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Firm-Training, Employment Quality and Social Mobility in Coahuila

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Firm-Training, Employment Quality and Social Mobility in Coahuila

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This paper studies the effect of firm-provided job training on labor market outcomes and intergenerational mobility in Coahuila, Mexico, using a cross-sectional survey of 3 098 workers. Our primary estimator is the AIPW-ATT with a rich control vector including parental socioeconomic background. Training increases the probability of social security coverage by 13.0 percentage points ($p < 0.01$) and the probability of a written contract by 16.9 percentage points ($p < 0.01$). These effects are robust to functional form and to wild cluster bootstrap inference with $G = 14$ clusters. We find no significant effect on employment probability or income under conservative inference. Intergenerational mobility analysis shows that training does not raise upward rank mobility for low-origin workers but reinforces top-tercile persistence for high-origin workers. These findings reveal a tension between efficiency and equity: firm-provided training improves job quality for trained workers but does not redistribute labor market opportunities across socioeconomic origins.

Keywords: job training, labor formalization, intergenerational mobility, AIPW, Mexico, Coahuila

JEL Classification: J24, J46, J62, C21

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I. Introduction

Firm-provided job training is one of the primary mechanisms through which workers in Mexico acquire formal skills and credentials. The premise underlying its potential welfare effects is twofold: training raises worker productivity via human capital accumulation and improves access to better-quality employment; and insofar as firms train workers across the socioeconomic spectrum, it could contribute to equalizing opportunities in labor markets characterized by high segmentation and persistent lack of social mobility. Both claims are theoretically plausible, but the empirical evidence is more nuanced than is commonly assumed.

This paper examines both premises simultaneously using data from the northern Mexican state of Coahuila. Coahuila offers a compelling case study: its highly industrialized economy, relatively low informality rate—the lowest in Mexico: 33.3 percent (INEGI, 2026)—and a dynamic manufacturing industry with active firm-level training activity. This set of characteristics makes Coahuila a favorable setting for studying labor market outcomes.

The results reveal a tension the literature has suggested but not documented: firm-provided training formalizes employment but does not generate upward social mobility. Workers who receive training are 13 percentage points more likely to have social security coverage and 17 percentage points more likely to have a written contract. However, training does not increase the probability that workers from low socioeconomic origins ascend in the income distribution. Transition matrix analysis shows that training reinforces persistence at the top tercile for those from privileged backgrounds without meaningfully altering mobility from the bottom.

Our findings connect three bodies of literature. First, the evaluation of training in Mexico. The most rigorous evaluation of PROBECAT/SICAT, Mexico's public training

program for the unemployed, finds a small but significant effect on employability and no effect on wages (Delajara, Freije, and Soloaga, 2006). More broadly, the literature on returns to education in Mexico documents a paradox of stagnant or declining earnings for more-educated workers alongside rising misallocation toward low-productivity informal firms (Levy and Lopez-Calva, 2020). These results suggest that access to formal employment, rather than credentials per se, is the binding constraint. Our study of firm-provided training addresses a different population, workers already attached to firms. However, the pattern of formalization without income gains resonates with this broader Mexican evidence and matches Acemoglu and Pischke's (1999) assertion that only when labor markets are competitive the productivity gains of training will produce wage returns.

Second, the literature on employment quality and informality in Latin America. Tokman's (1992) structural characterization of informal employment motivated extensive documentation of social security access gaps overlapping with productivity and human capital gaps (Gasparini and Tornarolli, 2009).

Third, the intergenerational mobility literature for Mexico. Rank-rank regressions based on the ESRU Survey on Social Mobility in Mexico (ESRU-EMOVI) document high intergenerational persistence (above 0.60 at the national level) with a pronounced gradient favoring northern regions over the south (Velez-Grajales and Monroy-Gómez-Franco, 2017; Monroy-Gómez-Franco and Corak, 2020; Monroy-Gómez-Franco, 2023). Whether training can attenuate this persistence is an interesting policy question.

The paper proceeds as follows. Section II describes the data. Section III presents the empirical strategy. Section IV discusses identification and sensitivity. Section V reports results. Section VI concludes.

II. Data

II.A. Source and sample

The data come from the ESRU-EMOVI Coahuila 2025, a cross-sectional social mobility survey of the state's working-age population. The analytic sample comprises 3 098[1] individuals aged 25-64 with complete information on labor market status, training participation, and sociodemographic characteristics. The survey design includes 14 primary sampling units (UPMs), which conditions the inference strategy. The survey includes retrospective information on the household of origin parental education and parental economic resources from which it is possible to construct quintiles, terciles or other splits of income, enabling us to situate treatment effects within workers' intergenerational position.

II.B. Treatment, outcomes, and selection

The treatment variable D is a binary indicator equal to one if the worker reports having received at least one formal job training course provided by their employer or a prior employer, and zero otherwise. Sixty-three percent of the sample reports having received training. We analyze four outcomes: (i) employment; (ii) formality defined as access to social security through employment; (iii) written contract; and (iv) the logarithm of income, winsorized at the 1st and 99th percentiles.

