Connecting the Disconnected:
Heterogeneous Returns to Broadband Infrastructure Investment

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Abstract

We exploit the engineering-based, staggered rollout of Connect America Fund Phase II to estimate heterogeneous returns to public broadband investment. CAF II raised labor force participation among workers with disabilities, a high search-costs population, by 1.6 percentage points relative to the general population in pre-pandemic data. The differential rises to 4.7 points including pandemic-era observations, exceeding the estimated Americans with Disabilities Act employment effect. Three mechanism tests reject remote work as the operative channel: telework grew less for workers with disabilities, employment gains are uniform across remote-feasible and other occupations, and commute reductions appeared only among workers with mobility impairments.

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I. Introduction

The central question for digital infrastructure policy is whether broadband expands employment primarily by serving as a spatial substitute that enables remote work, or by acting as an information catalyst that reduces search and matching frictions. Distinguishing these channels is central to understanding the distributional consequences of infrastructure investment. If broadband operates through remote work, the benefits accrue narrowly to workers in telework-amenable occupations. If it operates through search friction reduction, the benefits extend across the occupational distribution and reach spatially constrained workers who would otherwise remain outside the physical economy.

A large literature establishes that broadband increases employment (Hjort and Poulsen 2019; Zuo 2021) and reduces aggregate unemployment (Bhuller et al. 2023), but existing designs cannot separate the remote work channel from search friction reduction, because both mechanisms predict aggregate employment gains and both may operate at once (Kroft and Pope 2014; Hansen et al. 2023; Rupasingha et al. 2025). We propose a test that exploits differential labor supply responses across populations with different baseline search costs, examining workers with functional limitations. This identifying population faces exogenously high physical and informational search costs. Transportation barriers restrict the geographic scope of their job search, information asymmetries obscure which employers offer accessible workplaces, and the disclosure of a disability reduces callback rates by 26 percent (Ameri et al. 2018). The two hypotheses diverge for this group. If broadband primarily enables remote work, the employment gains should concentrate on telework-amenable occupations and appear as a differential increase in telework. If broadband reduces search frictions, the gains should extend across occupations that require physical presence, and telework should not be the operative margin.

To isolate the causal effect of broadband, we exploit the staggered, engineering-based rollout of the Connect America Fund Phase II between 2015 and 2021. Unlike competitive grant programs that select on unobservable community characteristics, CAF II eligibility was determined mechanically by the Connect America Cost Model, an engineering formula that incorporated exogenous geological factors including terrain slope, elevation, soil composition, and depth to bedrock. These variables predict the physical cost of deployment but bear no direct relationship to local labor market conditions, providing quasi-random variation in the timing of high-speed internet availability.

Using American Community Survey microdata from 2006 to 2024 linked to federal broadband deployment records, we estimate difference-in-differences models on approximately 71 million person-year observations, using recent estimators that address heterogeneous treatment timing and confirm parallel pre-trends (Borusyak et al. 2024; de Chaisemartin and D'Haultfoeuille 2023; Sun and Abraham 2021). First, we show that CAF II shifted household technology adoption. Broadband subscription rose 1.0 percentage points for the general population but show a negative differential effect on people with disabilities indicating that constrained households adopted entry-level service rather than premium connections. Second, our results indicate that the labor supply response concentrated among the constrained population. Labor force participation remained flat for the general population but increased 1.6 percentage points differentially for workers with disabilities in the pre-pandemic sample, and 4.7 percentage points in the full sample. From a pre-treatment baseline of 37 percent, the pre-pandemic differential represents a 4.3 percent relative improvement and the full-sample differential a 12.7 percent relative improvement, several times the magnitude of the measured Americans with Disabilities Act employment effect (Acemoglu and Angrist 2001), which the same study estimates at -0.8 percentage points.

The empirical patterns favor search friction reduction over remote work, although both channels operate. Following deployment, workers with disabilities are 0.8 percentage point less likely to telework than the general population, the opposite of what the remote work hypothesis would predict. The differential employment effect is statistically indistinguishable across remote-feasible occupations and in-person sectors including construction, food service, and production. Active search intensity among the unemployed remains flat for both groups. Commute times fall for workers with disabilities, but the reductions concentrate among those with physical mobility impairments rather than appearing uniformly across disability types. Taken together, the evidence indicates that broadband enables constrained workers to identify suitable employers closer to home rather than substituting telework for travel, generating extensive-margin returns by improving matching efficiency rather than through spatial substitution.

We provide a direct empirical test that isolates the mechanism behind the employment gains, showing that broadband operates as a coordination technology rather than only as a spatial substitute. We advance the literature on labor market frictions by studying a constrained population to reveal the binding nature of information costs in the broader economy. We also document heterogeneity in the returns to digital infrastructure. The differential employment gains concentrate in middle-income counties and urban areas with medium-to-high baseline unemployment, while in tight labor markets and thin rural markets the extensive-margin response is muted.

Our analysis connects to a literature on the disability employment gap, one of the largest and most persistent disparities in the labor market, where labor force participation among working-age adults with disabilities stands near 38 percent against 77 percent for those without (Bound and Burkhauser 1999). Supply-side explanations emphasize program incentives, as Autor and Duggan (2003) link the expansion of Social Security Disability Insurance to reduced labor supply and

Maestas et al. (2013) estimate that benefit denial raises employment by 28 percentage points among marginal applicants. Demand-side explanations emphasize accommodation costs and discrimination (Baldwin and Johnson 2000; Acemoglu and Angrist 2001; Ameri et al. 2018). We identify search frictions as a third constraint that infrastructure can address, a perspective that complements rather than displaces these explanations.

These findings carry direct implications for digital infrastructure policy. The $42.5 billion Broadband Equity, Access, and Deployment (BEAD) program allocates funds almost entirely on geographic connectivity gaps. Our results indicate that broadband also functions as a labor market matching technology whose returns depend on the search-cost characteristics of the population served. A back-of-the-envelope calculation suggests that CAF II generated 432,000 jobs at a federal cost of roughly $20,800 per job under full-sample estimates, or more conservative pre-pandemic estimates of 192,000 jobs at $46,900 per job. The return per dollar rises in the concentration of high-search-cost workers in the treated area.

The paper proceeds as follows. Section II develops the theoretical framework, situates the paper in related work, and derives the predictions that distinguish the two channels. Section III describes CAF II and the identification strategy. Section IV presents the data. Section V reports results on technology adoption and labor supply. Section VI implements the mechanism tests. Section VII examines heterogeneity. Section VIII presents robustness analyses. Section IX reports economic magnitudes. Section X concludes.

II. Theoretical Framework and Empirical Predictions

We embed the labor supply decision into a search and matching framework augmented with occupational heterogeneity and population-specific search costs. The framework clarifies why workers with disabilities are an informative test population and generates the empirical predictions tested in Section VI.

A. The Identification Problem

Broadband could increase employment through two principal channels with different testable implications. The remote work channel operates by enabling workers to perform jobs from locations other than employer premises. Workers who face prohibitive commuting costs, whether due to distance, physical limitations, or transportation barriers, can access jobs without traveling. Employment expands because matches that distance previously prevented can now form, with workers performing job tasks from home while remaining connected to employers and colleagues through high-speed internet. Under this channel, broadband operates by changing where work is performed rather than by changing how workers and firms identify each other.

The search friction channel operates by reducing the cost of identifying job vacancies, gathering information about employer characteristics and job requirements, evaluating fit between worker skills and position demands, and submitting applications. Employment expands because workers form matches that search costs previously precluded, where viable employment relationships go unrealized when workers cannot identify suitable opportunities at acceptable cost. Broadband lowers these costs by enabling workers to browse job postings from home, research employer reputations through websites and reviews, submit applications electronically, and conduct initial screening interviews remotely.

