployed (first panel), self-employed (second panel), salaried worker (third panel). The outcomes analyzed are overall employment, salaried work, self-employment, probability of having switched jobs after certification (for salaried workers only), and log of income. The running variable is the exam score and the discontinuity threshold is 90. All regressions include the controls described in Section 4, use a triangular kernel, and use the bandwidth that minimizes the mean squared error of the local polynomial regression discontinuity estimator. We report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical-norm level. Optimal bandwidths are displayed below the standard errors. The total number of observations changes across quarters given variation in the number of individuals with positive earnings (for log of income only); it further drops in quarter 8 due to missing information in the last quarter for individuals that certified in the last quarter of 2019. The effective number of observations changes across quarters given variation in the optimal bandwidth. The sample mean for the control group is displayed below the optimal bandwidth.

Table OA12: Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Advanced Certificate, by Potential Experience: Additional Outcomes

	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
1. Experience: 15 Years or Less								
1a. Acc. Job-to-Job Transitions	0.018	0.083	0.065	0.073	0.038	0.066	0.105	0.103
	(0.022)	(0.047)	(0.056)	(0.062)	(0.075)	(0.076)	(0.078)	(0.079)
Observations	16,374	16,374	16,374	16,374	16,374	16,374	16,374	15,244
Eff. # of Control Obs.	1,472	788	788	788	788	788	771	728
Eff. # of Treat. Obs.	3,225	1,457	1,457	1,460	1,458	1,456	1,442	1,304
Bandwidth	5.16	2.798	2.726	2.843	2.823	2.626	2.48	2.486
Mean	0.067	0.103	0.147	0.171	0.213	0.253	0.271	0.304
1b. Ln (Income)	0.235	0.261	0.230	0.171	0.225	0.201	0.207	0.112
	(0.057)	(0.099)	(0.102)	(0.059)	(0.066)	(0.113)	(0.111)	(0.091)
Observations	15,259	14,976	14,707	14,546	14,383	14,227	14,170	13,061
Eff. # of Control Obs.	733	813	812	784	779	782	766	967
Eff. # of Treat. Obs.	1,351	1,672	1,666	1,648	1,599	1,600	1,605	2,074
Bandwidth	2.621	3.331	3.506	3.394	3.209	3.673	3.546	4.921
Mean	13.909	13.910	13.929	13.947	13.951	13.962	13.981	13.977
2. 15< Experience <= 30								
2a. Acc. Job-to-Job Transitions	0.028	0.019	0.058	0.037	0.039	0.043	0.082	0.047
	(0.014)	(0.018)	(0.026)	(0.022)	(0.030)	(0.036)	(0.040)	(0.043)
Observations	73,826	73,826	73,826	73,826	73,826	73,826	73,826	66,732
Eff. # of Control Obs.	3,945	3,984	3,388	5,210	3,928	3,926	3,338	3,076
Eff. # of Treat. Obs.	8,352	8,373	6,582	11,360	8,298	8,142	6,507	5,729
Bandwidth	3.366	3.651	2.981	4.143	3.125	3.080	2.494	2.820
Mean	0.057	0.099	0.129	0.164	0.187	0.213	0.241	0.262
2b. Ln (Income)	0.019	0.032	0.038	0.122	0.098	0.061	0.067	0.069
	(0.056)	(0.060)	(0.048)	(0.052)	(0.049)	(0.046)	(0.052)	(0.049)
Observations	69,363	68,525	67,834	67,431	66,708	66,201	65,865	59,449
Eff. # of Control Obs.	3,164	3,106	3,095	3,076	3,044	3,042	3,011	2,709
Eff. # of Treat. Obs.	6,037	5,984	5,920	5,937	5,859	5,821	5,812	5,049
Bandwidth	2.115	2.165	2.312	2.489	2.459	2.514	2.516	2.309
Mean	13.896	13.913	13.929	13.930	13.944	13.964	13.978	13.971

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Table OA12 Continued. Sharp Regression Discontinuity Estimates of the Short- and Medium-Term Effects of Obtaining an Advanced Certificate for Salaried Workers by Initial Employment Status

	(1) Quarter 1	(2) Quarter 2	(3) Quarter 3	(4) Quarter 4	(5) Quarter 5	(6) Quarter 6	(7) Quarter 7	(8) Quarter 8
3. Experience: More than 30								
3a. Acc. Job-to-Job Transitions	0.043	0.054	0.040	0.041	0.037	0.061	0.069	0.079
	(0.025)	(0.024)	(0.034)	(0.036)	(0.041)	(0.041)	(0.044)	(0.050)
Observations	56,015	56,015	56,015	56,015	56,015	56,015	56,015	50,553
Eff. # of Control Obs.	2,215	2,217	2,218	2,218	2,218	2,218	2,218	2,040
Eff. # of Treat. Obs.	4,794	4,794	4,796	4,816	4,816	4,796	4,796	4,165
Bandwidth	2.113	2.145	2.236	2.387	2.352	2.293	2.267	2.188
Mean	0.042	0.071	0.100	0.124	0.150	0.169	0.190	0.212
3b. Ln (Income)	0.118	0.077	0.077	0.121	0.104	0.103	0.101	0.073
	(0.047)	(0.048)	(0.043)	(0.046)	(0.043)	(0.038)	(0.035)	(0.040)
Observations	53,529	52,727	52,350	51,849	51,170	50,463	49,970	44,729
Eff. # of Control Obs.	2,171	2,129	2,399	2,413	2,381	2,354	2,331	2,132
Eff. # of Treat. Obs.	4,664	4,557	4,526	4,517	5,190	5,219	5,168	4,536
Bandwidth	2.949	2.619	3.002	3.003	3.079	3.111	3.131	3.225
Mean	13.858	13.875	13.906	13.906	13.923	13.944	13.958	13.960

Notes: Each cell displays the estimate for the main coefficient of interest in Equation (1) for the advanced certificate, one to eight quarters after certification, for salaried workers (at certification) by potential experience: workers with 15 years or less, workers with more than 15 years but less than 30, and workers with more than 30 years. The outcomes analyzed are the probability of having switched jobs after certification and log of income. The running variable is the exam score and the discontinuity threshold is 90. All regressions include the controls described in Section 4, use a triangular kernel, and use the bandwidth that minimizes the mean squared error of the local polynomial regression discontinuity estimator. We report robust bias-corrected standard errors below the point estimates in parentheses. Standard errors are clustered at the technical-norm level. Optimal bandwidths are displayed below the standard errors. The total number of observations changes across quarters given variation in the number of individuals with positive earnings (for log of income only); it further drops in quarter 8 due to missing information in the last quarter for individuals that certified in the last quarter of 2019. The effective number of observations changes across quarters given variation in the optimal bandwidth. The sample mean for the control group is displayed below the optimal bandwidth.