Workers who receive training differ systematically from those who do not: they are on average 3.8 years younger, have higher educational attainment, belong to higher occupational classes, and come from higher-income households. The training participation

[1] The survey contains 4 808 observations, nonetheless 1 710 observations are lost because of the lack of answer to some questions.

rate rises monotonically from 55.8 percent in the lowest parental income quintile to 75.3 percent in the highest.

III. Empirical strategy

III.A. Primary estimator: AIPW-ATT

The parameter of interest is the Average Treatment Effect on the Treated (ATT), identified under the Conditional Independence Assumption (CIA). Our estimator is the Augmented Inverse Probability Weighting (AIPW) estimator, which combines a logistic propensity score model with separate linear outcome models for treated and control groups. The estimator is consistent if at least one model is correctly specified (Robins et al., 1994). The propensity score is estimated on a vector of controls X = {sex, age, age-squared, education, rural/urban, region, occupational class}. Survey weights are normalized to mean one.

The parameter of interest is defined as:

$$\text{ATT} = \text{E}(Y_i(1) - Y_i(0) \mid D_i = 1) \tag{1}$$

where Y_i (1) and Y_i (0) are potential outcomes.

The AIPW-ATT estimator is:

$$\hat{\text{ATT}} = \frac{1}{N_t} \sum_{i:\, D_i=1} \left(Y_i - \hat{\mu}_{0(X_i)}\right) - \frac{1}{N_t} \sum_{i:\, D_i=0} \frac{\hat{p}_{(X_i)}}{1 - \hat{p}_{(X_i)}} \left(Y_i - \hat{\mu}_{0(X_i)}\right) \tag{2}$$

III.B. Specifications and inference

Model A (no controls) and Model B (with controls X_i') are specified in the following way:

$$Y_i = \alpha + \beta D_i + \varepsilon_i \quad (3)$$

$$Y_i = \alpha + \beta D_i + X_i'\gamma + \varepsilon_i \quad (4)$$

where Y_i is the outcome, D_i is the training indicator, and ε_i is the error term.

We estimate four specifications: Model A (weighted OLS, no controls), Model B (OLS with X_i'), Model C (AIPW-ATT, primary), and Model D (AIPW with common support trimming at 1 percent). With G = 14 UPMs, conventional clustered standard errors could be unreliable (Cameron and Miller, 2015). Therefore, we report HC-robust standard errors for Model A and cluster-robust for Models B-C. As a robustness check we implement a wild cluster bootstrap with Rademacher weights on the AIPW influence function scores (B = 500, G = 14). Confidence intervals correspond to the 2.5-97.5 percentile of the bootstrap distribution.

For the intergenerational mobility analysis, the following rank-rank regression is estimated:

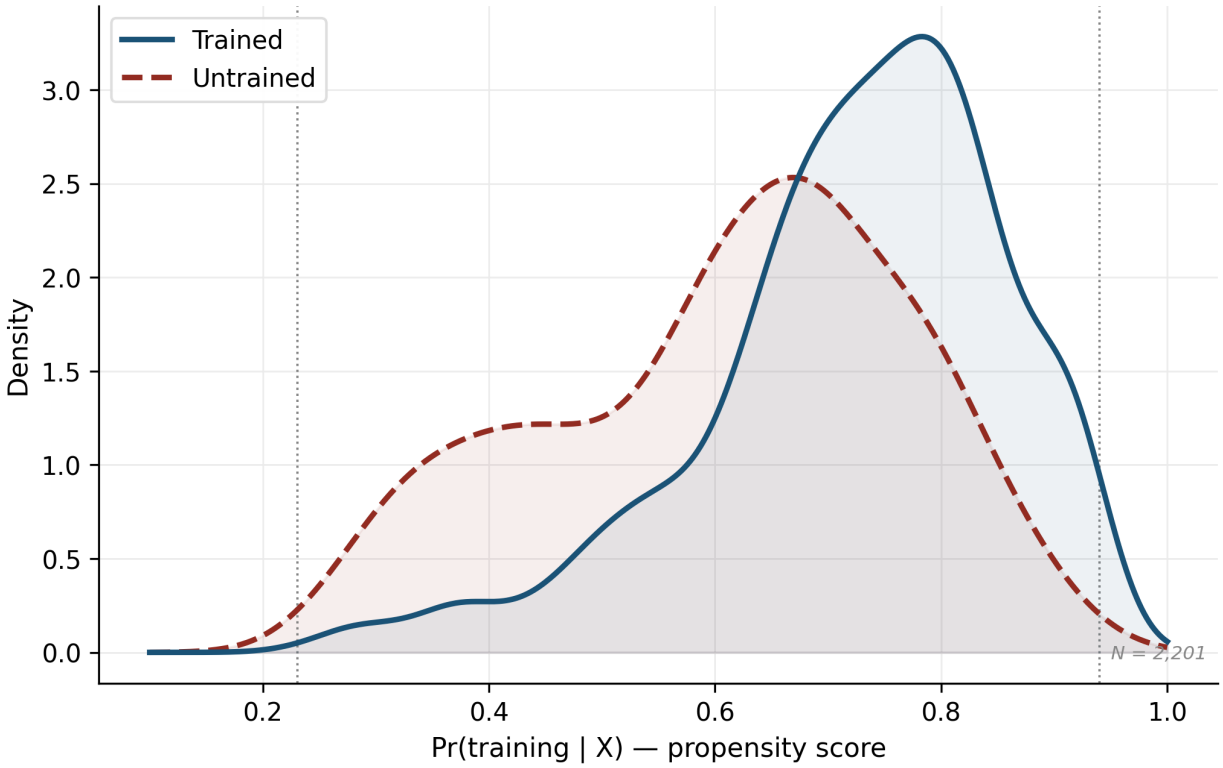
$$R_i^{\text{worker}} = \alpha + \rho R_i^{\text{parent}} + X_i'\delta + u_i \quad (5)$$