Both channels predict aggregate employment gains for the general population. This observational equivalence explains why existing studies document positive effects of broadband on employment but cannot identify which mechanism is responsible. The empirical challenge is that remote work and search friction reduction produce similar aggregate patterns, with both predicting that employment rises following broadband deployment and both consistent with positive effects documented in prior research. Our approach exploits the fact that the two channels generate different predictions for heterogeneous effects across populations and for the composition of employment gains across occupation types.

B. The Remote Work Channel

Consider a worker deciding whether to participate in the labor market. Participation requires that expected wages exceed reservation wages net of participation costs. Commuting represents a component of participation costs encompassing direct expenses for transportation fares and vehicle operation, time costs of travel, and the physical and psychological burden of regular journeys to and from work. For workers facing high commuting costs, the participation threshold may not be met even when jobs exist that the worker could perform productively and that would offer wages exceeding the worker's reservation wage absent commuting requirements. These workers are excluded from employment not because they lack relevant skills or because employers would not value their contributions, but because the costs of accessing job sites exceed the surplus that employment would generate.

Broadband relaxes this constraint by enabling remote work. Workers can access jobs without commuting, performing tasks from home while maintaining connection to employers through high-speed internet. The participation threshold falls as commuting costs are removed from the calculation, and workers who were previously excluded can enter the labor force and form employment relationships. Under this channel, broadband operates by changing where work is performed.

Workers with disabilities might benefit from remote work if they face disproportionate barriers to commuting relative to performing work tasks once at a job site. Physical impairments affecting mobility may make daily travel to an employer difficult or impossible even when the worker can perform job tasks effectively in an appropriately accommodated environment. Vision impairments may prevent driving while having limited effects on job performance in many occupations. Cognitive limitations may complicate travel through unfamiliar transit systems without affecting work productivity in many occupations. Mental health conditions may make regular travel and workplace attendance challenging while permitting productive work in a controlled home environment. Under this view, broadband benefits workers with disabilities by relaxing a constraint specific to reaching employers rather than to finding them or performing work once present.

The remote work channel operates through a specific intermediate outcome, namely the rate at which workers perform jobs from home, which generates testable predictions about the differential telework response.

Prediction R1: If remote work generates the differential employment response for workers with disabilities, telework rates should increase more for workers with disabilities than for the general population. Workers entering employment specifically through the channel of remote access should manifest as a positive differential effect on telework.

Prediction R2: Employment gains for workers with disabilities should concentrate in remote-feasible occupations including professional, technical, and administrative positions where work from home is common. Effects in occupations requiring physical presence such as construction, food service, manufacturing, and transportation should be small or absent under the remote work channel.

Prediction R3: Commute reductions should appear uniformly across disability types as workers of all impairment categories substitute working from home for traveling to employer locations.

C. The Search Friction Channel

The search friction channel draws on the framework developed by Diamond (1982), Mortensen (1982), and Pissarides (1985), in which employment depends on the rate at which workers and firms form matches. In these models, workers expend effort identifying job vacancies, gathering information about position requirements and working conditions, assessing the fit between their skills and employer needs, and submitting applications. Firms invest in recruitment activities, screen applicants, and make hiring decisions. The intensity of search on both sides of the market determines the rate at which matches form and hence the level of equilibrium unemployment.

An insight of search theory is that when search costs are sufficiently high, viable matches fail to form. Workers who would accept jobs at prevailing wages, and whom employers would willingly hire, remain unmatched because neither party can identify the other at acceptable cost. The unemployed worker and the firm with a vacancy would both benefit from forming an employment relationship, but the costs of search prevent this transaction from occurring. Reducing search costs enables more matches to form by shifting the matching function outward, with more employment relationships created at any given level of search effort.

Broadband reduces search costs through multiple channels. Workers can browse job boards and employer websites from home, eliminating the need to travel to locations where job postings are displayed or to visit employers in person to inquire about openings. Online resources enable research into employer characteristics, workplace culture, and position requirements before investing in applications or interviews. Electronic submission of applications eliminates printing, mailing, and delivery costs. Video interviewing technology reduces the need for in-person meetings during initial screening stages.

A body of empirical work supports the premise that information technology reduces these frictions. Autor (2001) analyzed the emergence of online job boards and argued that lower posting and search costs would improve matching efficiency. Kuhn and Skuterud (2004) found that internet job search shortened unemployment durations, and Stevenson (2009) documented that states with higher internet penetration experienced greater job-to-job mobility and shorter unemployment spells. Kuhn and Mansour (2014) estimate that online search reduces unemployment duration and improves match quality. Kroft and Pope (2014) exploit the staggered geographic rollout of Craigslist and find that the platform lowered local unemployment, with larger effects in thicker markets where more matches could form, indicating that search costs bind more tightly when the set of potential matches is large. Marinescu and Rathelot (2018) document that application rates fall sharply with distance between workers and jobs, indicating that geographic frictions constrain match formation. These studies establish that information technology reduces search frictions but do not examine broadband infrastructure specifically or separate the search channel from remote work.

An implication of the search friction framework is that cost reductions have heterogeneous effects depending on how binding the initial constraints are. Workers with low baseline search costs, including those with extensive professional networks, easy access to transportation, familiarity with job search processes, and resources to invest in search activities, already identify most suitable opportunities available in the market. For these workers, marginal reductions in search costs yield few additional matches because the binding constraint on employment lies elsewhere. Workers with high baseline search costs face a different situation in which viable matches go unformed because search costs prevent identification of suitable opportunities. For these workers, cost reductions can expand the effective opportunity set by enabling matches that would otherwise never occur.

Workers with disabilities face elevated search costs from multiple sources. Transportation barriers restrict the geographic scope of in-person job search. Workers who cannot drive or who have difficulty using public transit systems cannot canvas distant employers, attend multiple interviews in different locations, or explore unfamiliar neighborhoods for opportunities. The effective labor market is geographically constrained, limiting the set of potential matches that can form. Information asymmetries obscure which employers provide accessible workplaces and reasonable accommodations. Job postings rarely specify whether facilities are wheelchair accessible, whether flexible scheduling is available for medical appointments, whether assistive technologies are provided, or whether workplace culture is supportive of employees with disabilities. Workers must invest in costly screening through phone calls to human resources departments, site visits to assess physical accessibility, or applications that proceed through multiple stages before revealing whether the position is viable. Discrimination raises the applications required to generate each job offer, increasing the total cost of successful search.

Unlike remote work, search friction reduction does not operate through telework as an intermediate outcome. The framework generates predictions that differ from the remote work channel.

Prediction S1: The telework differential for workers with disabilities could be zero or negative. Search friction reduction helps workers find all types of jobs rather than specifically remote positions. If workers with disabilities have comparative advantage in on-site work where employers provide physical accommodations, assistive technologies, and structured environments rather than remote work where home environments may lack such supports, then reduced search frictions could increase on-site employment more than telework.

Prediction S2: Employment gains should extend across the occupation distribution with no concentration in remote-feasible jObservations Workers with disabilities can perform many jobs in construction, food service, retail, manufacturing, and transportation given appropriate accommodations. Search frictions prevent them from identifying such employers, and reducing these frictions enables matches across occupation types. The occupation distribution of employment gains should be uniform rather than concentrated.

