How Do State Retirement Savings Policies Affect Labor Supply?

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Abstract

This study investigates the labor market impacts of state-based retirement savings policies, often referred to as automatic-enrollment IRA (AutoIRA) programs. Utilizing data from the Annual Social and Economic Supplement to the Current Population Survey (CPS-ASEC) from 2010 to 2023, we estimate Two-Way Fixed Effects (TWFE) and staggered Difference-in-Differences (CSDiD) models. Despite the theoretical ambiguity surrounding the effects of workplace retirement savings options on labor markets, empirical findings reveal that these policies increase private-sector employment by 1.8% to 2.3% and may increase earnings by 2% to 4%. These findings contribute to the literature on how retirement savings policies, specifically private pensions (e.g., DC plans and IRAs), influence workers' labor supply behavior and firms' wage decisions.

Keywords: Retirement savings policies, labor supply, workplace benefits, AutoIRA

JEL codes: D14, J22, J26, J32

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1. Introduction

Employer-sponsored retirement plans (ESRPs) are the largest source of household retirement savings, yet many workers lack coverage. Individual Retirement Accounts (IRAs) are available to all workers, but take-up remains very low (Chen and Munnell, 2017).

To address this, states, such as California, Oregon, and Illinois, have adopted automatic enrollment IRA (AutoIRA) policies, under which employers without ESRPs must facilitate employee payroll deductions to Roth IRAs.[2,3] Like other employer-mediated retirement savings options, workers can opt out of these state-based AutoIRA programs. However, a large body of evidence from automatic enrollment in ESRPs suggests that many employees will continue to participate given behavioral inertia (Madrian and Shea, 2001).

This paper examines the effects of AutoIRA policy on labor supply and earnings. Prior research suggests that such policies increase the prevalence of retirement plans by inducing some employers to establish ESRPs (Bloomfield et. al., 2023) and others to enroll workers in state-facilitated IRAs. If so, these changes may influence both workers' behavior and wage rates.

We propose a conceptual framework to analyze adjustments in labor supply and wages post-policy implementation. We argue that while a standard labor economic model implies limited (if any) effects of state-facilitated IRAs on workers' labor supply decisions, increase in prevalence of ESRPs and behavioral biases could influence workers' labor supply as well as firms' wage decisions. Using data from the Current Population Survey's March supplement, the Annual Social and Economic Survey (CPS-ASEC), we find notable private-sector labor supply and wage responses to AutoIRA policies.

This paper contributes to gaps in the literature on retirement savings and labor market dynamics. While job lock related to private health benefits and Defined Benefit (DB) plans has been investigated (Madrian, 1994; Koedel and Xiang, 2017; Mitchell 1982), there is little if any empirical evidence on how Defined Contribution (DC) plans and IRAs affect worker trajectories. As DC plans increasingly dominate the retirement ecosystem, a better understanding of the labor supply and wage implications is crucial.

[2] Other states are developing similar policies. There are currently 19 states that have taken steps to adopt AutoIRA programs, though most are not yet implemented. The three states we focus on (i.e., Oregon, Illinois, and California) account for the vast majority of IRAs opened and assets saved (97%) under state AutoIRA programs (Georgetown University, Center for Retirement Initiatives, 2023).

[3] See Bloomfield et. al., 2023 for a review.

2. Conceptual Framework

In a standard labor model, wages offered by employers determine labor supply. Households optimize lifetime consumption and therefore some workers prefer to save a portion of earnings to consume in future non-working periods. These preferences, in conjunction with tax-advantaged savings rules, may motivate worker contributions to IRAs or ESRPs. Because all workers had access to IRAs before the policy, state-facilitated IRAs should, in theory, have no influence on workers' labor supply. However, if the policy increases the prevalence of ESRPs, workers' preferences for these plans and firms' decisions to pass on compliance costs to workers could influence labor supply and the wage rate.