where R_i^{worker} is the income rank of the worker and R_i^{parent} is the income rank of the worker's parent, and ρ is the rank-rank coefficient.

IV. Identification and sensitivity analysis

The control vector X_i' {parental education, parental income quintile, cohort, and occupational class} is remarkably rich for a cross-sectional training study in Mexico. Common support is favorable: only 0.5 percent of treated observations fall outside the control group's propensity score support (see Figure 1).

Figure 1. Propensity score overlap



Notes: estimated via logistic regression on X. Dashed vertical lines indicate limits of the control group's support. Only 0.5 percent of treated observations fall outside this support.

We assess identification robustness employing two methods. The Cinelli-Hazlett (2020) robustness value for non-significance is RVq = 0.18 percent for both formality and contract, low in absolute terms, but below the leave-one-out partial R-squared benchmark for education (approximately 2.5 percent). Under Oster's (2019) proportional selection test with

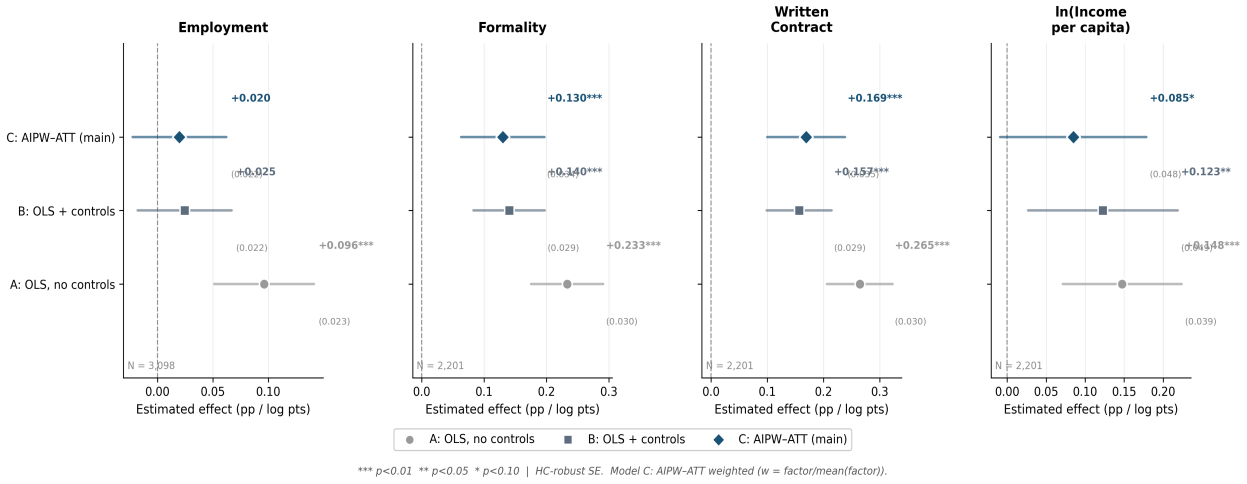
R-squared-max = 1.3 times R-squared-controlled, the delta estimates are +0.59 for formality and +0.55 for contract, both below the critical threshold of 1.0. Therefore, results should be interpreted with caution as evidence consistent with causality in a rigorous observational design, not as experimental inference.

V. Results

V.A. Employment: selection, not causation

The raw training-employment gap is 9.6 percentage points (Model A, $p < 0.01$), but is reduced to 2.5 pp under controls (Model B) and to 2.0 pp under AIPW-ATT (Model C), with no statistical significance in either case. Training does not generate additional employment but improves the quality of existing employment. See the main results in Figure 2 and Table 1.

Figure 2. Effects of job training on labor market outcomes



Notes: models A (OLS, no controls), B (OLS with controls), and C (AIPW-ATT) with 95 percent confidence intervals. ***p < 0.01, **p < 0.05, *p < 0.10.