Prediction S3: Commute time reductions should concentrate among workers whose disabilities affect physical mobility. These workers face the highest costs of traveling to search for jobs and commute to distant employers. If broadband enables them to identify suitable employers closer to home, commute reductions should appear disproportionately among workers with mobility limitations rather than uniformly across disability types.

D. Summary of Predictions

The two mechanisms generate opposing predictions across multiple dimensions, enabling empirical discrimination. The remote work channel predicts that workers with disabilities should show larger telework increases than the general population (R1), employment gains concentrated in remote-feasible occupations (R2), and uniform commute reductions across disability types (R3). The search friction channel predicts that the telework differential could be zero or negative (S1), that employment gains extend uniformly across occupation types (S2), and that commute reductions concentrate among workers with mobility impairments (S3). Section VI implements direct tests of each prediction using the differential responses of workers with disabilities to CAF II deployment.

III. Institutional Background and Identification

A. The Connect America Fund Phase II

The Federal Communications Commission established the Connect America Fund in 2011 as a structural pivot from subsidizing voice telephone service to high-speed broadband deployment in high-cost areas. CAF Phase II represents the largest federal broadband infrastructure investment prior to the 2021 BEAD program, disbursing approximately $9 billion between 2015 and 2021. The program targeted unserved census blocks where existing speeds fell below 10/1 Mbps, later raised to 25/3 Mbps, and where commercial deployment was deemed non-viable absent federal support.

The feature of CAF II most relevant for our identification strategy is how the FCC determined which areas would receive support and in what sequence. Unlike competitive grant programs such as the Broadband Technology Opportunities Program, where selection reflected application quality and might correlate with local capacity or political factors, CAF II eligibility was determined mechanically by the Connect America Cost Model.

The Connect America Cost Model was an engineering model developed by the FCC to estimate forward-looking costs of deploying broadband infrastructure to every census block in the country. The model predicted construction costs from the physical characteristics of each location. Terrain slope, elevation, and surface ruggedness determine whether network plant must be buried at high cost or strung on poles at lower cost. Soil composition and depth to bedrock determine the difficulty and expense of trenching where burial is required, and vegetation density affects the feasibility and cost of aerial deployment. Loop length from each location to the nearest central office or network node determines the amount of cable required. Using these geological inputs, the CAM calculated a monthly cost-per-location for every census block. The FCC established strict funding thresholds, with areas where the cost was below $52.50 per month deemed commercially viable and receiving zero support, and areas where the cost exceeded $198.60 deemed extremely high-cost and deferred to a separate satellite auction. CAF II funding was allocated exclusively to the intermediate band of census blocks between these thresholds.

Upon eligibility determination, incumbent price-cap carriers including AT&T, CenturyLink, Frontier, and Windstream received state-level support offers calculated from the CAM. Carriers could accept entire state offers or decline them, but they could not select individual census blocks within accepted states, preventing strategic selection of easily served areas within eligible territories. Upon acceptance, carriers committed to deploy broadband meeting speed thresholds to all supported locations following mandatory deployment milestones requiring 40 percent of supported locations by end of 2017, 60 percent by 2018, 80 percent by 2019, and 100 percent by 2020. The FCC monitored compliance through the High-Cost Universal Broadband portal, where carriers reported locations served.

Because terrain slope, bedrock depth, and historical loop lengths predict the physical cost of broadband deployment but have no direct relationship to labor market trajectories between 2015 and 2021, the CAM provides quasi-random variation in the timing of digital infrastructure expansion. Figure A1 presents a spatial map of CAF II eligible census blocks. Eligibility boundaries cut across county and municipal lines, following natural geological ridges, soil fault lines, and historical central-office loop limits rather than economic jurisdictions.

B. Identification Strategy

The CAM-based eligibility determination provides quasi-experimental variation in broadband access. Terrain slope, soil composition, depth to bedrock, and vegetation density affect the engineering costs of deploying network infrastructure, but these geological and topographical characteristics should have no direct effect on labor market outcomes conditional on location fixed effects. Two otherwise similar counties may receive broadband at different times solely because terrain and soil made deployment cheaper in one location than the other. This variation is plausibly orthogonal to the economic conditions that determine employment outcomes, providing an opportunity to estimate the causal effect of CAF II deployment on labor market outcomes. Our design is a reduced-form difference-in-differences that compares treated to never-treated counties before and after deployment. Because we cannot disentangle specifically what households are treated by the program and data limitations on pre-treatment broadband adoption, the engineering-based CAM eligibility supports the parallel-trends assumption underlying the difference-in-differences design rather than the exclusion restriction that a 2SLS design would require. However, we first show that technology-adoption is impacted by the CAF II policy shock which supports spillovers to labor market effects.

The empirical strategy is a canonical difference-in-differences design that compares labor market outcomes before and after CAF II deployment in treated counties relative to never-treated counties. Approximately 81 percent of counties in our sample received CAF II deployment at some point during the 2015 to 2021 period, with 19 percent remaining untreated throughout and serving as a comparison group. The staggered timing of deployment across treated counties provides additional variation for estimation.

We begin with a difference-in-differences specification on the general population, estimating whether deployment had an effect on the main outcomes of interest. The estimating equation is:

$$Y_{ict} = \delta(\mathrm{Post}_{ct} \times \mathrm{CAF}_c) + \beta_1 \mathrm{Post}_{ct} + \beta_2 \mathrm{CAF}_c + X_i\gamma + \alpha_c + \lambda_t + \epsilon_{ict}$$

where Y_{ict} is an outcome for individual i in county c in year t, Post_{ct} indicates whether year t is on or after the year of deployment in county c, CAF_c is an indicator for treated counties, X_i includes controls for age, education, race, sex, and marital status, and α_c and λ_t are county and year fixed effects respectively. The coefficient δ estimates the average intent-to-treat effect of CAF II deployment on the general population. Under parallel trends this equals the average treatment effect on treated counties. Because the specification is reduced-form on the CAF II shock rather than 2SLS on broadband subscription, the coefficient does not have a per-unit-broadband interpretation. Standard errors are clustered at the county level to account for serial correlation within counties over time.

To identify differential effects for workers with disabilities, we estimate a triple-difference specification:

$$Y_{ict} = \delta\left(\text{Post}_{ct} \times CAF_c \times \text{Disability}_i\right) + \beta_1\text{Post}_{ct} + \beta_2 CAF_c + \beta_3\text{Disability}_i + X_i\gamma + \alpha_c + \lambda_t + \epsilon_{ict}$$

The parameter of interest δ captures the differential effect of CAF II deployment for workers with disabilities relative to the general population. This is a heterogeneous-treatment-effect extension of the baseline DiD. Estimation and identification proceed under the same parallel-trends assumption as equation (1), now applied jointly to disability-status subpopulations. Standard errors are clustered at the county level.

Identification requires that deployment timing be uncorrelated with differential trends in labor market outcomes by disability status, conditional on county and year fixed effects. Table A1 reports balance tests regressing deployment year on 2010-2014 changes in county characteristics including population, median income, poverty rate, unemployment rate, and the employment share in major industries. Coefficients are predominantly small in magnitude. The handful of statistically significant coefficients reflect small differences in pre-treatment population and median income trends that are addressed through controls in the main specifications and through the event study analysis that explicitly tests for differential pre-trends.

To address potential bias from heterogeneous treatment timing in two-way fixed effects estimators (Goodman-Bacon 2021), we estimate dynamic event-study models using the imputation method of Borusyak et al. (2024), the heterogeneity-robust estimator of de Chaisemartin and D'Haultfoeuille (2023), and the interaction-weighted estimator of Sun and Abraham (2021). These estimators avoid the negative weighting problems that can arise in TWFE specifications when treatment effects vary across cohorts.