Summers (1989) argues that in competitive labor markets, employers offer non-wage benefits if their value to workers exceeds employers' provision costs. Thus, when firms newly offer benefits, rational workers who value them will remain at or sort into such firms and wages may adjust downwards to an equilibrium point where employers' benefit provision costs equal workers' perceived value of them, resulting in a mutually beneficial trade. Conversely, workers who do not value benefits (relative to the reduction in wages) may seek higher wages elsewhere. Gustman et. al. (1994) augments the standard labor model to explain demand for workplace retirement benefits and consider the desire for tax-preferred savings, economies of scale, and other factors.

In addition to potential preferential sorting across sectors or firms, rational workers with a desire to save for retirement may respond to a new workplace savings option by increasing labor supply. Simultaneously, if the pass through of compliance costs reduces wages, labor supply may decrease for some workers as the labor-leisure tradeoff adjusts. Labor supply decisions could also be influenced by behavioral factors such as reference dependence or salience (Farber, 2008), which may cause some workers to mistakenly equate ESRPs and state-facilitated IRAs.[4] Furthermore, workers that desire the benefit but expect wage reductions due to compliance costs might seek to compensate by taking on multiple jobs or working more hours, thereby increasing private-sector employment.

Though we expect affected firms to pass on compliance costs by reducing wages, such within-subject wage effects could be complicated by concurrent employment composition changes

[4] ESRPs and State facilitated IRAs differ considerably on several parameters, such as tax advantage limits and availability of employer contributions.

across sector, industry, or job types. These considerations suggest that the impacts of state retirement policy mandates on labor supply and wages are ambiguous and empirical study is necessary to identify them.

3. Data and Methods

Data

This study uses data from the CPS-ASEC, a nationally representative household-level survey.[5] Our sample consists of individuals aged 18 to 64 years over the period of 2010-2022. We exclude respondents that report attending school or in active military duty. Table 1 in the appendix provides summary statistics for the treated states (those with AutoIRA mandates) and control states (those without AutoIRA mandates); we find the two groups are similar in terms of key variables.[6]

Methods

Our identification strategy leverages the staggered rollout of AutoIRA regulations in California, Oregon, and Illinois to estimate the effects of AutoIRA laws on workers' labor supply. We employ Two-Way Fixed Effects (TWFE) and staggered Difference-in-Differences (CSDiD) models, following Callaway and Sant Anna (2021), which compare outcomes in treated states versus control states. We estimate the model:

$$(1)\ Y_{ist} = \alpha_0 + \alpha_1 AutoIRA_{st} + \alpha_2 \pi_s + \alpha_3 \tau_t + X_{ist}\lambda + e_{ist}$$

where Y_{ist} represents either private-sector employment or log of annual wages for individual i in state s at time t. $AutoIRA_{st}$ is an indicator for states s that implements AutoIRA legislation in year t and α_1 is the treatment effect. X_{ist} is a vector of individual-level demographic, job, and family structure characteristics. The model also includes state-level controls (e.g., state GDP, poverty rate, etc.), state and year fixed effects ($\pi_s$and τ_t).

We verify the identifying assumptions in equation (1) by estimating event study models:

[5] CPS-ASEC data were obtained from the University of Minnesota's IPUMS website. The CPS is a nationally representative survey conducted by the Department of Labor and the Census Bureau.
[6] We observe largely similar demographic characteristics between the treatment and control group.

$$(2)\ Y_{ist} = \alpha_0 + \sum_{i=-6}^{-2} \alpha_{1i} AutoIRA_{st} \times 1(t - T_s^*) + \sum_{i=0}^{5} \alpha_{2i} AutoIRA_{st} \times 1(t - T_s^*) + \alpha_3 \pi_s + \alpha_4 \tau_t + X_{ist}\lambda + e_{ist}$$

where α_{1i} and α_{2i} capture the interaction between treatment status and event-year indicators $1(t - T_s^*)$ for pre and post treatment periods, respectively; and i = -1 is the reference year.[7]

4. Results

We estimate policy effects on labor market outcomes using two distinct samples: all workers (aged 18-64) and prime-age workers (aged 25-55). Table 1 presents the main results for private-sector employment and earnings for both samples from estimating TWFE and CSDiD models. Across both samples and estimation methods, we find that the introduction of AutoIRA policies led to a statistically significant increase in private-sector employment and earnings.