V.B. Formality and contract: the central result

For formal employment with social security, the AIPW-ATT is 13.0 pp (SE = 0.034, $p < 0.01$; bootstrap CI: [+6.6, +18.8] pp). For written contract, it is 16.9 pp (SE = 0.035; bootstrap CI: [+9.4, +25.0] pp). Average marginal effects from probit (14.7 pp) and logit (14.6 pp) are consistent with the linear estimates, this consistency between specifications rules out functional form concerns. These results suggest that training operates as a human capital or productivity signal recognized by firms, who translate it into regulated contracts with social security access.[2]

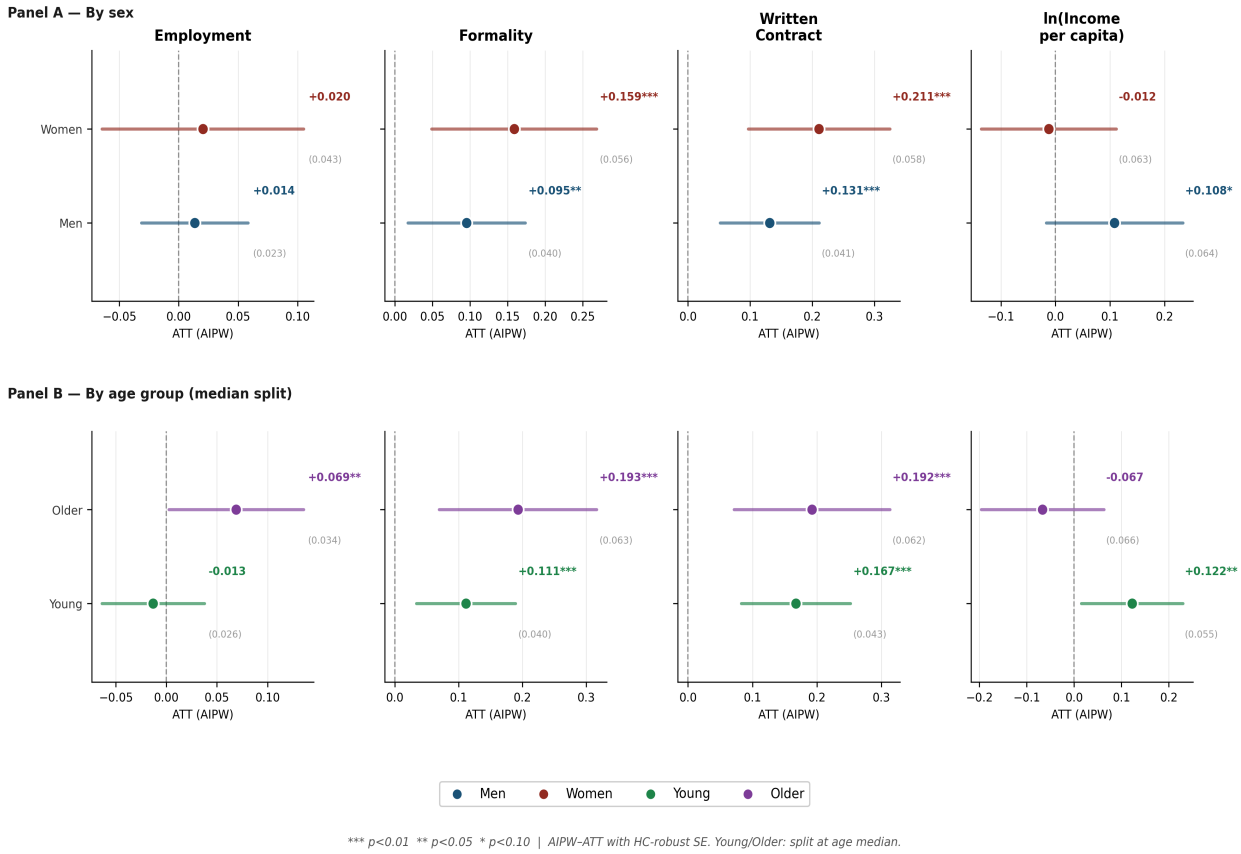
V.C. Income: a fragile result

The AIPW-ATT on log income is 8.5 pp, marginally significant at the 10 percent level with HC-robust standard errors (SE = 0.048). The wild cluster bootstrap raises the SE to 0.081, yielding a 95 percent CI of [–5.1, +21.3] pp, statistically non-significant. The uncertainty in the confidence interval is likely the result of the low number of clusters (G = 14) as Cameron-Miller (2015) demonstrate.

Figure 3 presents heterogeneity analysis. Women benefit more from training on quality outcomes: formality effects are +15.9 pp for women versus +9.5 pp for men; contract effects are +21.1 pp versus +13.1 pp. Older workers show the only significant employment effect (+6.9 pp, $p < 0.05$); younger workers show the only significant income effect (+12.2 pp, $p < 0.05$). Rural results are not statistically significant due to small subsample size.

[2] This interpretation is reinforced by Figure A4 in the Appendix. Considering the whole sample (N = 3 098), that is including those currently unemployed, the coefficients for formalization and written contract do not change much, indicating that training functions as for those already employed and not as a mechanism to access employment. Income on the other hand becomes more significant, suggesting that for the unemployed having experienced training could be translated into income gains.

