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# Can affordable internet increase employment opportunities for low-income workers? Evidence from the Affordable Connectivity Program

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## ABSTRACT

This study investigates the labor market impacts of the Affordable Connectivity Program (ACP), the largest U.S. initiative to date aimed at reducing income-based disparities in Internet access. We assess ACP's effects on labor force participation and employment and test the hypothesis that a key impact mechanism is the expansion of remote work opportunities for program recipients. Using large-scale national datasets, we also explore heterogeneity in program effects by gender, occupation, and connection type (fixed vs. mobile). The analysis employs two complementary empirical strategies: (1) difference-in-differences estimators based on repeated cross-sectional data from the American Community Survey for 2016–2023 ( $N \approx 29.8$  million), and (2) augmented inverse propensity weighting (AIPW) models using cross-sectional data from the 2023 Current Population Survey ( $N = 35,561$ ). The results provide robust evidence that ACP participation is associated with improved labor market outcomes, particularly among women and individuals with high-speed residential connections. These gains appear to be driven, in part, by increases in both the incidence and intensity of remote work. The findings suggest that a narrow focus on first-level adoption outcomes underestimates the broader socioeconomic benefits of affordable broadband initiatives. Theoretically, they indicate that the so-called Matthew effect – whereby digitization amplifies existing social inequalities – is not inevitable and can be partially offset by well-designed, targeted policy interventions.

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Digital inequality; third-level outcomes; remote work; Affordable Connectivity Program; program evaluation

## 1. Introduction

Theorization about digital inequality has evolved from its original centering on disparities in access to devices and connectivity (first-level divide), to differences in digital skills and modalities of use (second-level divide), and more recently to outcomes and impacts of digital engagement (third-level divide).<sup>1</sup> While empirical findings on the first and second levels are reasonably well-established, understanding the broader socioeconomic impacts of digital engagement across large, heterogeneous populations has proven more elusive (Scheerder et al., 2017). At least two factors explain the slower progress in this

area. First, as digital technologies have become embedded in virtually all aspects of modern life, disentangling impacts in a single domain from overlapping effects in others becomes increasingly complex (Helsper, 2012). Furthermore, identifying plausible causal links between digital engagement and outcomes in employment, education and other socioeconomic domains presents substantial methodological challenges.

One of the domains most extensively theorized and studied in relation to the impacts of Internet access and use is employment (Atasoy, 2013; De Marco et al., 2025; DiMaggio & Bonikowski, 2008; Garcia-Murillo et al., 2018; Karaoglu et al., 2022; Lobo et al., 2020; Zuo, 2021). Internet use has been shown to lower job search costs and expand access to labor opportunities beyond the personal networks that shaped employment in the pre-Internet era (Granovetter, 1995). Evidence also suggests that online job search improves worker-employer matching and mitigates stereotypes affecting certain groups of workers (Leung & Koppman, 2018). More recently, the rapid rise of remote work following the onset of the COVID-19 pandemic has been linked to increased opportunities for workers who require flexible hours or face stigmatization in traditional labor settings (Barrero et al., 2021; Robinson & Reisdorf, 2024).

This study contributes to our understanding of the socioeconomic impacts of Internet adoption by examining the labor market effects of the Affordable Connectivity Program (ACP). Launched in January 2022, ACP was a means-tested program designed to expand Internet adoption among low-income households in the aftermath of the COVID-19 pandemic. Before its expiration in early 2024, the program served approximately 22.6 million U.S. households. With a budget of \$14.2 billion, it remains the largest U.S. initiative to date aimed at reducing income-based disparities in Internet access.

Following the conventional digital inequality framework, the study distinguishes between two types of ACP impacts. Our starting point is to assess the impact of ACP on broadband adoption. These are first-level impacts that align with the program's immediate goal of promoting residential Internet access among low-income households. Our primary focus, however, is on third-level, broader socioeconomic impacts associated with ACP. In particular, building on prior findings (Dettling, 2017; Lobo et al., 2020; Zuo, 2021), we examine ACP's effects on labor force participation and employment. Further, we test the hypothesis that one of the primary impact mechanisms is the expansion of remote work opportunities for ACP recipients, both in terms of overall incidence and share of hours worked remotely.

The main empirical challenge in evaluating the outcome of programs such as ACP lies in identifying a credible counterfactual. In other words, what would have happened in the absence of the program? We address this challenge in two ways. First, we estimate difference-in-differences models that compare labor market outcomes of ACP-eligible and ineligible individuals, restricting the sample to a narrow household income range around the ACP program eligibility cutoff. Second, to probe for impact mechanisms and address potential self-selection into ACP, we employ an augmented inverse propensity weighted (AIPW) estimator that combines regression adjustment with inverse probability weighting. This mitigates endogeneity bias in cross-sectional data by explicitly accounting for self-selection into the ACP program.

The study contributes to two related strands of literature. Broadly, our results corroborate earlier findings that broadband adoption promotes labor force participation and employment (this literature is reviewed in the next section). However, whereas prior

research typically identifies average effects across the universe of working adults, we show that these effects also hold among households at the lower end of the income distribution. In addition, the identification of impact variations by gender, occupation and connection type (fixed vs. mobile) is another important contribution to the existing literature that deepens our understanding of how broadband adoption shapes employment opportunities in the aftermath of COVID-19. Second, the study offers evidence that affordable Internet programs such as ACP have positive equity effects that go beyond closing first-level access gaps. Given mixed findings in prior studies of third-level outcomes in other domains (e.g., Fairlie, 2021; Manlove & Whitacre, 2019), this is an important result that validates affordable Internet as an effective tool to reduce socioeconomic inequality.

The remainder of the paper is structured as follows. Section 2 reviews prior research on the labor market impacts of broadband, with particular attention to the small set of studies on subsidy programs comparable to ACP. Section 3 describes the data and methods and presents our main difference-in-differences estimates of ACP's effects on labor market outcomes. Section 4 examines the expansion of remote work as a potential mechanism underlying these effects, drawing on results from the AIPW estimations. Section 5 concludes with a discussion of the theoretical and policy implications of our findings and outlines directions for future research.

## 2. Internet access and employment before and after COVID-19

Numerous studies have examined how Internet adoption shapes labor market outcomes. While the evidence generally indicates that Internet access and use positively affects labor force participation, employment, and wages, the results also suggest that impacts are not uniform and tend to favor those with higher skills or areas where information-intensive industries are concentrated (Akerman et al., 2015; Atasoy, 2013; De Marco et al., 2025; Kolko, 2012; Van Deursen & Helsper, 2017). These patterns are consistent with the 'Matthew effect' hypothesis, which suggests that the benefits of digital engagement grow with baseline levels of resources and skills (Hargittai, 2003; Helsper, 2021; Lutz, 2019). There are also questions about whether Internet availability, adoption (at the individual, household or firm level) or specific types of use are driving these effects (Whitacre et al., 2014). Notably, relatively few studies offer disaggregated analyses that shed light on the labor market impacts of Internet adoption for lower-income individuals, who by definition face greater barriers to Internet access. This is in part due to the level of spatial aggregation in the data, which limits the ability to identify heterogeneous effects and different impact mechanisms for specific populations.

A small but growing subset of this literature examines the relationship between Internet access and remote work. Broadly speaking, findings from pre-pandemic studies are mixed. Using U.S. zip code-level data for 2001-2007, Kolko (2012) finds that expanded broadband provision had no measurable effect on the incidence of remote work, even among high-skilled workers. By contrast, Dettling (2017) finds that Internet access increased labor force participation by about four percentage points among married women but not among single women or men. Similarly, using administrative data from a large online labor platform, Braesemann et al. (2020) show that despite lower levels of high-speed Internet access, rural residents are more likely to engage in remote

work than their urban counterparts, although this pattern is largely driven by high-skilled workers.