Table 1 presents the estimated policy effect on workers' private-sector labor supply. Columns (1) and (2) show estimates from TWFE models and columns (3) and (4) show estimates from CSDiD models for the full and prime age samples respectively. We find that private-sector employment increased by 1 percentage point (ppt) (1.8 percent) for the full sample and 1.1 ppts (1.9 percent) for the prime age sample in states that instituted AutoIRA mandates compared to those that did not. Estimates from the CSDiD models show that the effect is consistent and marginally larger than in the TWFE approach. We find that private-sector employment rose by 1.3 ppts (2.3 percent) for the full sample and 1.2 ppts (1.8 percent) for the prime age sample, though the estimate for the latter is significant at the 10 percent level. These increases in private sector employment could have resulted from workers shifting their labor from other sectors, including non-employment or self-employment.[8]

The estimated policy effect on private-sector wages, measured by log annual wages, is presented in the bottom panel of Table 1. We find the policy led to a modest increase in wages of 2.2% and 2.5% for the two samples using TWFE models. Using CSDiD models, we find similarly

[7] Figures 1-3 in Appendix A display event-study graphs for the two main outcomes: private-sector employment and log weekly earnings. We do not observe differences in pre-trends for private-sector employment and weekly earnings.

[8] We test for shifts in labor supply between self-employment and private sector employment (results are in Table 2 in the appendix) and find that the policies led to a statistically significant decline in self-employment. These results suggest that AutoIRA policies influenced sectoral shifts in employment, but further research is needed to understand such inter-sectoral changes in employment better.

sized coefficients for the wage effect (i.e. 1.8% and 4.2%, respectively), though the estimates are not statistically significant. These potential wage increases could have resulted from some workers increasing their earnings through part-time work, working multiple jobs, or increasing the number of hours worked to compensate for lower earnings as a result of savings deposited into an AutoIRA.

Table 1: Effects of AutoIRA Policies on Private-Sector Employment and Wages

	TWFE		CSDiD	
	(1)	(2)	(3)	(4)
	Full Sample (18-64 years old)	Prime Age (25-55 years old)	Full Sample (18-64 years old)	Prime Age (25-55 years old)
Private-Sector Employment	0.0099***	0.0112***	0.0132**	0.0108*
	{0.0025}	{0.0025}	{0.0058}	{0.0062}
Pre-Policy Mean	*0.5673*	*0.5956*	*0.5673*	*0.5956*
N	1,228,042	913,417	1,228,042	913,417
Annual Wages (log)	0.0250**	0.0224***	0.0184	0.0420
	{0.0104}	{0.0083}	{0.0790}	{0.0683}
Pre-Policy Mean	*9.8840*	*10.0073*	*9.8840*	*10.0073*
N	775,850	595,707	775,850	595,707

Note: Each cell presents coefficients from separate regressions. Wage estimates are log of real wages in 2023 dollars. As information on wages are for the previous calendar year, our data for wages is for the period of 2010 and 2022. Regressions include year and state FEs as well as demographic and state-level controls. * p<0.10, ** p<0.05, *** p<0.01.

5. Discussion and Conclusion

This study evaluates the effects of retirement savings policies on labor supply and wages. Using CPS-ASEC data, we estimate the effect of AutoIRA policies that were implemented in three states on two key labor market outcomes. We find that the state AutoIRA policies significantly increased private-sector employment. Additionally, the results indicate a potential modest increase in wages following the introduction of AutoIRA policies. Our estimates on the increase in private-sector employment and the wage rate are consistent across different samples and specifications. Taken together, these findings suggest that AutoIRA policies resulted in a non-trivial increase in private-sector employment and had no negative impact on wages.