IV. Data

A. American Community Survey

The primary data source is the American Community Survey, an annual survey conducted by the Census Bureau that replaced the decennial census long form beginning in 2005. The ACS collects detailed information on demographic characteristics, economic outcomes, housing, and household resources from approximately 3.5 million households per year, representing roughly 1 percent of the U.S. population annually. For our purposes, the ACS offers several advantages over alternative data sources. First, the survey provides consistent measurement of labor market outcomes including labor force status, employment, earnings, hours worked, occupation, industry, and work location throughout our study period of 2006 to 2024. Second, geographic identifiers are matched to county-level administrative records on broadband deployment timing through a Public Use Microdata Area to county crosswalk. Third, the disability module identifies individuals with functional limitations using a consistent set of questions that have remained stable since 2008, avoiding breaks in series that would complicate longitudinal comparisons.

The ACS disability module asks respondents about six types of difficulty. Hearing difficulty is defined as being deaf or having serious difficulty hearing, and vision difficulty as being blind or having serious difficulty seeing even when wearing glasses. Cognitive difficulty is serious difficulty concentrating, remembering, or making decisions because of a physical, mental, or emotional condition. Ambulatory difficulty is serious difficulty walking or climbing stairs, self-care difficulty is difficulty bathing or dressing, and independent living difficulty is difficulty doing errands alone, such as visiting a doctor's office or shopping. An individual is classified as having a disability if reporting serious difficulty on any of these six items. This definition captures approximately 10 percent of working-age adults in our sample and encompasses a heterogeneous population with varying functional limitations, health conditions, and labor market prospects.

The search friction hypothesis predicts that broadband should benefit workers facing elevated search costs regardless of the specific source of those costs, while pooling across disability types provides a direct test of the prediction. We examine heterogeneity by disability type in Section VI.C to assess whether effects vary with the nature of functional limitation, with particular attention to commute time responses that distinguish mobility-related from sensory limitations.

Labor market outcomes include labor force participation defined as either currently employed or actively seeking work, employment defined as working for pay during the reference week, usual hours worked per week, full-time status defined as usually working 35 or more hours per week, self-employment, annual wage and salary earnings, and telework defined as working primarily from home. The ACS also captures job search activity among the unemployed through questions about methods used to look for work in the past four weeks, which we use to construct measures of search intensity. Occupation is coded using Census SOC categories and aggregated into four groups following Dingel and Neiman (2020), comprising remote-feasible occupations where work from home is common and defined as occupations with more than half of jobs exposed to remote work in the Dingel-Neiman classification, coordination-intensive occupations requiring interpersonal interaction, technical and skilled occupations requiring specific training, and manual occupations requiring physical presence at a work site defined as occupations with fewer than 1 percent job exposure in the Dingel-Neiman classification.

Technology access is measured at the household level through questions about internet subscription of any type, broadband subscription specifically meeting FCC speed thresholds, and computer ownership. Technology questions were added to the ACS in 2013, so technology adoption analysis uses the 2013 to 2024 sample. Labor market outcome analysis uses the full 2006 to 2024 sample.

B. PUMA-County Crosswalk

The publicly available ACS microdata provides geographic identifiers only at the PUMA level for most observations, with county identifiers available only for sufficiently populous counties to protect respondent privacy. We construct a PUMA-county crosswalk using the 2020 PUMA boundary definitions and the proportion of each PUMA's population residing in each constituent county. For PUMAs containing a single county or where one county comprises nearly all of the PUMA's population, the assignment is deterministic. For PUMAs spanning multiple counties, we reweight ACS observations using the proportion of the PUMA's working-age population residing in each county based on Census Bureau data. We report main results using the reweighted sample and verify in the appendix that the differential effect is robust to restricting the sample to counties that match a PUMA on a one-to-one basis, the subset for which geographic assignment involves no probabilistic reweighting.

C. Deployment Data

Information on CAF II deployment timing comes from administrative records filed with the Federal Communications Commission through the High-Cost Universal Broadband portal. Carriers receiving CAF II support were required to report the locations they served at each deployment milestone deadline, and the FCC made these filings publicly available for compliance monitoring. The data include geographic coordinates for each served location, which we geocode to counties and aggregate to construct county-year measures of CAF II presence.

We define a county as treated in year t if the first CAF II deployment occurred within the county by the end of year t. This binary treatment definition captures the extensive margin of broadband availability rather than the intensity of deployment within counties. Table A2 reports the distribution of deployment years across counties. The largest cohorts began deployment in 2015 (800 counties, 25 percent of the sample), 2016 (484 counties, 15 percent), and 2017 (643 counties, 20 percent). Deployment continued through 2021 with smaller cohorts in the later years. Three counties report deployment in 2005 or 2011, but providers in these counties filed for CAF II funding in 2015 and the early deployment dates reflect grandfathered infrastructure rather than the program effect. We retain these counties in the analysis with their reported deployment years.

D. Sample Construction and Summary Statistics

The analysis sample includes individuals ages 16 to 64 who are not residing in group quarters such as institutional settings, prisons, nursing homes, or college dormitories, from counties with consistent ACS coverage throughout the 2006 to 2024 period. We exclude individuals outside the conventional working-age range to focus on labor supply decisions most likely affected by search costs, and we exclude group quarters residents because their labor supply decisions may be constrained by institutional factors unrelated to job search. These restrictions yield an analysis sample of approximately 71 million person-year observations across 3,144 counties in all 50 states and the District of Columbia.

Table 1 presents summary statistics for the pre-treatment period from 2006 to 2014, separately for individuals with and without disabilities. The statistics document the pre-treatment labor market disparities that motivate our analysis. Workers with disabilities have labor force participation of 37 percent compared to 77 percent for those without disabilities, a gap of 38.9 percentage points. Employment conditional on participation is 85 percent for workers with disabilities and 93 percent for those without, a gap of 7.8 percentage points. The near-equality of the unconditional participation gap and the conditional employment gap indicates that conditional on entering the labor force workers with disabilities find employment at rates similar to others, with barriers operating primarily at the participation margin rather than the job-finding margin conditional on search.

Conditional on employment, workers with disabilities earn lower annual wages of $28,700 compared to $37,900 for those without disabilities, and work fewer hours per week at 14.5 compared to 31.2. These differences likely reflect a combination of factors including occupation sorting, discrimination, and differences in labor supply preferences. The proportion of employed workers with disabilities working full-time is 28 percent compared to 63 percent for the general population. The higher rate of part-time work among employed workers with disabilities partly reflects the role of part-time positions as a feasible labor market option for individuals with health limitations or care responsibilities. Telework rates are similar at baseline, with 5 percent of employed workers with disabilities working primarily from home compared to 4 percent of employed workers without disabilities. The difference is less than 1 percentage point but statistically significant.

Technology access in the pre-treatment period differs across the two populations. Among individuals with disabilities, 73 percent live in households with internet subscriptions compared to 86 percent of individuals without disabilities, a gap of 13 percentage points. Broadband subscription rates are 80 percent versus 82 percent, and computer ownership rates are 73 percent versus 86 percent. These gaps reflect the intersection of disability status with lower income, since many individuals with disabilities rely on fixed incomes from disability benefits or work in lower-wage occupations, limiting their ability to afford internet service and computing equipment even when infrastructure is available.