The abrupt rise in remote work following the COVID-19 pandemic has renewed interest in understanding how broadband access can expand employment opportunities, especially as evidence points to the persistence of remote work arrangements even as the pandemic subsides (Barrero et al., 2024). Carvalho et al. (2022) find that remote work helped mitigate employment losses during the pandemic in U.S. counties with high Internet adoption rates. A similar result is reported by Männasoo et al. (2023) using microdata from a survey in 27 European countries, as the authors show that Internet access boosted employment during the pandemic in areas most affected by COVID-19.

Early projections suggested that women's labor force participation would fall sharply during the pandemic due to increased caregiving demands and the disproportionate representation of women in certain industries (Goldin, 2022). However, this decline never materialized, prompting questions about whether remote work may have played a role in preventing these losses. While evidence remains preliminary, several studies indicate that Internet-enabled work-from-home arrangements helped sustain female employment during the pandemic – and that these benefits have persisted even as the pandemic receded (Song, 2025; Tito, 2024).

The literature on affordable Internet programs comparable to ACP remains relatively limited and has largely focused on first-level impacts on adoption. Generally speaking, there are mixed results that depend on program design and target population characteristics. Rosston and Wallsten (2020) evaluate the impact of Internet Essentials, an affordable Internet program launched in 2011 by Comcast, one of the U.S.'s largest ISPs. The authors find a positive effect on residential broadband adoption of about seven percentage points, relative to a control group of eligible households located outside Comcast territory. In contrast, author (2022a) analyzes three affordable Internet programs in California (established through regulatory commitments by ISPs in the context of merger approvals) and finds minimal effects on adoption among eligible households.

The two studies most closely related to the present are Zuo (2021) and Pender et al. (2022). Zuo (2021) examines the labor market impacts of Comcast's Internet Essentials using individual-level microdata for the 2009–2015 period. The author finds that the program increased employment among eligible individuals relative to comparable individuals outside Comcast's service areas. However, unlike prior research, it reports no evidence of heterogeneous effects by gender, education, or age. Pender et al. (2022) investigate the labor impacts of the Broadband Initiatives Program (BIP), a U.S. Department of Agriculture initiative supporting Internet infrastructure expansion and digital skills training in underserved rural areas. Using tract-level data for 2013–2016, they find that both Internet adoption and remote work increased more in areas receiving BIP funding, relative to adjacent tracts that did not. Because of the use of geographically aggregated data, however, the study does not examine impact variations for specific subpopulations.

This study differs from previous research in several key ways. First, it extends prior findings on the positive labor market impacts of affordable Internet programs by testing whether the expansion of remote work serves as a primary impact mechanism in the post-pandemic context. Second, it examines impact heterogeneity along dimensions that have received little attention in prior studies, specifically differences by occupational category and type of Internet connection. Finally, it situates the findings within the

broader digital inequality literature, and more specifically suggests that the often-cited Matthew effect whereby Internet adoption exacerbates preexisting social inequalities can, at least in part, be mitigated through well-designed and targeted policy interventions.

### 3. Examining the impact of ACP

#### 3.1. ACP fundamentals

The onset of the COVID-19 pandemic catalyzed the need for government programs to support Internet connectivity for low-income households. Initially, a patchwork of local, state and federal emergency programs was put into place in the U.S., the largest of which was the Emergency Broadband Benefit (EBB). In late 2021, Congress passed the Infrastructure Investment and Jobs Act (IIJA) that created the ACP through a one-time funding appropriation of \$14.2 billion. Launched in January 2022, ACP was implemented as a discount on Internet access (either fixed or mobile service) of up to \$30/month per household.<sup>2</sup>

To be eligible for ACP, households needed to meet at least one of the following criteria: have an income at or below 200% of the Federal Poverty Line (FPL) or have a household member participating in a qualifying safety net program. Most ISPs participated in the program, and many offered entry-level plans at or near the \$30/month price point such that the cost to eligible households was near zero. Program uptake varied considerably throughout the country, driven by differences in service availability, household characteristics and the presence of local support organizations such as libraries and community centers (Horrigan et al., 2024). Once the initial Congressional appropriation was exhausted in early 2024, the program's funding was not renewed and ACP was discontinued shortly after.

#### 3.2. Data and methods

Our first set of estimates relies on a repeated cross-section panel of the American Community Survey (ACS).<sup>3</sup> The dataset contains approximately 29.8 million individual observations spanning five pre-ACP periods (2016-2019 and 2021) and two post-ACP periods (2022 and 2023).<sup>4</sup> An important limitation is that individual ACP recipients cannot be identified – in other words, there is no ACS question about program enrollment. Instead, the study identifies ACP-eligible individuals following the methodology proposed by *author* (2022b). The model results below (sections 3.3 and 3.4) must therefore be interpreted as intention-to-treat estimates, similar to those in several of the prior studies reviewed in section 2.

Our program impact assessment implements a difference-in-difference estimator that compares outcomes for eligible and ineligible individuals before and after the launch of ACP. This can be written as:

$$Y_{igt} = \alpha + \beta(\text{Eligible}_i \times \text{Post}_t) + \delta(\text{Year}_t \times \text{PUMA}_g) + X'_{igt} + \mu_{igt} \quad (1)$$

where  $Y_{igt}$  represents the outcome of interest for individual  $i$  in PUMA  $g$  in period  $t$ ,  $\text{Year}_t$  are year fixed effects,  $\text{PUMA}_g$  are PUMA fixed effects,  $\text{Eligible}_i$  is a dummy that indicates

whether the individual is eligible for ACP,  $Post_t$  is a dummy that equals 1 for post-treatment year,  $X'_{igt}$  is a vector of individual-level covariates, and  $\mu_{igt}$  is the error term.<sup>5</sup> The vector of demographic covariates includes gender, age (and age squared), race, Hispanic ethnicity, education, having children, marital status, and (in the case of Internet adoption) employment status and income. Note that, in addition to the conventional use of time and location fixed effects, the interaction parameter  $Year_t \times PUMA_g$  absorbs any PUMA-specific trends that may affect the outcome of interest. The parameter of interest is  $\beta$ , which captures the difference in outcomes between eligible and ineligible individuals before and after the introduction of ACP.

In [Equation 1](#), all eligible individuals are compared to all ineligible individuals. For the estimation of labor market impacts, however, this raises concerns about comparing individuals who are fundamentally different (in ways that may not be captured in the data) in terms of employment opportunities and therefore potential outcomes. To mitigate these concerns, and taking advantage of the large sample size, we restrict the analysis to prime working-age individuals (25–54 years old) whose incomes fall within a narrow band around the ACP eligibility cutoff of 200% of the federal poverty line (FPL). This is analogous to a regression discontinuity design in which program recipients are compared to nonrecipients within a narrow band of the program eligibility threshold.

To determine the optimal sample restriction bandwidth around the cutoff point of 200% of the FPL, we apply the mean squared error (MSE) bandwidth selector proposed by Calonico et al. (2017). This yields an optimal bandwidth of  $\pm 25$  percentage points, corresponding to a sample restricted to individuals with incomes between 175% and 225% of the FPL. In the Appendix, we report robustness checks that replicate the main results for alternative income bandwidths. [Table A1](#) presents descriptive statistics, disaggregated by ACP eligibility status. As shown, the restricted sample is significantly more balanced in covariates than the full sample. This sample is smaller than the full sample yet still contains 821,057 observations.