Given the recency of these state mandates, our estimates should be interpreted as early evidence with opportunities for future research. Specifically, follow-up work should consider additional states as more AutoIRA policies are implemented. Additionally, analysis of large-scale longitudinal labor market data may help identify the channels through which these employment and wage effects we observe occur, such as compliance cost incidence on workers and employers, variation in such incidence, changes in worker composition across sectors, and other patterns of worker sorting in response to heterogeneous savings and wage preferences.

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APPENDIX

Table 1: Sample Statistics

	Auto-IRA States		Non-AutoIRA States	
	Mean	SD	Mean	SD
Private Employment	0.5785	0.4938	0.5997	0.4900
Annual Wages (log) in 2023 real dollars	9.8674	3.1737	9.9824	2.9169
Self-Employment	0.0887	0.2843	0.0781	0.2684
Demographic Characteristics				
Age	42.044	12.483	42.220	12.709
Age squared	1923.523	1061.561	1944.020	1079.860
Female	0.500	0.500	0.507	0.500
Married	0.563	0.496	0.573	0.495
Separated/Divorced/Widowed	0.127	0.333	0.144	0.351
Single	0.310	0.462	0.283	0.450
White	0.757	0.429	0.784	0.411
Black	0.073	0.261	0.135	0.342
Asian	0.128	0.334	0.049	0.216
Other Races	0.041	0.198	0.031	0.173
Hispanic	0.315	0.464	0.149	0.356
Living in metropolitan area	0.877	0.328	0.704	0.457
Less than high school	0.122	0.328	0.086	0.280
HS graduate	0.252	0.434	0.300	0.458
Some college	0.259	0.438	0.263	0.441
College plus	0.366	0.482	0.350	0.477
Immigrant	0.317	0.465	0.178	0.383
Number of children	0.940	1.192	0.895	1.172
Household size	3.215	1.730	2.987	1.541
Firm size				
Missing value	0.187	0.390	0.168	0.374
Under 10 employees	0.170	0.376	0.155	0.362
10-49 employees	0.117	0.321	0.117	0.322
50-99 employees	0.061	0.239	0.062	0.241
100-499 employees	0.100	0.299	0.104	0.305
500 plus employees	0.366	0.482	0.394	0.489
State variables				
Gross Products (log)	14.328	0.777	13.043	0.882
State EITC	0.290	0.349	0.093	0.133
State minimum wages	9.815	1.851	8.079	1.660
Poverty rate	13.072	2.372	13.123	3.204
N	180,602		1,047,440	

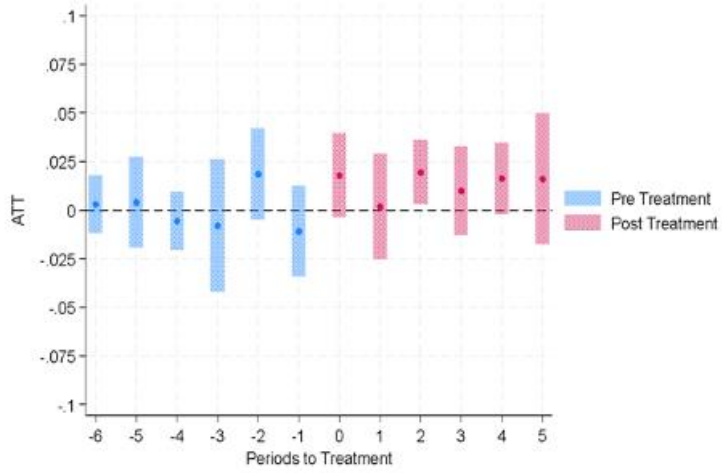
Note: Data comes from CPS-ASEC 2010-2022. Sample includes individuals aged 18-64, not attending school, in active military duty or have no work disability. Treated AutoIRA states include OR, CA, and IL; and control group includes all other states. All statistics are adjusted by sample weights.