Figure 3. Heterogeneity of training effects

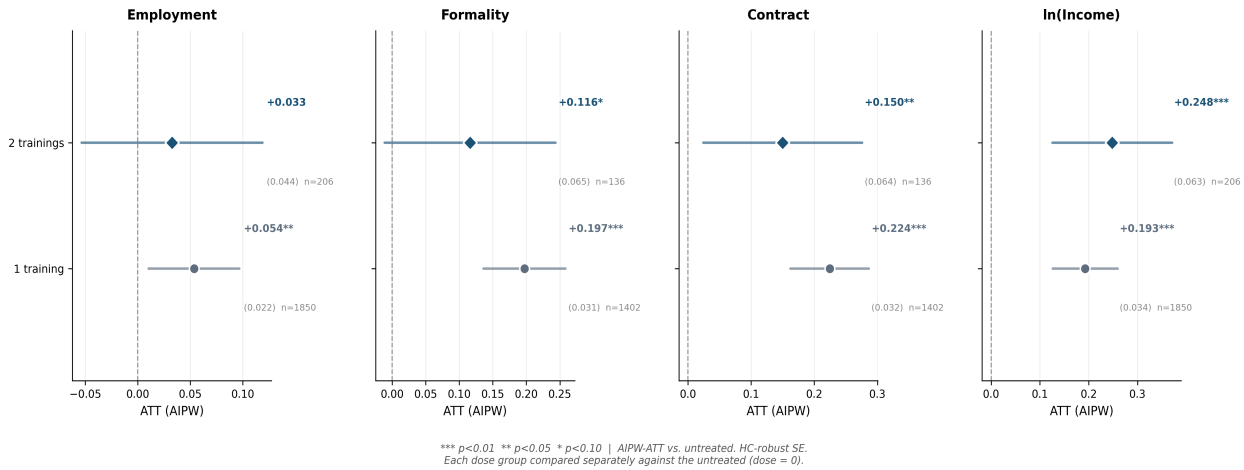


Notes: AIPW-ATT by subgroup with 95 percent confidence intervals. Panel A: by sex. Panel B: by age group (median split). ***p < 0.01, **p < 0.05, *p < 0.10.

V.D. Dose-Response

Figure 4 presents the dose-response analysis. Workers who received one training course show effects of +19.7 pp on formality, +22.4 pp on written contract, and +19.3 pp on log income. Workers who received two courses show somewhat different point estimates (+11.6 pp, +15.0 pp, and +24.8 pp, respectively). The sample of workers with two courses is substantially smaller, thus confidence intervals overlap considerably, and differences across dose levels are not statistically distinguishable.