V. Results

A. Reduced-Form Check on Technology Adoption

For broadband infrastructure to affect labor market outcomes, deployment must translate into increased household technology access. Infrastructure that is deployed but not adopted cannot affect individual behavior. However, due to data limitations, the estimates below serve as a mechanism check on the CAF II shock rather than as an instrumental variable. Their function is to document the channel through which the reduced-form DiD estimates propagate. Table 2 examines this technology-adoption channel, reporting effects of CAF II deployment on household broadband subscriptions.

Broadband subscriptions, defined as high-speed service meeting FCC minimum thresholds, increase 1.2 percentage points for the general population following deployment. The differential effect for workers with disabilities is negative at 0.9 percentage points, indicating that the total broadband subscription response for workers with disabilities is essentially zero. The results hint at the different constraints faced by workers with disabilities, who may instead access Internet with cheaper low-speed Internet services and have constraints due to lower likelihood of device ownership.

A2. The Connectivity Margin

The technology-adoption estimates show an asymmetry that bears on interpretation. Workers with disabilities exhibit a differential change in high-speed broadband subscription that is negative at 0.9 percentage points while the general population increases their broadband access instead. CAF II deployment lowers the cost of provisioning service and raises the availability of all service tiers in treated areas. Cost-constrained households, which are overrepresented among workers with disabilities given their lower baseline earnings and reliance on fixed disability income, respond by adopting the most affordable entry-level tier rather than premium high-speed plans.

We explore this hypothesis in Table 3, which shows the change in broadband subscriptions and low-speed Internet subscriptions after CAF II deployment by the pre-program Internet speed in the county. Column 1 reveals that, for workers with disabilities living in low-speed areas before deployment, the differential tends toward zero. Therefore, it appears that the negative response concentrates in counties with higher-speeds before the program. On the other hand, Column 2 shows that low-speed Internet adoption increases among people with disabilities across all counties while decreases for the general population. The price tier of internet service appears to be a binding constraint for households with workers with disabilities, who adopt the most affordable connection available following infrastructure deployment rather than upgrading to higher-speed tiers as the general population does. Furthermore, Table A3 shows that broadband adoption may be influenced by device ownership, which is lower for people with disabilities at the baseline.

The labor market mechanism therefore operates through the extensive margin of any internet connectivity rather than through high-speed broadband specifically. Throughout the paper, broadband refers to the deployment program, while the household margin relevant to the differential labor supply response is connectivity at any service tier.

B. Labor Force Participation and Employment

Table 2 reports the main labor market results in columns 2 and 3. Column 2 examines labor force participation, the primary outcome of interest because participation captures the decision to enter the labor market at all, the margin where search costs are most likely to bind. Column 3 examines employment.

Broadband deployment has null effects on labor force participation for the general population, with a coefficient of 0.001 and a standard error of 0.001 in the disability interaction specification. The small magnitude indicates that the general population faced less binding search constraints at baseline. For workers with little difficulty identifying job opportunities, marginal improvements in search technology yield few additional matches because the binding constraint on employment lies elsewhere.

For workers with disabilities, the picture differs. The differential effect on labor force participation is 1.6 percentage points in the pre-pandemic sample and 4.7 percentage points in the full sample, with standard errors of 0.2 and 0.3 percentage points respectively and statistical significance at the one-percent level. From a pre-treatment baseline participation rate of 37 percent for workers with disabilities, the pre-pandemic differential represents a 4.3 percent relative improvement, while the full-sample differential represents a 12.7 percent relative improvement. We treat the pre-pandemic estimate as the more conservative benchmark because the full-sample estimate incorporates 2020 and 2021 observations for which the counterfactual labor supply path cannot be cleanly identified. We benchmark this effect against measured impacts of major prior disability employment policies. Maestas, Mullen, and Strand (2013) estimate that SSDI denial increases employment by 28 percentage points among marginal applicants, but this comparison involves the difference between benefit receipt and non-receipt, a different margin than reducing search costs for workers seeking employment. Workers denied SSDI must find income through other means, creating strong incentives to search intensively regardless of costs. Acemoglu and Angrist (2001) estimate that the Americans with Disabilities Act reduced employment of workers with disabilities by 0.8 percentage points in the years following enactment, possibly because accommodation mandates increased hiring costs and deterred employers from hiring workers who might require accommodations. The finding that a single infrastructure investment produces participation gains that exceed the absolute magnitude of the ADA-era employment change several times over indicates that search frictions impose binding constraints on disability employment that existing policies have not addressed.

Consistent with previous literature (Nazareno et al. 2025), employment increases differentially by 1.6 percentage points for workers with disabilities, with a standard error of 0.1 percentage points and statistical significance at the one-percent level. The smaller employment differential relative to the participation differential (1.6 percentage points versus 4.7 percentage points) indicates that most of the labor market response operates through inducing labor force entry rather than through improving job-finding rates conditional on participation. Workers with disabilities induced into the labor force by broadband deployment may take time to identify and match suitable positions. The relatively smaller employment response is consistent with this gradual matching process and with the role of search frictions specifically at the participation margin.

The extensive margin dominates the labor market response. The participation differential of 4.7 percentage points is approximately three times larger than the conditional employment differential. This pattern is consistent with search frictions affecting the participation decision, since workers who could succeed in the labor market choose not to enter when the costs of search exceed the expected benefits. Broadband reduces these costs, inducing entry among workers at the margin of participation. Conditional on entering, workers with disabilities find jobs at rates similar to the general population over the period studied, indicating that the binding constraint was identification of opportunities rather than qualification for available positions.

C. Intensive Margin: Hours and Full-Time Status

Table 2 columns 4 and 5 report intensive margin outcomes that speak to the type of employment relationships formed following broadband deployment. The differential effect on usual weekly hours among employed workers with disabilities is 1.8 percent, with a standard error of 0.2 percent. The differential effect on full-time employment, defined as working 35 or more hours per week, is 1.5 percentage points, with a standard error of 0.2 percentage points and statistical significance at the one-percent level.

This pattern is consistent with workers entering quality employment rather than part-time positions or underemployment. The intensive margin effect indicates that workers with disabilities induced into employment by broadband are entering full-time positions that the search friction reduction made identifiable, increasing employment quality.

D. Dynamic Effects and the Event Study Framework

To validate our difference-in-differences design and rule out anticipatory effects, we examine the dynamic evolution of labor supply relative to the year of CAF II deployment. Because CAF II deployment was staggered across counties between 2015 and 2021, traditional two-way fixed effects estimates may be biased by heterogeneous treatment effects over time (Goodman-Bacon 2021). We therefore estimate dynamic event-study models using the imputation method in

Borusyak et al. (2024), the heterogeneity-robust estimator in de Chaisemartin and D'Haultfoeuille (2023), and the interaction-weighted estimator in Sun and Abraham (2021), mapping coefficients for the identifying population relative to the general population.

Figure 1 plots event-study coefficients for labor force participation and employment in panels A through D, with the year prior to initial deployment specified as the omitted baseline. The pre-treatment coefficients for pre-treatment event years are economically small and statistically indistinguishable from zero across outcomes and estimators. The absence of pre-trends strongly hints in favor of the parallel trends assumption underlying the difference-in-differences design. The flat pre-trends also rule out anticipatory effects. While the FCC announced CAF II funding rules in 2015, actual trenching and network activation took years, and the flat pre-trends indicate that workers did not preemptively alter their labor search behavior based on policy announcements but rather responded once the physical infrastructure was activated.