### 3.3. ACP impact on Internet adoption (first-level outcomes)

For context, we first examine whether ACP is associated with increases in residential broadband adoption among low-income households, which align with the program's most immediate objective. To answer this question, we estimate a series of difference-in-differences models using two outcome indicators: (1) having any internet connection at home, and (2) having high-speed fixed broadband (cable, DSL, or fiber) at home.

The results in [Table 1](#) suggest that ACP increased overall adoption among eligible households by nearly 5 percentage points (Model 1), or about 5% above the baseline (0.047/0.872). By contrast, the estimated increase in high-speed broadband adoption (Model 2) is considerably lower at approximately 1 percentage point, or 1.3% above the baseline (0.01/0.77). As a robustness check, Models 3 and 4 weigh individual observations by the average ACP uptake rate in their PUMA, which approximates local treatment intensity in the absence of individual-level information about program enrollment. As shown in [Table 1](#), the results remain essentially unchanged.

Prior research indicates that while mobile access can facilitate labor force participation (for example by supporting job search and communication with employers), remote work generally depends on reliable, high-speed residential connections (Barrero et al.,

**Table 1.** ACP impact on internet adoption.

| Variables              | (1)<br>Any<br>Internet                | (2)<br>High-speed<br>Internet         | (3)<br>Any Internet<br>(weighed by ACP uptake) | (4)<br>High-speed Internet<br>(weighed by ACP uptake) |
|------------------------|---------------------------------------|---------------------------------------|--|---|
| <b>Eligible x Post</b> | <b>0.0470***</b><br><b>(0.000595)</b> | <b>0.0103***</b><br><b>(0.000760)</b> | <b>0.0492***</b><br><b>(0.000690)</b>          | <b>0.0129***</b><br><b>(0.000836)</b>                 |
| Constant               | 0.858***<br>(0.00130)                 | 0.770***<br>(0.00136)                 | 0.846***<br>(0.00144)                          | 0.763***<br>(0.00142)                                 |
| Observations           | 22,118,367                            | 19,983,288                            | 22,051,977                                     | 19,922,596  |
| R-squared              | 0.139                                 | 0.078                                 | 0.143  | 0.076   |
| PUMA x Year FE         | Yes                                   | Yes                                   | Yes  | Yes   |
| Demographic controls   | Yes                                   | Yes                                   | Yes  | Yes   |
| Treatment group mean   | 0.872                                 | 0.771                                 | 0.872  | 0.771   |

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Note: Errors clustered at the PUMA level. Models 3 and 4 are weighed by the average ACP uptake rate at the PUMA level. High-speed Internet includes cable, DSL and fiber residential connections.

2021; Briglauer et al., 2024; Gonzales & Zhang, 2025). Accordingly, in the examination of labor market outcomes and impact mechanisms that follows (and to the extent that the data permits), we examine how these impacts are moderated by differences in access technologies (fixed vs. mobile).

### 3.4. ACP impact on labor force participation and employment (third-level outcomes)

Our primary research question is whether ACP is associated with increased labor force participation and employment among eligible individuals, above and beyond what would be expected in the absence of the program. We present separate model estimations by gender to test for impact heterogeneity, consistent with theorization and emerging evidence that female workers have disproportionately benefited from the persistence of remote work arrangements in the aftermath of the pandemic (Barrero et al., 2021; Robinson & Reisdorf, 2024; Tito, 2024).

Overall, the results point to positive ACP effects on labor market outcomes (Table 2). The aggregate coefficient for labor force participation (Model 1) is small and only marginally significant, but the gender disaggregation shows that this is largely driven by nonsignificant effects among men (Model 3). In contrast, the estimated impact for women (Model 2) is positive and statistically significant at  $p < 0.05$ . The coefficient magnitude for women is relatively small (about 0.6 percentage points), which is expected given the small number of post-treatment periods and the multiple factors that affect individuals' decisions to enter or leave the workforce. Relative to the baseline rate (0.749), ACP is associated with a 0.75% increase in labor force participation among eligible women (0.0056/0.749).

The estimated impacts on employment are both more statistically robust and larger in magnitude. The aggregate effect is about half a percentage point (Model 4), rising to nearly a full percentage point for women (Model 5). This represents an increase of about 1.3% (0.0095/0.713) over the employment baseline rate for the treated group. These results are broadly consistent with prior research. For example, Zuo (2021) finds that Comcast's Internet Essentials program increased employment among eligible individuals by 0.009 percentage points, or 1.6% above the baseline. To put our estimates in context, between 2021 (the last pre-ACP period) and 2023, the employment rate among ACP-eligible

**Table 2.** ACP impact on labor force participation and employment by gender.

| Variables              | Labor Force Participation           |                                      |                                     | Employment                            |                                       |                                     |
|------------------------|-------------------------------------|--------------------------------------|-------------------------------------|---------------------------------------|---------------------------------------|-------------------------------------|
|                        | (1)<br>Total                        | (2)<br>Female                        | (3)<br>Male                         | (4)<br>Total                          | (5)<br>Female                         | (6)<br>Male                         |
| <b>Eligible x Post</b> | <b>0.00291*</b><br><b>(0.00158)</b> | <b>0.00561**</b><br><b>(0.00232)</b> | <b>-0.00108</b><br><b>(0.00211)</b> | <b>0.00547***</b><br><b>(0.00175)</b> | <b>0.00954***</b><br><b>(0.00257)</b> | <b>0.000472</b><br><b>(0.00238)</b> |
| Constant               | -0.312***<br>(0.0110)               | -0.410***<br>(0.0147)                | -0.195***<br>(0.0160)               | -0.594***<br>(0.0120)                 | -0.616***<br>(0.0157)                 | -0.629***<br>(0.0185)               |
| Observations           | 729,502                             | 356,587                              | 372,831                             | 729,502                               | 356,587                               | 372,831                             |
| R-squared              | 0.167                               | 0.198                                | 0.170                               | 0.189                                 | 0.211                                 | 0.204                               |
| PUMA x Year FE         | Yes                                 | Yes                                  | Yes                                 | Yes                                   | Yes                                   | Yes                                 |
| Demographic controls   | Yes                                 | Yes                                  | Yes                                 | Yes                                   | Yes                                   | Yes                                 |
| Treatment group mean   | 0.812                               | 0.749                                | 0.881                               | 0.772                                 | 0.713                                 | 0.836                               |

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Note: Errors clustered at the PUMA level. The sample is restricted to individuals 25–54 years old in households with incomes between 175% and 225% of the FPL. High-speed Internet includes cable, DSL and fiber residential connections.

prime working-age women rose from about 0.70–0.74, an increase of 0.04 percentage points. The estimated ACP effect of 0.0095 percentage points therefore accounts for nearly one-quarter of the observed growth in employment for this group over the period.

To corroborate the main findings in Table 2, we estimate an event study specification in which Model 2 (female labor force participation) and Model 5 (female employment) are estimated separately for each year, using 2021 (the last pre-treatment year) as the reference period. This serves as a placebo test that evaluates the treatment effect in each pre – and post-treatment period separately. The time-varying coefficients in Figures A1 and A2 in the Appendix reveal no significant effects in pre-treatment periods, while positive impacts emerge for labor force participation in 2023 and for employment in both post-treatment periods. These results reinforce the main findings and suggest that the labor market impacts of affordable broadband increase over time, a finding consistent with prior studies. Further, the bandwidth sensitivity analysis (Tables A2 and A3 in the Appendix) shows that the main findings are robust across alternative bandwidth specifications around the program’s eligibility cutoff of 200% of the FPL.