Figure 4. Dose-Response: effects by number of training courses

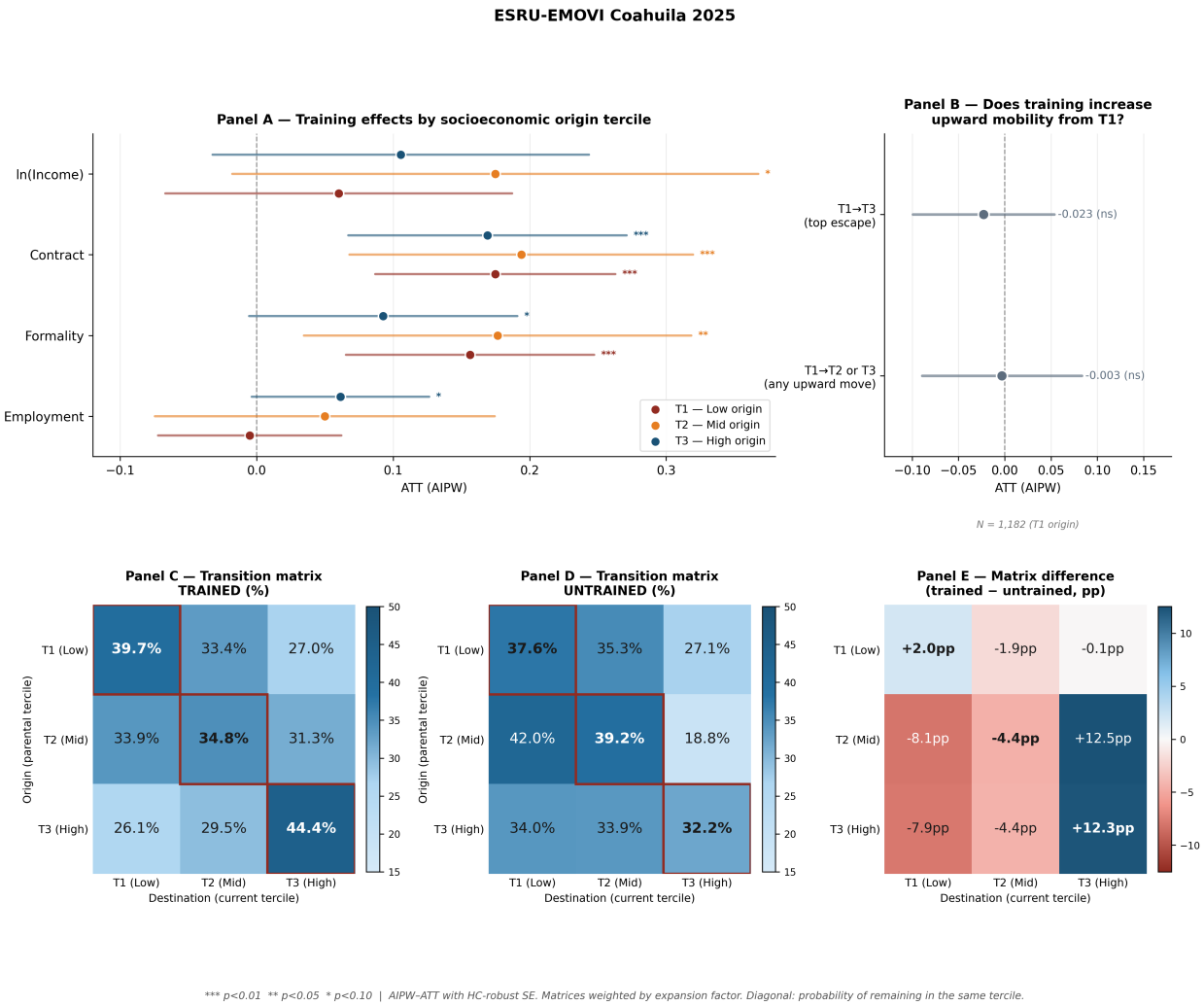


Notes: AIPW-ATT vs. untreated for each dose group separately. 95 percent confidence intervals. Sample sizes reflect only treated units at each dose level. ***p < 0.01, **p < 0.05, *p < 0.10.

V.E. Intergenerational social mobility

The rank-rank correlation between parental and own income in Coahuila is 0.205 ($p < 0.001$). The AIPW-ATT on the probability of ascending from the bottom tercile (T1) to T2 or T3 is –0.3 pp (SE = 0.044, not significant); on reaching T3 it is –2.3 pp (SE = 0.039, not significant). Transition matrices confirm that the probability of remaining in T1 is virtually identical for trained (39.7 percent) and untrained (37.6 percent) workers, while top tercile workers who receive training are 12.2 pp more likely to remain in T3. Training consolidates advantage at the top without enabling upward mobility from the bottom.

Figure 5. Training and intergenerational mobility



Notes: Panel A: AIPW-ATT by origin tercile. Panel B: effect on upward mobility from T1. Panels C-E: weighted transition matrices and their difference. ***p < 0.01, **p < 0.05, *p < 0.10.

Table 1. Effect of job training on labor market outcomes

	(A)		(B)		(C)		Bootstrap		
	Coef.	*(SE)*	**Coef.**	*(SE)*	**ATT**	*(SE)*	**SE**	**95% CI**	**N**
Employment	0.096***	*(0.023)*	0.025	*(0.022)*	0.020	*(0.022)*	*0.021*	[−0.019, 0.059]	3 098
Formality	0.233***	*(0.030)*	0.140***	*(0.029)*	0.130***	*(0.034)*	*0.039*	[0.066, 0.188]	2 201
Written contract	0.265***	*(0.030)*	0.157***	*(0.029)*	0.169***	*(0.035)*	*0.045*	[0.094, 0.250]	2 201
ln(Income)	0.148***	*(0.039)*	0.123**	*(0.049)*	0.085*	*(0.048)*	*0.081*	[−0.051, 0.213]	2 201

Notes: Model A: weighted OLS, no controls. Model B: weighted OLS with X = {sex, age, age-squared, education, rural/urban, region, occupational class}. Model C: AIPW-ATT with logistic propensity score. Bootstrap SE and CI: wild cluster bootstrap (B=500, Rademacher, G=14 UPMs). HC-robust SE in Model A; UPM-clustered in Models B-C. ***p < 0.01, **p < 0.05, *p < 0.10.

Table 2. Heterogeneity of training effects by sex and age -- AIPW-ATT

	Subgroup	ATT	*(SE)*	N	Sig.
A. By sex					
Employment	Men	0.014	*(0.023)*	1 715	—
	Women	0.020	*(0.043)*	1 383	—
Formality	Men	0.095**	*(0.040)*	1 376	**
	Women	0.159***	*(0.056)*	825	***
Written contract	Men	0.131***	*(0.041)*	1 376	***
	Women	0.211***	*(0.058)*	825	***
ln(Income)	Men	0.108*	*(0.064)*	1 376	*
	Women	−0.012	*(0.063)*	825	—
B. By age group (median split)					
Employment	Young	−0.013	*(0.026)*	1 604	—
	Older	0.069**	*(0.034)*	1 494	**
Formality	Young	0.111***	*(0.040)*	1 271	***
	Older	0.193***	*(0.063)*	930	***
Written contract	Young	0.167***	*(0.043)*	1 271	***
	Older	0.192***	*(0.062)*	930	***
ln(Income)	Young	0.122**	*(0.055)*	1 271	**
	Older	−0.067	*(0.066)*	930	—

Notes: AIPW-ATT with HC-robust standard errors. Young/Older split at sample median age. ***p < 0.01, **p < 0.05, *p < 0.10. — denotes p > 0.10.

VI. Discussion and conclusions

VI.A. Why does training formalize without generating social mobility?