Post-treatment dynamics reveal a compounding effect rather than a sudden structural break. At event year 0, the year of initial deployment, the extensive margin response is positive but small. By event year +1, the effect grows to approximately 0.5 percentage points for the general population participation outcome. By event years +6 and +7, the effect stabilizes at approximately 0.7 percentage points. Similar evidence appears for employment in panels C and D. The de Chaisemartin and D'Haultfoeuille (2023) estimator in panel C shows small pre-trends for the general population that are not consistent across methodologies.

The compounding dynamic is consistent with the mechanics of both infrastructure deployment and search friction reduction. First, CAF II carriers were bound by multi-year deployment milestones requiring 40 percent of locations by year two, 60 percent by year three, and 80 percent by year four. County-level exposure to broadband infrastructure deepened over time as carriers worked through their deployment commitments. Second, reducing search frictions involves a learning curve in which workers facing high baseline barriers to entry do not match with employers immediately upon broadband activation. Households require time to subscribe, build digital search capital, and systematically evaluate newly visible local labor markets, and the delayed plateau in the event study tracks this structural matching process.

VI. Mechanisms

This section implements three empirical tests derived in Section II to distinguish whether remote work or search friction reduction generates the differential employment gains. The tests examine telework rates, the occupational distribution of induced employment, and commute patterns by disability type. Figure 2 summarizes the differential effects across these mechanism tests. The three tests provide convergent evidence rejecting the remote work hypothesis. The pattern of evidence is consistent with broadband operating through non-telework matching channels.

A. Telework

If remote work is the operative mechanism, the employment response should operate by substituting for the physical commute. The identifying population must exhibit a larger differential increase in telework than the baseline population. Table 4 panel A column 1 reports effects on telework, defined as working primarily from home.

Broadband deployment increases telework by 1.7 percentage points for the general population, with a standard error of 0.3 percentage points and statistical significance at the one-percent level. The 1.7 percentage point increase represents a 34 percent increase from the pre-treatment mean of 5 percent. This general-population effect is consistent with broadband enabling remote work arrangements that were previously infeasible, since workers who lacked reliable high-speed connections could not participate in video meetings, access cloud-based applications, or maintain consistent communication with remote colleagues.

For workers with disabilities, the telework differential is negative at 0.8 percentage points, with a standard error of 0.1 percentage points and statistical significance at the one-percent level. Workers with disabilities increase telework by approximately 0.9 percentage points following deployment, or half the general-population increase. Workers with disabilities exhibit participation gains four times larger than the general population (4.7 percentage points versus null), but telework gains are half as large.

This pattern contradicts Prediction R1. If remote work were the mechanism through which broadband expanded employment for workers with disabilities, they should show larger increases in telework rather than smaller increases, because the workers gaining employment should be those accessing remote positions and telework should be the intermediate outcome through which employment expanded. Instead, workers with disabilities are disproportionately finding on-site positions rather than remote work. The negative telework differential supports Prediction S1 and indicates that the differential employment response does not operate through remote work.

The smaller telework gains for workers with disabilities are consistent with several non-mutually exclusive interpretations. Workers with disabilities may have comparative advantage in on-site work where employers provide physical accommodations, assistive technologies, and structured work environments. Home environments may lack wheelchair accessibility, specialized equipment, or the routine and supervision that some workers with disabilities find beneficial. Information asymmetries about remote positions may be smaller in magnitude than information asymmetries about on-site accommodations. Workers can assess whether remote work is feasible based on their own home setup, but cannot easily assess whether an employer will provide needed accommodations without costly screening. Broadband reduces the cost of screening on-site employers, enabling matches that previously failed to form. Employer discrimination may operate more strongly in remote hiring where employers cannot directly observe worker capability, so when workers with disabilities are present in person they can demonstrate competence directly and partially overcome statistical discrimination that might exclude them from remote positions. Regardless of which specific interpretation accounts for the smaller telework response, the negative differential indicates that the channel through which broadband expands employment for workers with disabilities is not remote work.

B. *Occupational Composition of Employment Gains*

The remote work and search friction hypotheses generate opposing predictions for the occupational distribution of employment gains. Under Prediction R2, if remote work is the mechanism, employment gains should be largest in telework-amenable occupations where working from home is feasible. Under Prediction S2, if search friction reduction is the mechanism, employment gains should extend uniformly across occupation types with no concentration in remote-feasible jObservations

Table 4 panel B reports employment effects by occupation category, classifying occupations following Dingel and Neiman (2020). Remote-feasible occupations include computer, mathematical, professional, technical, education, training, library, arts, design, entertainment, sports, and media occupations where work from home is common and job tasks can typically be performed remotely. Technical and skilled occupations include healthcare practitioners, healthcare support, protective service, and skilled trades occupations where specific training is required. Coordination-intensive occupations include management, business, financial, sales, and office support occupations where interpersonal interaction is important. Manual occupations include construction, extraction, installation, maintenance, repair, production, transportation, material moving, food preparation, serving, building, grounds cleaning, and personal care occupations where physical presence at a work site is required.

The differential employment effect for workers with disabilities is statistically significant in all four occupation categories and remarkably uniform across categories. The differential is 1.0 percentage points in remote-feasible occupations (1.09% of the baseline), 0.9 percentage points in technical and skilled occupations (0.96% of the baseline), 1.3 percentage points in coordination-intensive occupations (1.46% of the baseline), and 1.2 percentage points in manual occupations (1.38% of the baseline). The range across categories spans only 0.4 percentage points, and all coefficients are statistically distinguishable from zero at the one-percent level. The uniform distribution of employment effects across occupation types indicates that broadband expanded employment for workers with disabilities across the occupational distribution rather than concentrating effects in any particular category.

This uniform pattern contradicts Prediction R2 and supports Prediction S2. If remote work were generating employment gains for workers with disabilities, those gains should concentrate in telework-amenable positions where workers could perform jobs from home, with effects declining as occupations require greater physical presence. The observed effect is essentially flat across the four categories. Workers with disabilities entered manual labor occupations such as construction, food service, manufacturing, and transportation at the same rate they entered remote-feasible occupations such as professional, technical, and administrative positions. The uniform distribution is consistent with reduced search costs enabling matches across the occupation distribution rather than concentrating in positions amenable to remote work.

Table A4 reports robustness using a stricter Dingel-Neiman occupation classification that separates physical-presence occupations from in-person service occupations and from telework-feasible occupations. The differential effects are 1.0 percentage points in telework-feasible occupations, 1.2 percentage points in physical-presence occupations, and 1.3 percentage points in in-person service occupations. The finer classification preserves the conclusion that effects are distributed uniformly across occupation types, with the largest effects appearing in in-person service occupations rather than in telework-feasible positions. The strictness of the occupation classification does not change the substantive finding.

The occupational distribution of induced employment indicates that workers with disabilities can perform jobs in construction, food service, manufacturing, transportation, and other manual labor occupations given appropriate accommodations, but search frictions prevent them from identifying employers willing to provide such accommodations. Broadband reduces the cost of searching for accommodating employers, enabling matches in occupations that were previously inaccessible not because the work itself was infeasible but because suitable employers were too costly to identify in the absence of digital search tools.

C. Commute Patterns by Disability Type

A final test exploits heterogeneity across disability types to distinguish mechanisms. Under Prediction R3, if remote work is the mechanism generating employment gains, commute time should fall uniformly across disability types as workers of all impairment categories substitute working from home for traveling to employer locations. Under Prediction S3, if reduced physical search costs underlie the response, commute reductions should concentrate among workers whose disabilities create mobility barriers and who therefore face the highest costs of traveling to search for jobs and commute to distant employers.