Our last set of difference-in-difference models examines heterogeneity in ACP’s impact by connection type. As noted, we hypothesize that one of ACP’s primary impact mechanisms is the expansion of remote work opportunities, which depend on reliable high-speed residential connectivity. Accordingly, we expect to observe larger labor market impacts for ACP-eligible individuals in households with fixed broadband, relative to those with mobile connectivity only. To test this hypothesis, we estimate the following triple-difference specification:

$$\begin{aligned}
 Y_{igtj} = & \alpha + \beta_1(\text{Eligible}_i) + \beta_2\text{Post}_t + \beta_3(\text{Fixed}_j) + \beta_4(\text{Eligible}_i \times \text{Post}_t) \\
 & + \beta_5(\text{Eligible}_i \times \text{Fixed}_j) + \beta_6(\text{Post}_t \times \text{Fixed}_j) \\
 & + \beta_7(\text{Eligible}_i \times \text{Post}_t \times \text{Fixed}_j) + \delta(\text{Year}_t \times \text{PUMA}_g) + \theta X'_{igt} + \mu_{igt}
 \end{aligned} \tag{2}$$

The coefficient of interest is  $\beta_7$  which captures the differential effect on the labor market outcome of interest for individuals with fixed broadband relative to those with mobile connections only. The results in Table 3 are broadly consistent with our hypothesis, particularly for women, the subpopulation for which the largest ACP impacts are observed in Table 2. Taken together, these findings suggest that ACP’s labor market impacts are

**Table 3.** ACP impact on labor force participation and employment by gender and connection type (fixed vs. mobile).

| Variables                      | Labor force participation          |                                     |                                     | Employment                         |                                     |                                     |
|--------------------------------|------------------------------------|-------------------------------------|-------------------------------------|------------------------------------|-------------------------------------|-------------------------------------|
|                                | (1)<br>Total                       | (2)<br>Female                       | (3)<br>Male                         | (4)<br>Total                       | (5)<br>Female                       | (6)<br>Male                         |
| <b>Eligible x Post x Fixed</b> | <b>0.00616</b><br><b>(0.00436)</b> | <b>0.0164**</b><br><b>(0.00663)</b> | <b>-0.00170</b><br><b>(0.00551)</b> | <b>0.00437</b><br><b>(0.00478)</b> | <b>0.0139**</b><br><b>(0.00722)</b> | <b>-0.00393</b><br><b>(0.00621)</b> |
| Constant                       | -0.283***<br>(0.0113)              | -0.388***<br>(0.0154)               | -0.153***<br>(0.0161)               | -0.538***<br>(0.0137)              | -0.566***<br>(0.0123)               | -0.597***<br>(0.0164)               |
| Observations                   | 666,516                            | 328,892                             | 337,530                             | 666,516                            | 328,892                             | 337,530                             |
| R-squared                      | 0.168                              | 0.201                               | 0.170                               | 0.189                              | 0.215                               | 0.204                               |
| PUMA x Year FE                 | Yes                                | Yes                                 | Yes                                 | Yes                                | Yes                                 | Yes                                 |
| Demographic controls           | Yes                                | Yes                                 | Yes                                 | Yes                                | Yes                                 | Yes                                 |

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Note: Errors clustered at the PUMA level. The sample is restricted to individuals aged 25–54 years with incomes between 175% and 225% of the FPL. *Fixed* = 1 indicates cable, DSL and fiber residential connections.

stronger among households with fixed broadband connections, a point we explore in greater depth in the following section.

## 4. Affordable Internet and the expansion of remote work

### 4.1. Remote work in the aftermath of COVID-19

One of the most significant shifts brought about by COVID-19 is the lasting adoption of remote work. What started as an emergency response has evolved into a defining feature of the modern labor market. While estimates vary, the most recent data (September 2025) from the Survey of Working Arrangements and Attitudes (SWAA) suggests that 27% of paid full days in the U.S. correspond to work from home (Barrero et al., 2025). This is down from a peak of 61.5% in early 2020, but almost four times pre-pandemic levels. Women report higher levels of remote work than men, reflecting both a greater need for and stronger preference for hybrid work arrangements (Bartik et al., 2024; Tito, 2024).

Naturally, not all jobs can be performed remotely, however lack of reliable high-speed Internet at home has been shown to reduce labor force participation and employment opportunities. For example, Hedge and Van Parys (2024) find that restrictions on municipal broadband projects are associated with lower labor force participation and employment among mothers over the 2019–2023 period. Controlling for income and industry of employment, Barrero et al. (2021) find that lack of reliable Internet is associated with lower levels of remote work as well as lower productivity. Building on these findings, we explore whether the labor gains observed among ACP-eligible individuals (and women in particular) are linked to the expansion of remote work opportunities. Further we explore impact variations by occupation, or more precisely the extent to which jobs can be performed remotely. Finally, we validate results by assessing whether impacts are larger for those with fixed broadband connections.

### 4.2. Data and methods

To examine these questions, we rely on cross-section data from the U.S. Census Bureau's Current Population Survey (CPS). This survey has a smaller sample size than the ACS but

has two main advantages. First, the 2023 CPS questionnaire included a question about ACP program enrollment, which allows for identifying actual ACP recipients (as opposed to simply establishing eligibility). A second advantage is that CPS includes detailed information about employment arrangements, including remote work. This allows for capturing two related outcomes of interest. First, a discrete variable indicating whether an individual engaged in remote work for pay in the previous week (regardless of total hours worked or hours worked remotely), which captures the overall incidence of remote work. The second outcome of interest is the share of remote work hours relative to total work hours, which represents the intensity of remote work.

Our dataset combines the CPS March 2023 Supplement with the March 2023 Basic Survey. [Table A4](#) in the Appendix reports descriptive statistics for the two main outcome variables, along with demographic covariates, separately for ACP recipients and nonrecipients. Large baseline differences are observed across both demographic characteristics and labor outcomes. Overall, the incidence of remote work in the sample is approximately 21%, and the average share of remote hours (as a fraction of total hours worked) is about 15%, both consistent with previous estimates (Barrero et al., 2025). However, both indicators are markedly lower among ACP recipients – 12% and 8% respectively – a pattern likely reflecting differences in educational attainment, disability status, and other factors that jointly affect ACP eligibility and remote work opportunities.

To mitigate these baseline differences between treated (ACP recipients) and untreated individuals (nonrecipients), we restrict the analysis to ACP-eligible individuals only. This restriction yields a sample of 14,706 prime working-age adults. As shown in [Table A4](#), the restricted sample used in the model estimations below is considerably more balanced for both outcomes of interest and demographic covariates relative to the full sample.

Because ACP enrollment is not randomly assigned, we estimate impacts within a potential outcomes framework (Rubin, 1974), using an augmented inverse propensity weighting (AIPW) estimator to address selection bias. The AIPW is a semi-parametric estimator that combines regression adjustment with inverse probability weighting in a two-step procedure. First, we fit a propensity score model to estimate the probability of ACP enrollment conditional on demographic characteristics. Second, we estimate separate outcome models for treated and untreated individuals. A key advantage of AIPW is its double robustness: the estimator remains consistent if either the propensity score model or the outcome model is correctly specified (Dudík et al., 2014; Glynn & Quinn, 2010).<sup>6</sup> The vector of individual covariates includes gender, age, education, race, Hispanic ethnicity, disability status, housing tenure, having children, poverty status and marital status. [Figure A3](#) in the Appendix shows a large common support area in the estimated probability of ACP enrollment (the treatment of interest) between recipients and nonrecipients, thus supporting the overlap assumption required for the validity of the AIPW estimator.