The central result is consistent with signaling theory (Spence, 1973), though with an important caveat for the firm-provided context. When training is provided by the employer,

the firm already observes the worker's performance directly, the training credential is therefore not primarily a signal to the current employer but to future employers in the formal sector. Workers who have received firm-sponsored training arrive at subsequent job searches with a credential that reduces information asymmetry for outside employers and lowers their screening costs. These employers translate the credential into formal contracts with social security access. The mechanism is compatible with formalization without higher wages because the signal raises the probability of formal employment, not necessarily of employment in a higher wage strata of the formal sector. Mexico's labor market is heterogeneous and extremely monopsonistic (Cazzuffi et al., 2023); workers accessing the formal sector via training credentials may enter its lower rungs, consistent with formalization. However, the lack of competitive labor markets blocks their capacity to translate training into income gains (Acemoglu and Pischke, 1999).

The social mobility result reinforces this interpretation. Bottom-tercile workers who receive training show formality effects (+15.6 pp) comparable to top-tercile workers (+9.3 pp): firms do not discriminate by origin in formal employment access. Yet tercile ascent probabilities are unchanged, while training seems to reinforce T3 persistence for those already at the top (+12.2 pp). This is consistent with training complementing the social capital and networks that advantaged-origin workers already possess.

VI.B. Policy implications

Three implications follow for labor market policy. First, the evidence reveals ambiguity in how training can be evaluated. If the objective is formalization, the data clearly show that firm-provided training is an efficient tool. If the objective is income growth or upward social mobility, the same data indicate that training alone may not be the proper tool.

This distinction matters for labor and economic policy toward training: tax incentives or regulations that simply increase training incidence will likely generate more formalization, a desirable outcome, but not more mobility. Other complementary policies at the state level need to be in place to produce social mobility.

Second, the distributional pattern raises a concern about access. Firm-provided training is allocated by employers, not by workers, and the data show that participation rates are substantially higher among workers of privileged origin (75.3 percent in the top quintile versus 55.8 percent in the bottom). If firms preferentially train workers who are already more productive or better-networked, which is consistent with our signaling interpretation, then firm-level decisions alone will not produce mobility. Complementary state policies that extend training access to disadvantaged workers, or that combine training with labor intermediation for workers without established firm relationships, could improve the distributional results. Policies to combat monopsonistic power in the labor market have potential to improve social mobility outcomes.

Third, the gender heterogeneity suggests a high-return strategy: women benefit substantially more from training in formalization (+15.9 vs. +9.5 pp) and contract attainment (+21.1 vs. +13.1 pp). Policies that increase female participation in firm training programs would maximize impact at the most effective margin.

VI.C. Limitations and conclusion

There are four important limitations in this study. First, identification rests on the Conditional Independence Assumption (CIA), which is untestable with observational data; the Cinelli-Hazlett (2020) and Oster (2019) analyses indicate that effects are technically fragile. Second, the cross-sectional design prevents detection of dynamic income effects with

temporal lag. Third, the rural subsample is too small for precise inference. Fourth, we cannot observe the type, duration, or quality of training received. These shortcomings could be addressed in the future with panel data methods if the survey is repeated with some periodicity.

Firm-provided job training in Coahuila increases formal employment with social security and written contracts. But the social mobility analysis reveals that this efficiency gain does not translate into greater distributional equity: training improves employment quality within each worker's socioeconomic position without redefining that position.

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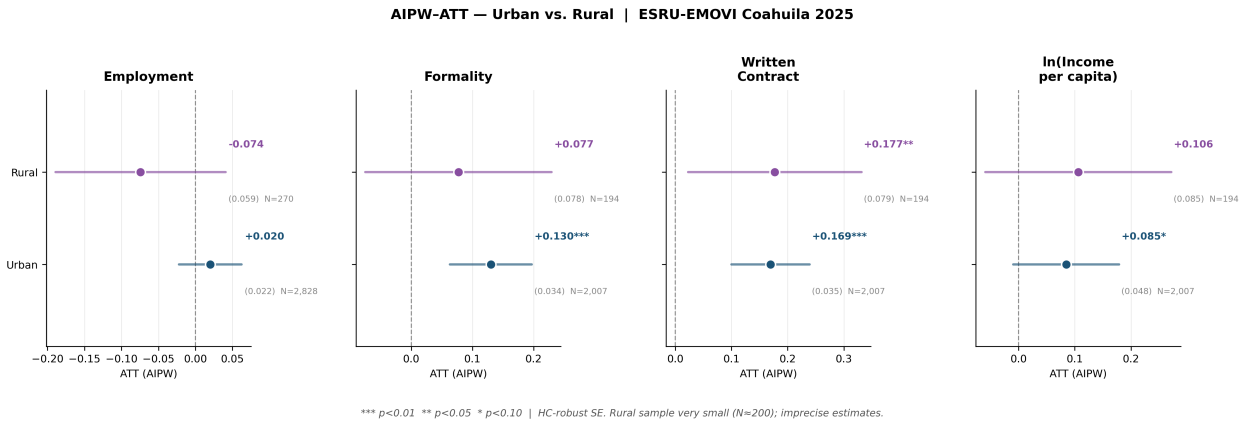
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Appendix