Table 4 panel C reports effects on commute time in minutes for employed workers, with separate estimates by disability type. Workers with independent living limitations, who have difficulty doing errands alone such as visiting doctors' offices or shopping, show commute time reductions of 0.84 minutes, with a standard error of 0.30 minutes and statistical significance at the one-percent level. Workers with ambulatory limitations, who have serious difficulty walking or climbing stairs, show reductions of 0.65 minutes, with a standard error of 0.24 minutes and statistical significance at the one-percent level. Workers with cognitive limitations show reductions of 0.55 minutes, with a standard error of 0.21 minutes and statistical significance at the one-percent level. In contrast, workers with vision and hearing impairments show no statistically distinguishable change in commute time.

The pattern across disability types is informative about mechanisms. The disability types showing measurable commute reductions share the common feature of impeding physical mobility and the ability to traverse unfamiliar environments. Workers with independent living, ambulatory, and cognitive limitations face elevated costs of traveling to search for jobs in distant or unfamiliar locations because they may be unable to drive, may have difficulty using public transit, or may find route-finding cognitively demanding. These workers face the highest costs of geographically extensive job search and the most binding constraints on identifying distant employers, and broadband enables them to search online and identify suitable local opportunities they could not previously locate. Their commutes shorten not because they are working from home but because they are finding jobs closer to where they live.

Workers with vision and hearing impairments face different constraints. Sensory impairments may limit driving ability but do not necessarily prevent use of public transit or use of familiar routes, and these workers may face narrower geographic constraints on job search and consequently show smaller responses to reduced search costs. The absence of commute effects for sensory disabilities is inconsistent with remote work as the mechanism, because if workers with disabilities were shifting to telework, commute reductions should appear across disability types rather than only among those with mobility impairments. The disability-specific pattern of commute responses provides additional evidence consistent with broadband enabling mobility-constrained workers to identify accessible employers rather than substituting telework for travel.

D. Auxiliary Checks: Migration and Search Intensity

The three core tests reject remote work and point to search friction reduction. Two further outcomes rule out alternative channels through which the differential could arise. We first examine whether the labor force responses reflect geographic relocation rather than improved local matching. Table 4 panel A columns 3 and 4 report migration effects. If broadband enabled workers with disabilities to identify employment opportunities in distant labor markets, we might observe increased between-state or within-state migration following deployment.

Between-state migration shows essentially no response for the general population and a small negative differential for workers with disabilities of 0.1 percentage points. Within-state migration declines 0.8 percentage points for the general population and an additional 0.6 percentage points for workers with disabilities. Both effects on migration are negative or zero, indicating that the labor force gains documented in Section V did not arise through workers relocating in response to broadband deployment but rather through improved matching with employers in their existing local labor markets. The pattern is consistent with broadband reducing the cost of identifying nearby employers that workers could not previously locate, generating local match formation without geographic relocation.

We next examine job search intensity among the unemployed. Search theory predicts that improvements in matching efficiency could reduce search intensity by enabling unemployed workers to identify suitable positions with less effort, or could increase search intensity by raising the marginal return to additional search. The differential effect on search intensity is small and not statistically distinguishable from zero, with a point estimate of essentially zero and a standard error of 0.1 percentage points. The general population effect is also small and not statistically significant. The absence of a detectable effect on search intensity indicates that the matching process changes occur through channels other than the intensity of active search by unemployed workers. The labor force participation response is concentrated among individuals who entered the labor force from non-participation rather than among unemployed workers reducing their search intensity. This pattern is consistent with the binding constraint being the cost of initial entry into the labor force rather than the search effort of those already searching. Workers with disabilities who were out of the labor force entirely faced the largest barriers to identifying suitable employment opportunities, and broadband reduced these barriers sufficiently to induce entry. Once these workers enter the labor force, their search behavior conditional on searching does not differ from the general population.

E. Ruling Out Alternative Explanations

The differential participation response could in principle reflect forces other than reduced search frictions. Table 5 presents results from two checks addressing likely alternatives. First, the response is not produced by benefit substitution, since the differential in column 2 decreases but remains significant when Social Security Disability Insurance and Supplemental Security Income receipt are controlled for, indicating that the participation gain does not operate through changes in program enrollment. Second, the response is not produced by industry composition, since the differential remains stable when local industry composition is controlled for, indicating that it does not reflect treated counties differentially gaining industries that employ workers with disabilities.

Notes: To be generated. Each row reports the differential participation effect for workers with disabilities under the indicated specification. Stability across rows would indicate that the response reflects reduced search frictions rather than benefit substitution, industry composition, or measurement of disability status.

VII. Heterogeneity

The effects of broadband on employment may vary with local economic conditions in ways that inform infrastructure targeting decisions. Search friction reduction enables matches to form, but matching requires both workers seeking jobs and employers with vacancies, and in labor markets with different characteristics the returns to reduced search costs may differ. This section examines heterogeneity along three dimensions, including county unemployment rate, urbanicity, and income level. Table 6 reports the estimates.

A. County Unemployment Rate

Table 6 panel A reports results separately by tercile of pre-treatment county unemployment rate. Low-unemployment counties are those below the 33rd percentile of the distribution, medium-unemployment counties fall between the 33rd and 67th percentiles, and high-unemployment counties are above the 67th percentile.

In low-unemployment counties where labor markets are tight and vacancies are scarce relative to job seekers, the labor force participation differential for workers with disabilities is 0.2 percentage points with a standard error of 0.7 percentage points, statistically indistinguishable from zero. In medium-unemployment counties, the differential rises to 1.9 percentage points, with a standard error of 0.3 percentage points and statistical significance at the one-percent level. In high-unemployment counties, the differential is 1.8 percentage points, with a standard error of 0.3 percentage points and statistical significance at the one-percent level.

This pattern is consistent with search friction reduction operating through matching. Reduced search costs enable workers to identify suitable job openings more easily, but improved identification only increases employment if suitable openings exist. In tight labor markets with low unemployment rates, vacancies are scarce and competition for available positions is intense. Improved search technology yields few additional matches because job availability rather than search costs constrains employment. Workers may identify more openings, but those openings are quickly filled by other applicants in tight markets.

In labor markets with higher unemployment, the calculus differs. Jobs exist as evidenced by the positive vacancy rates that accompany unemployment even in slack markets, but workers have difficulty identifying suitable positions or employers have difficulty identifying suitable workers. Search costs create a wedge between the available opportunities and the matches that actually form. Reducing these costs enables more matches to form, generating employment gains. The concentration of effects in medium and high unemployment areas supports the search friction interpretation and has implications for infrastructure targeting, indicating that broadband investments may generate larger employment returns in areas where unemployment is elevated but vacancies remain.

B. Urbanicity

Table 6 Panel B reports results separately for rural and urban counties, using the USDA rural-urban continuum codes to classify counties. Rural counties are those with populations below

20,000 that are not adjacent to metropolitan areas. Urban counties include metropolitan areas and non-metropolitan counties that are either larger or adjacent to metro areas.

The labor force participation differential for workers with disabilities is essentially zero in rural counties, with a point estimate of 0.0 percentage points and a standard error of 0.2 percentage points. In urban counties, the differential is 1.5 percentage points, with a standard error of 0.3 percentage points and statistical significance at the one-percent level. Effects concentrate in urban areas despite CAF II explicitly targeting rural areas with limited connectivity.

This pattern reflects search friction reduction operating through market thickness. Urban labor markets have more employers, more job openings, and more potential matches between workers and firms. The set of possible employment relationships that could form if search costs were zero is large in urban areas. When search costs fall, workers can identify many more opportunities than they previously could, and the matching rate increases proportionally with the reduction in search costs.