### 4.3. Results

[Table 4](#) reports the average treatment effect of ACP on the incidence of remote work across different populations (estimated from the AIPW equation). Overall, ACP recipients are about 2 percentage points more likely to report working remotely in the previous week (Model 1), a 15% increase relative to the baseline (0.207/0.13). Disaggregating by gender confirms the hypothesis of a substantially larger impact among female workers, both in

**Table 4.** ACP impact on the incidence of remote work by gender.

| Variables                  | (1)<br>All                           | (2)<br>Male                           | (3)<br>Female                        | (4)<br>Female w/children             |
|----------------------------|--------------------------------------|---------------------------------------|--------------------------------------|--------------------------------------|
| <b>Marginal Effect/ATE</b> | <b>0.0207***</b><br><b>(0.00038)</b> | <b>0.00229***</b><br><b>(0.00041)</b> | <b>0.0326***</b><br><b>(0.00063)</b> | <b>0.0472***</b><br><b>(0.00118)</b> |
| Observations               | 9,517                                | 4,830                                 | 4,687                                | 898                                  |
| Demographic controls       | Yes                                  | Yes                                   | Yes                                  | Yes                                  |
| Treatment group mean       | 0.130                                | 0.107                                 | 0.156                                | 0.150                                |

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Note: AIPW logit estimates of the average treatment effect of ACP on the incidence of remote work.

absolute and relative terms: female ACP recipients are 3.3 percentage points more likely to work remotely than eligible nonrecipients (Model 2), a 20% increase over the baseline (0.0326/0.156). The results show a statistically significant but small 0.2 percentage point effect for male workers (Model 3), or a 2% increase over baseline (0.0023/0.107).

Prior studies find that the value of remote work increases for mothers due to the time flexibility of work-from-home arrangements (Bartik et al., 2024; Buckman et al., 2025). Our results validate this finding: female workers with children who receive ACP are about 31% more likely to work remotely (0.0472/0.15) than comparable nonrecipients (Model 4).

The results for our second outcome of interest indicate a large positive effect of approximately 29% (0.0272/0.095) of ACP on the share of remote work hours relative to total work hours (Model 1 in Table 5). Interestingly, the gender disaggregation reveals a slightly larger relative impact among men (Models 2 and 3). While female recipients generally work a higher share of hours remotely (11.6% vs. 7.6% for men), ACP enrollment has a stronger proportional increase for men (27% over baseline) relative to women (22% over baseline). Another notable result is that ACP's effect on the intensive margin of remote work is similar for mothers (Model 4). Overall, these findings support our hypothesized impact mechanism while also pointing to heterogeneity in the effects of affordable broadband across different subgroups of recipients.

To further validate our hypothesis, we test for impact heterogeneity by connectivity type (fixed vs. mobile). However, because connectivity type is not available in the CPS data, we use a proxy that matches individuals with the fixed broadband adoption rate at the county level in 2023. The expectation is that larger impacts will be observed for individuals in counties with higher levels of fixed broadband adoption. We proceed by

**Table 5.** ACP impact on the share of remote work hours by gender.

| Variables                  | (1)<br>All                            | (2)<br>Male                           | (3)<br>Female                         | (4)<br>Female w/children             |
|----------------------------|---------------------------------------|---------------------------------------|---------------------------------------|--------------------------------------|
| <b>Marginal Effect/ATE</b> | <b>0.0272***</b><br><b>(0.000354)</b> | <b>0.0207***</b><br><b>(0.000399)</b> | <b>0.0261***</b><br><b>(0.000563)</b> | <b>0.0271***</b><br><b>(0.00104)</b> |
| Observations               | 8,889                                 | 4,481                                 | 4,408                                 | 845                                  |
| Demographic controls       | Yes                                   | Yes                                   | Yes                                   | Yes                                  |
| Treatment group mean       | 0.095                                 | 0.076                                 | 0.116                                 | 0.120                                |

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Note: AIPW fractional logit estimates of the average treatment effect of ACP on the share of remote work.

**Table 6.** ACP impact on remote work (WFH) incidence and share of remote work hours by high vs. low fixed broadband adoption at the county level.

| Variables                  | (1)<br>WFH incidence<br>(high fixed BB) | (2)<br>WFH incidence<br>(low fixed BB) | (3)<br>WFH share<br>(high fixed BB)  | (4)<br>WFH share<br>(low fixed BB)    |
|----------------------------|---|--|--------------------------------------|---------------------------------------|
| <b>Marginal Effect/ATE</b> | <b>0.0806***</b><br><b>(0.00103)</b>    | <b>0.0468***</b><br><b>(0.000880)</b>  | <b>0.0760***</b><br><b>(0.00119)</b> | <b>0.0647***</b><br><b>(0.000826)</b> |
| Observations               | 1,734                                   | 2,085                                  | 1,734                                | 2,085                                 |
| Demographic controls       | Yes                                     | Yes                                    | Yes                                  | Yes                                   |
| Treatment group mean       | 0.188                                   | 0.119                                  | 0.137                                | 0.088                                 |

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Note: AIPW estimates of the average treatment effect of ACP on the incidence of remote work and the share of remote work hours by county-level fixed broadband adoption rate.

binning individuals into counties with above median ('high') or below median ('low') fixed broadband and estimate separate AIPW models for each subgroup. It must be noted that county identifiers are not available for all CPS respondents due to privacy concerns. As a result, this analysis is limited to a smaller sample of 10,525 prime working-age individuals who are eligible for ACP. Therefore, the results in Table 6 below are not directly comparable to those in Tables 4 and 5.

The results confirm that the impact of ACP on remote work is stronger for individuals in counties with above-median fixed broadband adoption compared to those in below-median counties. The estimated effect on the incidence of remote work in high-adoption counties is nearly twice as large as in low-adoption counties (Models 1 and 2). Although the difference is smaller for the share of remote work hours, it remains statistically significant at the 5% level (Models 3 and 4).

Finally, we examine whether ACP's impact on remote work is larger among individuals employed in occupations that can more readily be performed remotely. To test this, we draw on the occupational classification developed by Dingel and Neiman (2020), which algorithmically determines the feasibility of remote work across occupation categories in the CPS. For analytical simplicity, we categorize individuals into two groups based on their occupation's telework propensity (OTP). The high OTP group includes occupations such as management and professional roles, while the low OTP group generally encompasses jobs with limited remote work potential. Approximately 43% of individuals in the sample fall into the high-OTP category.

The results in Table A5 (Appendix) indicate that ACP's impact on remote work is substantially larger among individuals employed in occupations with a higher fraction of tasks that can be performed remotely. The difference is large for both the incidence and the intensity of remote work. Because our data is cross-sectional and occupational categories are broadly defined, we cannot determine whether these effects also capture changes in job arrangements within occupations. Instead, these findings provide baseline evidence for future research on post-pandemic changes in labor markets and the role of affordable broadband in shaping employment opportunities and occupational sorting.