Table 2: Effects of AutoIRA Programs on Self-Employment

	TWFE		CSDID	
	(1)	(2)	(3)	(4)
	Full Sample (18-64 years old)	Prime Age (25-55 years old)	Full Sample (18-64 years old)	Prime Age (25-55 years old)
Self-Employment	-0.0047**	-0.0062***	-0.0108**	*-0.0111***
	{0.0018}	{0.0020}	{0.0054}	*{ 0.0045}*
Pre-Policy Mean	*0.0908*	*0.0904*	*0.0908*	*0.0904*
N	1,228,042	913,417	1,228,042	913,417
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Demographics Control	Yes	Yes	Yes	Yes
State Characteristics	Yes	Yes	Yes	Yes

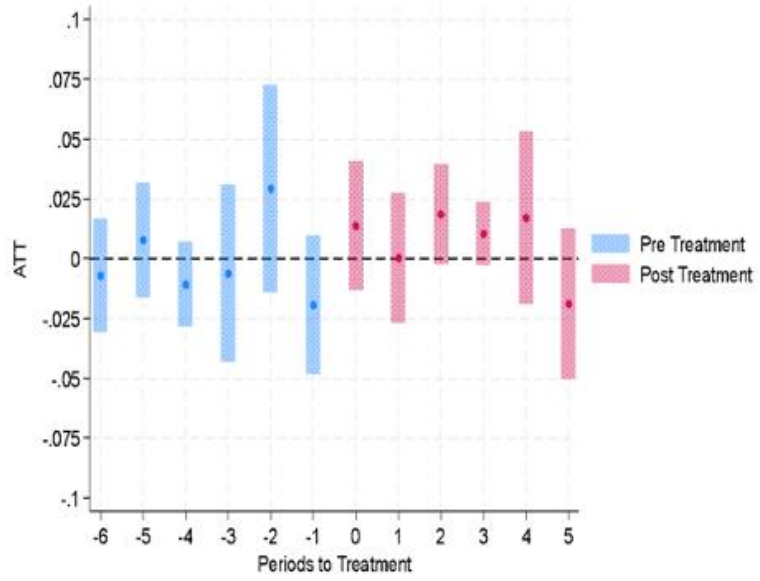
Note: Each cell presents coefficients from separate regressions. Regressions include year and state FEs as well as demographic and state-level controls. * p<0.10, ** p<0.05, *** p<0.01.

Figure 1: Event Study for Private-Sector Employment Using the Full Sample



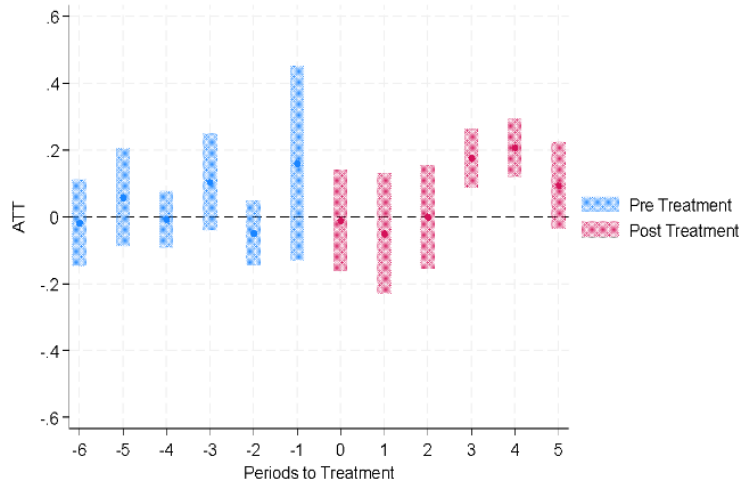
Note: Data comes from CPS-ASEC from 2010 to 2022. Sample includes all individuals aged 18-64. Those who reported in active duty, in school, or not working due to disability are excluded. Outcome variable: Indicator for working in the private-sector. Each dot displays coefficient β and its 95% confidence interval from the event study regression. The model is adjusted for year fixed effects, state effects, individual demographics (age, gender, marital status, race, Hispanic origin, education, family income categories, family size, living in metropolitan area, immigrant status, indicators for occupations and industries), and state characteristics (EITC rates, minimum wages, poverty rates, and gross domestic products). All estimates are adjusted by sample weights. Standard errors are robust and clustered by state level.