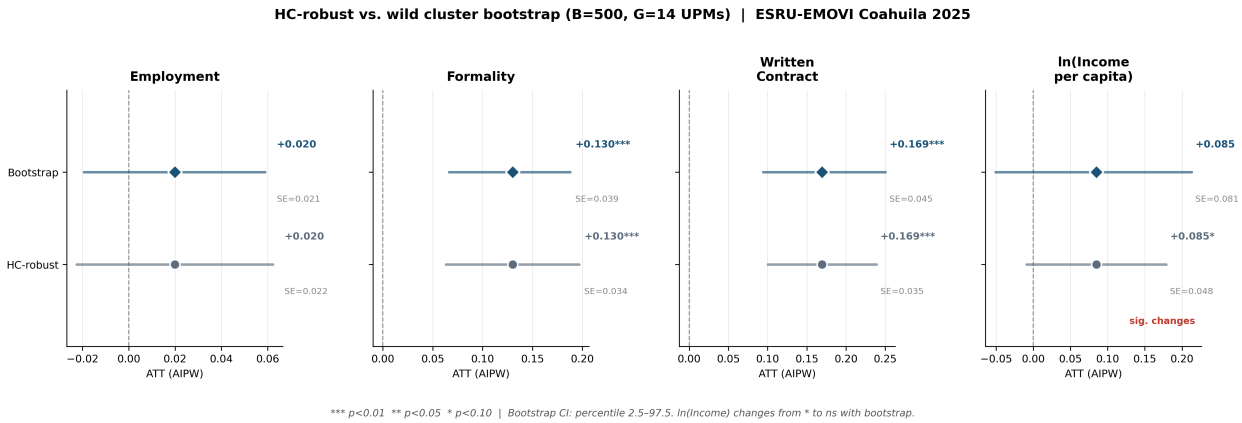
This appendix presents supplementary figures for the sensitivity and robustness analyses discussed in the main text.

Figure A1. Heterogeneity by geographic location (urban/rural)



Notes: AIPW-ATT with 95 percent confidence intervals. Rural subsample N approximately 200-270; estimates are imprecise. ***p < 0.01, **p < 0.05, *p < 0.10.

Figure A2. Sensitivity of inference to standard error method



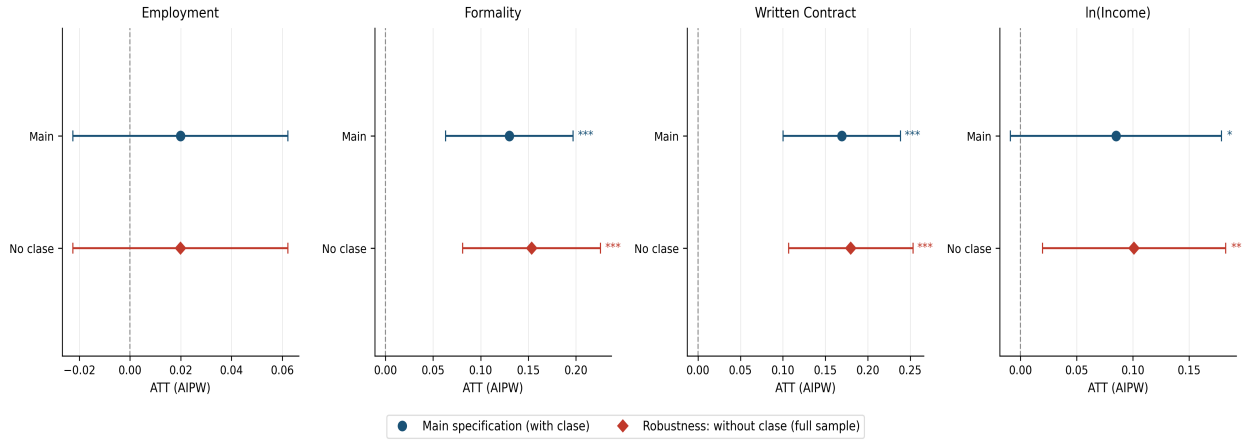
Notes: HC-robust versus wild cluster bootstrap (B = 500, Rademacher, G = 14 UPMs). Warning symbol indicates a change in statistical significance; log(Income) moves from marginally significant (HC) to not significant (bootstrap).

Figure A3. Cinelli-Hazlett (2020) sensitivity analysis



Notes: contours show adjusted estimates under varying levels of confounder partial R-squared. Diamond: Robustness Value. Triangles: leave-one-out benchmarks. Dashed line: estimate = 0. Dotted line: p = 0.05.

Figure A4. Robustness to occupational class control



Notes: AIPW-ATT estimates with (Main, blue) and without (No clase, red) occupational class in the control vector. The comparison for these three outcomes is a test of sensitivity to occupational class as a covariate among employed workers. For ln(Income), excluding class expands the sample from N = 2 201 to N = 3 098, recovering workers outside formal employment for whom household income is observed; the ATT rises from 0.085 to 0.101 and becomes significant at the 95 % level, consistent with positive income associations among informally employed and non-employed trained workers. ***p < 0.01, **p < 0.05, *p < 0.10.