## 5. Conclusions

One of the most consistent findings in digital inequality research is that baseline levels of resources and skills are positively associated with benefits from digital engagement (Lutz,

2019; Ragnedda et al., 2020; Van Deursen & Helsper, 2017; Van Dijk, 2020). It follows that the increased digitization of social and economic activities will not simply reflect pre-existing inequalities, but rather is likely to amplify them in the long run. This theorization is consistent with empirical findings (discussed in section 2) across a variety of socio-economic domains, including (but not limited to) employment.

Affordable Internet programs aim to mitigate the role of baseline disparities in Internet access by lowering the cost of connectivity for low-income households. The central premise of these initiatives is that reducing affordability barriers can weaken the link between individuals' existing endowments and the potential benefits of Internet engagement. Target populations often include not only households lacking reliable Internet access but also the so-called subscription vulnerable. Prior research estimates that up to 40% of low-income households in the U.S. experience intermittent connectivity due to fluctuations in disposable income, housing instability, and other vulnerability factors (Gonzales, 2016; Horrigan, 2025).

This study centers on the labor market impacts of ACP, the largest U.S. initiative to date aimed at reducing income-based disparities in Internet access. Our results confirm that ACP is associated with higher rates of Internet adoption, though these gains are modest (about 1.3 percentage points above the baseline) for fixed broadband services. This reflects several structural factors identified in prior research on first-level digital inequality. Households with volatile earnings and limited disposable income are often hesitant to subscribe to higher-tier access services, even when service providers adjust prices to match subsidy levels. Although ACP included incentives to encourage fixed broadband subscriptions (such as a one-time discount of up to \$100 for the purchase of a personal computer), more than half of ACP recipients (about 56%) applied the subsidy for mobile broadband.<sup>7</sup> In turn, this raised questions about the program's cost effectiveness, particularly as growing evidence suggests that fixed residential access is more strongly associated with welfare-enhancing online activities (Gonzales & Zhang, 2025).

However, our findings suggest that affordable Internet programs such as ACP must be evaluated within a broader assessment framework that accounts for the socioeconomic benefits associated with lower connectivity barriers, and that a narrow focus on first-level outcomes risks overlooking potential gains in key domains such as employment. Further, neglecting third-level impacts may lead to insufficient policy support and suboptimal funding decisions, which is illustrated by the discontinuation of ACP in early 2024.

The findings offer robust evidence of improved labor opportunities for ACP-eligible individuals (in particular women) relative to a control group of comparable ineligible individuals. Our estimates suggest that, without ACP, the post-pandemic recovery in employment among ACP-eligible prime working-age women would have been as much as 25% lower. Factoring in these third-level impacts substantially alters the cost-benefit assessment of ACP. Consider this back-of-the-envelope calculation: the estimated employment impact of ACP among prime working-age women (nearly one percentage point) represents roughly 180,000 additional employed women. Taking the average annual earnings of female ACP recipients in 2023 (approximately \$34,600), this translates to about \$6.2 billion in additional annual income, already exceeding the program's annual expenditure of roughly \$6 billion. This is naturally a conservative estimate that ignores benefits in educational attainment, health outcomes and several other domains identified in previous studies (Campbell, 2024; Hampton et al., 2021).

The positive labor impacts of ACP are shown to be closely tied to the expansion of remote work, both in terms of overall incidence and share of hours worked remotely. This suggests that affordable Internet programs can broaden employment opportunities for low-income workers in some of the more dynamic sectors of the economy. This is an important result given that prior research generally finds that the digitization of labor markets favors high-skill, high-income workers and reinforces wage inequality (Akerman et al., 2015; De Marco et al., 2025; Van Deursen & Helsper, 2017). When appropriately designed and targeted, affordable Internet programs can be an effective tool for leveling the playing field in modern labor markets.

Several limitations to this study are worth noting. First, as noted earlier, the results from the difference-in-differences models should be interpreted as intention-to-treat estimates, given the absence of individual-level data on ACP enrollment in the ACS. Second, the study's context and relatively short observation window (2016–2023) limit the generalizability of results. The onset of COVID-19 abruptly accelerated the digitization of work and led to changes in employment patterns that are still unfolding. In addition, some of these shifts have been more pronounced in the U.S. than in other developed countries, and certainly more so than in less developed countries (Barrero et al., 2025). As a result, the observed effects of ACP identified in this study may reflect context-specific factors. Future research should examine whether similar programs yield comparable outcomes in other settings and whether the observed impacts persist over longer time spans.

## Notes

1. Among many other studies, see Mossberger et al. (2003), DiMaggio et al. (2004), Gonzales (2016), Van Deursen and Helsper (2017), Correa et al. (2018), Van Dijk (2020), and Helsper (2021).
2. An increased level of support (up to \$75/month) was available in Tribal lands and qualifying high-cost areas.
3. ACS is a large-scale, nationwide survey conducted annually by the U.S. Census Bureau. The sample contains approximately 3.5 million households per year.
4. Due to the COVID-19 pandemic, the ACS was not completed in 2020.
5. A PUMA (Public-Use Microdata Area) is a spatial aggregation of at least 100,000 residents (comparable to a neighborhood) defined by the U.S. Census Bureau and is the lowest level of geography in the ACS microdata.
6. The AIPW estimator is given by:

$$AIPW = \frac{1}{N} \sum_{i=1}^n \left( \mu_1(X_i) - \mu_0(X_i) + \frac{D_i}{e(X_i)} (Y_i - \mu_1(X_i)) - \frac{(1 - D_i)}{1 - e(X_i)} (Y_i - \mu_0(X_i)) \right)$$

where  $\mu_{(d)}(X_i)$  is the expected outcome for individual  $i$  conditional on a vector of characteristics  $X$  and treatment status  $D$  ( $1 = \text{treated}$ ), and  $e(X_i)$  is the propensity score for individual  $i$  estimated in the first-stage model ( $Pr(D = 1 | X_i)$ ).

7. Source: USAC.

## Author contributions

CRediT: **Hernan Galperin**: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **François Bar**: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision,

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## Appendix

**Table A1.** ACS data: descriptive statistics and balance diagnostics (full sample vs. restricted sample).

| Variable          | Full sample    |       |              |       |            | Restricted sample |       |              |       |            |
|-------------------|----------------|-------|--------------|-------|------------|-------------------|-------|--------------|-------|------------|
|                   | ACP ineligible |       | ACP eligible |       | Std. diff. | ACP ineligible    |       | ACP eligible |       | Std. diff. |
|                   | Mean           | SD    | Mean         | SD    |            | Mean              | SD    | Mean         | SD    |            |
| Internet access   | 0.96           | 0.192 | 0.87         | 0.333 | 0.325      | 0.94              | 0.226 | 0.93         | 0.249 | 0.053      |
| Wireline access   | 0.87           | 0.341 | 0.77         | 0.422 | 0.248      | 0.81              | 0.392 | 0.79         | 0.408 | 0.045      |
| In labor force    | 0.74           | 0.439 | 0.60         | 0.489 | 0.294      | 0.85              | 0.356 | 0.79         | 0.406 | 0.154      |
| Employed          | 0.58           | 0.493 | 0.32         | 0.465 | 0.555      | 0.82              | 0.382 | 0.74         | 0.435 | 0.186      |
| Age               | 44.3           | 22.37 | 38.3         | 25.1  | 0.250      | 38.6              | 8.601 | 38.5         | 8.664 | 0.008      |
| White             | 0.83           | 0.377 | 0.69         | 0.460 | 0.315      | 0.74              | 0.439 | 0.69         | 0.460 | 0.099      |
| Education (years) | 12.7           | 4.933 | 9.96         | 5.196 | 0.544      | 13.1              | 3.061 | 12.7         | 3.144 | 0.145      |
| Child             | 0.36           | 0.483 | 0.43         | 0.495 | -0.125     | 0.52              | 0.499 | 0.50         | 0.499 | 0.044      |
| Married           | 0.54           | 0.497 | 0.27         | 0.442 | 0.597      | 0.53              | 0.498 | 0.47         | 0.499 | 0.126      |
| Income (log)      | 10.7           | 1.119 | 9.50         | 1.130 | 1.031      | 10.1              | 0.813 | 9.99         | 0.851 | 0.191      |
| Hispanic          | 0.11           | 0.311 | 0.22         | 0.415 | -0.307     | 0.225             | 0.417 | 0.25         | 0.433 | -0.060     |
| Poverty to income | 419.8          | 99.07 | 168.3        | 128.4 | 2.193      | 213               | 7.273 | 192.9        | 12.51 | 1.969      |
| Gender            | 0.49           | 0.500 | 0.46         | 0.498 | 0.079      | 0.489             | 0.499 | 0.47         | 0.499 | 0.032      |
| Observations      | 19,112,173     |       | 10,706,248   |       |            | 291,805           |       | 529,252      |       |            |