Figure 2: Event Study for Private-Sector Employment Using a Prime Age Sample



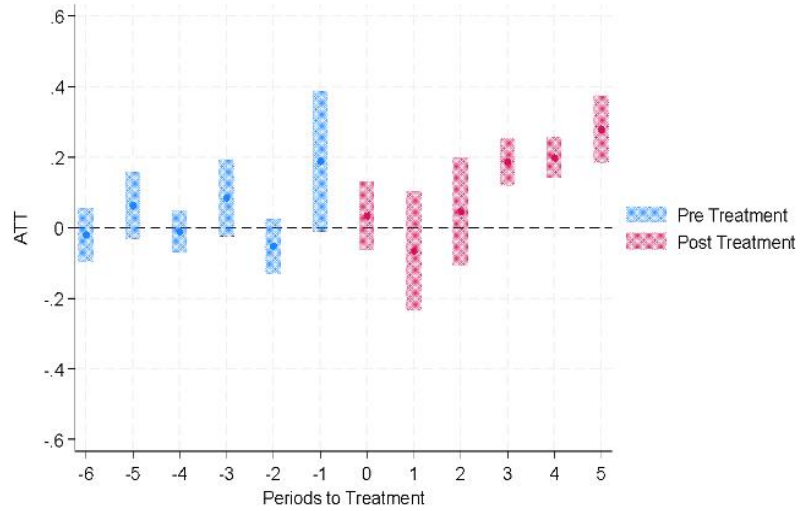
Note: Data comes from CPS-ASEC from 2010 to 2022. Sample includes all individuals aged 25-55. Those who reported in active duty, in school, or not working due to disability are excluded. Outcome variable: Indicator for working in the private-sector. Each dot displays coefficient β and its 95% confidence interval from the event study regression. The model includes year fixed effects, state fixed effects, controls for individual demographics (age, gender, marital status, race, Hispanic origin, education, family income categories, family size, living in metropolitan area, immigrant status, indicators for occupations and industries), and state characteristics (EITC rates, minimum wages, poverty rates, and gross domestic products). All estimates are adjusted by sample weights. Standard errors are robust and clustered by state level.

Figure 3: Event Study for Wages Using a Full Sample



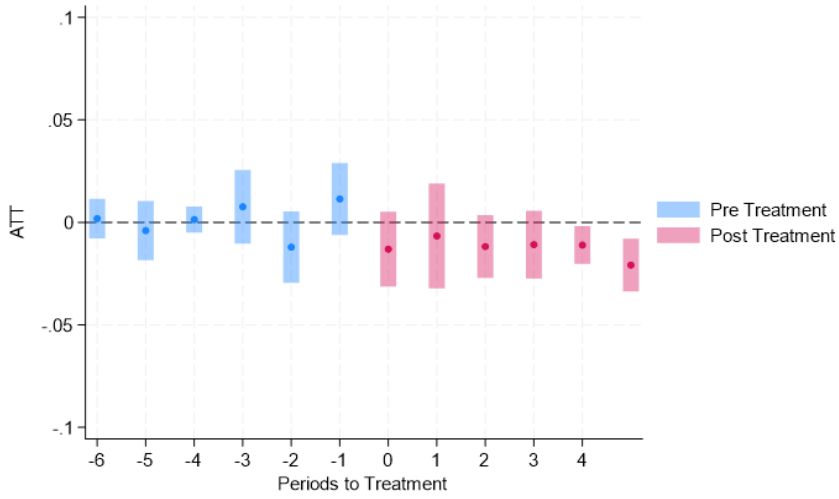
Note: Data comes from CPS-ASEC from 2010 to 2022. Sample includes workers aged 18-64 in the private sector. Those who reported in active duty, in school, or not working due to disability are excluded. Outcome variable: log of real annual wages (in 2023 dollars). Each dot displays coefficient β and its 95% confidence interval from the event study regression. The model includes year fixed effects, state fixed effects, controls for individual demographics (age, gender, marital status, race, Hispanic origin, education, family income categories, family size, living in metropolitan area, immigrant status, indicators for occupations and industries), and state characteristics (EITC rates, minimum wages, poverty rates, and gross domestic products). All estimates are adjusted by sample weights. Standard errors are robust and clustered by state level.