Source: ACS 1-year estimates (2016-2023).

Note: the restricted sample includes individuals aged 25–54 with incomes between 175% and 225% of the FPL.

**Table A2.** ACP impact on labor force participation using alternative sample restriction bandwidths around the income eligibility cutoff of 200% of FPL

| Variables              | Household income bandwidth (% of FPL) |                  |                  |                  |                  |                   |                   |
|------------------------|---------------------------------------|------------------|------------------|------------------|------------------|-------------------|-------------------|
|                        | (1)                                   | (2)              | (3)              | (4)              | (5)              | (6)               | (7)               |
|                        | 195–205                               | 190–210          | 185–215          | 180–220          | 175–225          | 170–230           | 165–235           |
| <b>Eligible x Post</b> | <b>0.00171</b>                        | <b>0.00483**</b> | <b>0.00168</b>   | <b>0.00200</b>   | <b>0.00291*</b>  | <b>0.00422***</b> | <b>0.00525***</b> |
|                        | <b>(0.00355)</b>                      | <b>(0.00245)</b> | <b>(0.00205)</b> | <b>(0.00181)</b> | <b>(0.00158)</b> | <b>(0.00144)</b>  | <b>(0.00136)</b>  |
| Constant               | (0.00152)                             | (0.00110)        | (0.000925)       | (0.000809)       | (0.000740)       | (0.000695)        | (0.000650)        |
|                        | -0.319***                             | -0.338***        | -0.326***        | -0.320***        | -0.312***        | -0.306***         | -0.301***         |
| Observations           | 161,720                               | 309,116          | 449,419          | 589,490          | 729,502          | 876,359           | 1,018,323         |
| R-squared              | 0.236                                 | 0.195            | 0.180            | 0.172            | 0.167            | 0.164             | 0.161             |
| PUMA x Year FE         | Yes                                   | Yes              | Yes              | Yes              | Yes              | Yes               | Yes               |
| Demographic controls   | Yes                                   | Yes              | Yes              | Yes              | Yes              | Yes               | Yes               |
| Treated group mean     | 0.813                                 | 0.815            | 0.813            | 0.812            | 0.812            | 0.813             | 0.813             |

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Note: Errors clustered at the PUMA level.

**Table A3.** ACP impact on employment using alternative sample restriction bandwidths around the income eligibility cutoff of 200% of FPL.

| Variables              | Household income bandwidth (% of FPL) |                   |                  |                   |                   |                   |                   |
|------------------------|---------------------------------------|-------------------|------------------|-------------------|-------------------|-------------------|-------------------|
|                        | (1)                                   | (2)               | (3)              | (4)               | (5)               | (6)               | (7)               |
|                        | 195–205                               | 190–210           | 185–215          | 180–220           | 175–225           | 170–230           | 165–235           |
| <b>Eligible x Post</b> | <b>0.00591</b>                        | <b>0.00771***</b> | <b>0.00529**</b> | <b>0.00522***</b> | <b>0.00547***</b> | <b>0.00747***</b> | <b>0.00895***</b> |
|                        | <b>(0.00404)</b>                      | <b>(0.00276)</b>  | <b>(0.00230)</b> | <b>(0.00200)</b>  | <b>(0.00175)</b>  | <b>(0.00161)</b>  | <b>(0.00152)</b>  |
| Constant               | −0.591***                             | −0.613***         | −0.604***        | −0.595***         | −0.594***         | −0.584***         | −0.583***         |
|                        | (0.0234)                              | (0.0171)          | (0.0145)         | (0.0128)          | (0.0120)          | (0.0111)          | (0.0103)          |
| Observations           | 161,720                               | 309,116           | 449,419          | 589,490           | 729,502           | 876,359           | 1,018,323         |
| R-squared              | 0.254                                 | 0.215             | 0.202            | 0.193             | 0.189             | 0.186             | 0.184             |
| PUMA x Year FE         | Yes                                   | Yes               | Yes              | Yes               | Yes               | Yes               | Yes               |
| Demographic controls   | Yes                                   | Yes               | Yes              | Yes               | Yes               | Yes               | Yes               |
| Treated group mean     | 0.774                                 | 0.775             | 0.773            | 0.772             | 0.772             | 0.773             | 0.773             |

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Note: Errors clustered at the PUMA level.

**Table A4.** CPS data: descriptive statistics (March 2023).

| Variable          | Full sample    |                |              | Restricted sample |                |              |
|-------------------|----------------|----------------|--------------|-------------------|----------------|--------------|
|                   | ACP recipients | Non-recipients | Total        | ACP recipients    | Non-recipients | Total        |
| Remote work       | 0.12 (0.329)   | 0.21 (0.408)   | 0.21 (0.407) | 0.12 (0.330)      | 0.12 (0.336)   | 0.12 (0.335) |
| Share remote work | 0.08 (0.265)   | 0.15 (0.326)   | 0.15 (0.325) | 0.09 (0.270)      | 0.09 (0.270)   | 0.09 (0.270) |
| Labor force       | 0.66 (0.471)   | 0.84 (0.367)   | 0.83 (0.371) | 0.63 (0.482)      | 0.72 (0.448)   | 0.71 (0.451) |
| Gender (male = 1) | 0.41 (0.493)   | 0.49 (0.500)   | 0.48 (0.500) | 0.40 (0.491)      | 0.46 (0.499)   | 0.46 (0.498) |
| Age               | 39.0 (7.945)   | 39.5 (8.588)   | 39.5 (8.572) | 39.1 (7.914)      | 39.2 (8.301)   | 39.2 (8.279) |
| Bachelor's degree | 0.18 (0.392)   | 0.42 (0.495)   | 0.41 (0.494) | 0.16 (0.374)      | 0.26 (0.439)   | 0.25 (0.436) |
| Hispanic origin   | 0.25 (0.437)   | 0.17 (0.376)   | 0.17 (0.378) | 0.26 (0.441)      | 0.23 (0.426)   | 0.24 (0.427) |
| White             | 0.71 (0.453)   | 0.78 (0.409)   | 0.78 (0.410) | 0.71 (0.450)      | 0.75 (0.427)   | 0.75 (0.429) |
| Tenure (own = 1)  | 0.43 (0.496)   | 0.67 (0.469)   | 0.66 (0.472) | 0.41 (0.493)      | 0.59 (0.491)   | 0.58 (0.493) |
| Below poverty     | 0.28 (0.451)   | 0.08 (0.273)   | 0.08 (0.281) | 0.32 (0.467)      | 0.20 (0.401)   | 0.20 (0.406) |
| Disability (any)  | 0.16 (0.367)   | 0.06 (0.244)   | 0.06 (0.249) | 0.17 (0.378)      | 0.10 (0.308)   | 0.11 (0.313) |
| Has children      | 0.68 (0.466)   | 0.53 (0.499)   | 0.53 (0.499) | 0.70 (0.456)      | 0.65 (0.476)   | 0.65 (0.475) |
| Marital status    | 1.77 (0.761)   | 1.56 (0.716)   | 1.56 (0.718) | 1.80 (0.767)      | 1.67 (0.754)   | 1.68 (0.755) |
| Observations      | 964            | 34,597         | 35,561       | 848               | 13,858         | 14,706       |

Source: CPS Basic Survey and Supplement (March 2023).

Note: the full sample includes all individuals of prime working age (25–54 years old), while the restricted sample includes only ACP-eligible individuals of prime working age. Standard deviation in parenthesis.

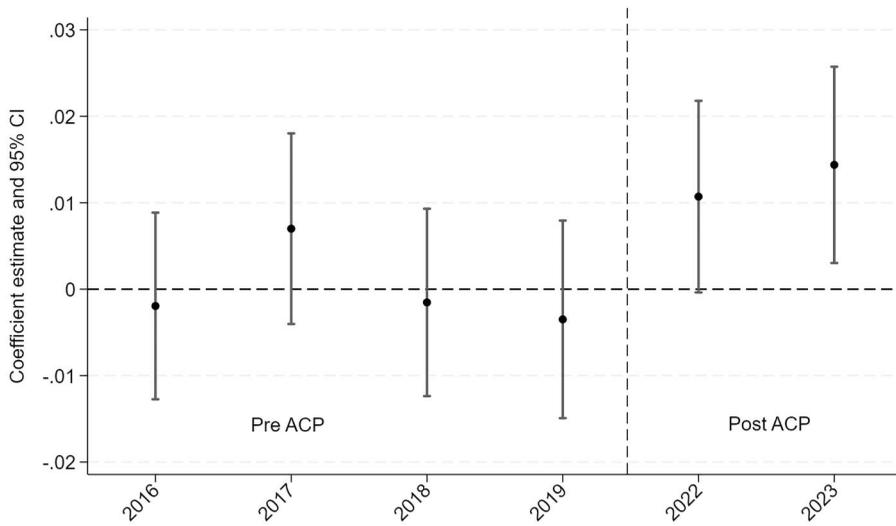
**Table A5.** ACP impact on remote work (WFH) by occupation telework propensity (OTP).

| Variables                  | (1)                      | (2)                     | (3)                  | (4)                 |
|----------------------------|--------------------------|-------------------------|----------------------|---------------------|
|                            | WFH incidence (high OTP) | WFH incidence (low OTP) | WFH share (high OTP) | WFH share (low OTP) |
| <b>Marginal Effect/ATE</b> | <b>0.0391***</b>         | <b>0.00968***</b>       | <b>0.0771***</b>     | <b>0.00569***</b>   |
|                            | <b>(0.000860)</b>        | <b>(0.000326)</b>       | <b>(0.000858)</b>    | <b>(0.00569***)</b> |
| Observations               | 3,191                    | 6,326                   | 3,191                | 6,326               |
| Demographic controls       | Yes                      | Yes                     | Yes                  | Yes                 |
| Treatment group mean       | 0.249                    | 0.068                   | 0.178                | 0.049               |

Robust standard errors in parentheses

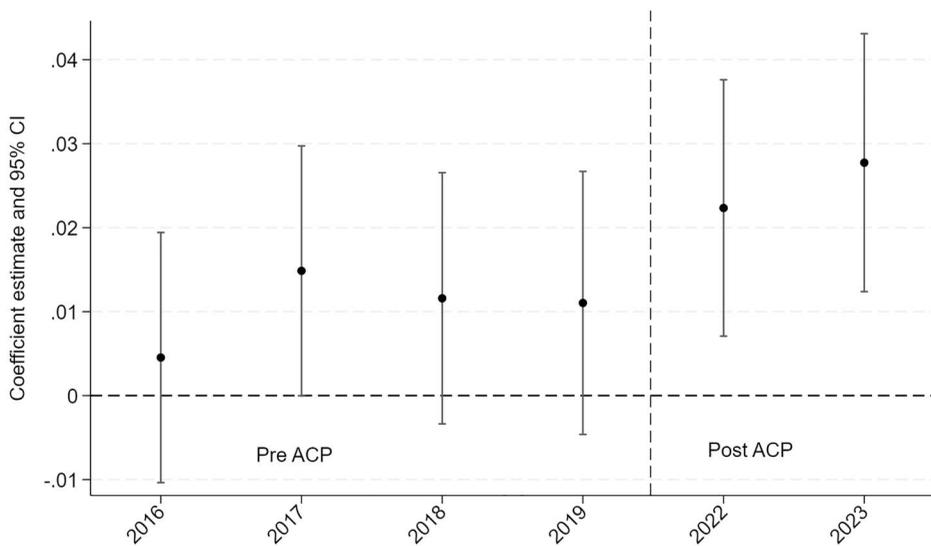
\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Note: AIPW estimates of the average treatment effect of ACP on the incidence of remote work and the share of remote work hours by occupation telework propensity.



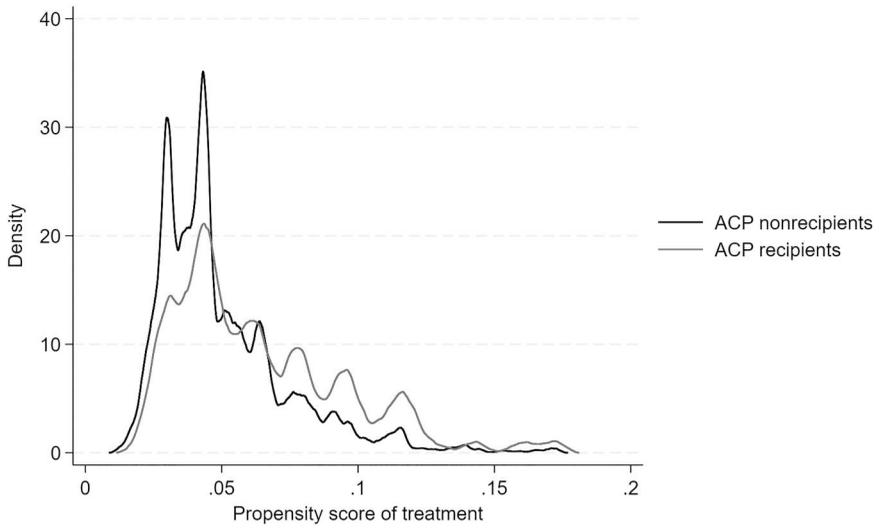
**Figure A1.** Event study for ACP impact on labor force participation (female only).

Note: Coefficients and 95% confidence intervals for the impact of ACP on labor force participation based on Equation 1, with each year evaluated separately against 2021 (the reference period).



**Figure A2.** Event study for ACP impact on employment (female only).

Note: Coefficients and 95% confidence intervals for the impact of ACP on employment based on Equation 1, with each year evaluated separately against 2021 (the reference period).



**Figure A3.** Probability density function of treatment for ACP recipients (treated) and nonrecipients (nontreated).