Figure 4: Event Study for Wages Using a Prime Age Sample



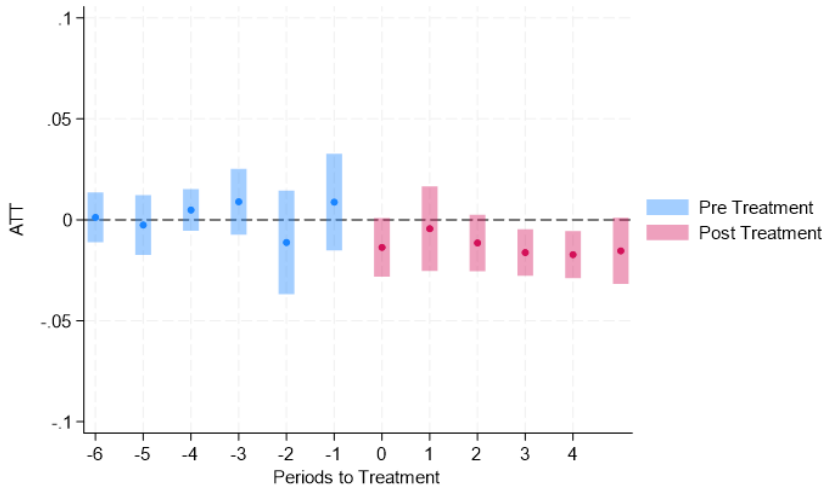
Note: Data comes from CPS-ASEC from 2010 to 2022. Sample includes workers aged 25-55 in the private sector. Those who reported in active duty, in school, or not working due to disability are excluded. Outcome variable: log of annual real wages (in 2023 dollars). Each dot displays coefficient β and its 95% confidence interval from the event study regression. The model includes year fixed effects, state fixed effects, controls for individual demographics (age, gender, marital status, race, Hispanic origin, education, family income categories, family size, living in metropolitan area, immigrant status, indicators for occupations and industries), and state characteristics (EITC rates, minimum wages, poverty rates, and gross domestic products). All estimates are adjusted by sample weights. Standard errors are robust and clustered by state level.

Figure 5: Event Study for Self-Employment Using a Full Sample



Note: Data comes from CPS-ASEC from 2010 to 2022. Sample includes workers aged 18-64. Those who reported in active duty, in school, or not working due to disability are excluded. Outcome variable: indicator for working as self-employed. Each dot displays coefficient β and its 95% confidence interval from the event study regression. The model includes year fixed effects, state fixed effects, controls for individual demographics (age, gender, marital status, race, Hispanic origin, education, family income categories, family size, living in metropolitan area, immigrant status, indicators for occupations and industries), and state characteristics (EITC rates, minimum wages, poverty rates, and gross domestic products). All estimates are adjusted by sample weights. Standard errors are robust and clustered by state level.

Figure 6: Event Study for Self-Employment Using a Prime Age Sample



Note: Data comes from CPS-ASEC from 2010 to 2022. Sample includes workers aged 25-55. Those who reported in active duty, in school, or not working due to disability are excluded. Outcome variable: indicator for working as self-employed. Each dot displays coefficient β and its 95% confidence interval from the event study regression. The model includes year fixed effects, state fixed effects, controls for individual demographics (age, gender, marital status, race, Hispanic origin, education, family income categories, family size, living in metropolitan area, immigrant status, indicators for occupations and industries), and state characteristics (EITC rates, minimum wages, poverty rates, and gross domestic products). All estimates are adjusted by sample weights. Standard errors are robust and clustered by state level.