In thin rural markets, the situation differs. The set of potential matches is small regardless of search costs because few employers operate in the area and few positions are available. Even with perfect information about all available jobs, workers in rural areas face a limited opportunity set. Reducing search frictions provides little benefit when few opportunities exist to be found. Rural workers may successfully identify all suitable local employers, but if there are only a handful of such employers, matching gains are inherently limited.

This heterogeneity has implications for infrastructure policy. Programs like CAF II and BEAD that prioritize rural areas based on connectivity gaps may find smaller employment returns than programs targeting urban areas with connectivity gaps. The policy rationale for rural targeting often emphasizes equity in access to essential services, and this rationale may justify rural prioritization even if labor market employment returns are smaller. Policymakers seeking to maximize employment gains per dollar invested should consider that returns depend on market thickness as well as connectivity gaps.

C. County Income Level

Table 6 Panel C reports results by tercile of pre-treatment county median household income. Low-income counties are those below the 33rd percentile, middle-income counties fall between the 33rd and 67th percentiles, and high-income counties are above the 67th percentile.

The labor force participation differential is largest in middle-income counties at 1.7 percentage points, with a standard error of 0.3 percentage points and statistical significance at the one-percent level. In low-income counties, the participation differential is small and negative at -0.3 percentage points, with a standard error of 0.4 percentage points, not statistically distinguishable from zero. In high-income counties, the differential is also small and negative at -0.2 percentage points, with a standard error of 0.3 percentage points, similarly not statistically distinguishable from zero.

These patterns indicate that baseline conditions affect returns to public infrastructure investment in non-monotonic ways. High-income areas were likely already well-served by commercial broadband providers who found deployment profitable even without subsidies. CAF II deployment in these areas provided incremental service improvements rather than first-time service availability. Employment effects are correspondingly small.

In low-income areas, employment effects are muted despite large connectivity gaps. Low-income areas may face constraints beyond search frictions that limit employment responses, including few local employers, limited transportation infrastructure, or health conditions that reduce work capacity. Complementary investments in job training or support services may be required to translate connectivity into employment, and the pattern indicates that broadband alone may be insufficient absent complementary local economic conditions and opportunities.

Middle-income counties combine connectivity gaps that CAF II addresses with employer density that permits match formation. Workers in these areas can take advantage of improved search technology to identify opportunities, and local labor markets have employer density sufficient to provide opportunities worth identifying. The concentration of effects in middle-income areas indicates that broadband investments generate the largest returns when they address binding connectivity constraints in areas where local labor markets contain vacancies that the reduction in search costs can help workers identify.

D. Disability Type

Table A5 reports labor force participation effects estimated separately for each of the six disability types in the ACS classification. All disability types except hearing impairment show positive and statistically significant participation effects. Cognitive limitations show a participation effect of 0.9 percentage points, ambulatory limitations 0.6 percentage points, self-care limitations 0.5 percentage points, independent living limitations 0.8 percentage points, vision impairments 0.8 percentage points, and hearing impairments a smaller and statistically insignificant 0.2 percentage points. The pattern across disability types indicates that the participation response operates broadly across functional limitations rather than being concentrated in a single category, while showing somewhat larger effects for limitations associated with cognitive demands and independent living that align with the search friction interpretation. The broad response across disability types parallels the commute evidence in Section VI, where reductions concentrate among workers whose limitations raise the cost of physical search. Figure A2 plots the mechanism tests estimated separately by disability type.

E. Education and Age

Table A6 reports participation effects by education level. The differential effect for workers with disabilities increases with education, from 1.8 percentage points among high school dropouts to 4.5 percentage points among high school graduates to 5.2 percentage points among those with a bachelor's degree or more. The gradient indicates that the returns to reduced search costs are larger for workers whose skills command a wider range of potential matches, for whom the value of identifying a suitable employer is correspondingly higher.

Table A7 reports participation effects by age group. The differential effect is 2.6 percentage points among workers aged 16 to 24, 4.9 percentage points among those aged 25 to 34, 6.0 percentage points among those aged 35 to 44, 5.2 percentage points among those aged 45 to 54, and 1.3 percentage points among those aged 55 to 65. The inverted U-shape pattern shows larger effects among prime-age workers and smaller among the youngest and oldest workers, consistent with the response concentrating among workers attached to potential employment who face the search costs that broadband reduces.

VIII. Robustness and Sensitivity

We subject the main results to a battery of robustness checks designed to address potential threats to identification, sample composition concerns, the role of the pandemic period, and sensitivity to specification choices.

A. Period Comparison and Pandemic Interaction

A robustness question is whether the documented effects reflect a durable response to broadband infrastructure or a transient response to the unique labor market conditions of the COVID-19 pandemic. Table A8 reports the main specifications separately for the pre-pandemic period through 2019, the full sample including pandemic and post-pandemic years, and a post-2019 subsample.

In the pre-pandemic period, the participation differential for workers with disabilities is 1.6 percentage points, with a standard error of 0.2 percentage points and statistical significance at the one-percent level. Table A9 reports the full set of broadband access and labor-supply estimates restricted to the pre-pandemic sample, where the differential effects on internet adoption, participation, and employment all retain their sign and significance. Figure A3 plots the year-by-year differential effect on participation, and Figure A4 plots the event study separately for the pre-pandemic and full samples. In the full sample, the differential is 4.7 percentage points, and in the post-2019 subsample the differential is undistinguishable from zero. The effects are essentially zero in the post-2019 subsample, and are two to three times larger in periods that include pandemic and post-pandemic years relative to the pre-pandemic baseline.

Table A10 reports a direct test using a pandemic interaction specification. The baseline differential for workers with disabilities is 4.7 percentage points for participation. The interaction with the pandemic indicator yields an additional differential of -1.7 percentage points, indicating that the differential effect on participation was smaller during the pandemic years 2020 and 2021 than during the surrounding non-pandemic years. For telework, the baseline differential is -0.7 percentage points, while the pandemic interaction is positive at 1.4 percentage points. The total differential during the pandemic period indicates that workers with disabilities increased telework more during the pandemic relative to the general population, partially reversing the negative differential observed outside the pandemic years. This pattern is consistent with the pandemic temporarily relaxing the comparative advantage of on-site work for workers with disabilities as employers shifted broadly to remote arrangements.

The period analysis demonstrates that broadband generates measurable participation effects for workers with disabilities both before and after the pandemic. The pandemic period amplified some effects and reduced others, but the labor market responses do not arise from the COVID-19 disruption. Effects in the pre-pandemic sample are smaller than in the full sample because the deployment cohorts had less post-treatment exposure by 2019, given that most deployment occurred in 2015 through 2017 and effects compound over time as documented in the event study analysis. Effects in the post-2019 sample are similar in magnitude to the full sample, indicating that participation gains established during the pandemic persisted rather than reverting after pandemic-era policies ended.

Pandemic amplification is consistent with search friction reduction rather than remote work, but the pre-pandemic estimate is what we treat as the primary causal effect. During 2020 and 2021 the number of accommodating and flexible positions expanded sharply, which raised the return to identifying suitable employers precisely for workers facing high baseline search costs, so connectivity became the binding constraint on converting newly available matches into employment. That the differential decreases after 2019 indicates structural changes in labor participation after the pandemic. On the other hand, these tests are merely suggestive as estimates in the post-2019 sample lack an appropriate control group. The amplification reinforces the search-friction interpretation, because a remote-work channel would predict gains concentrated in telework-amenable positions, which Section VI rejects.

B. Placebo Tests via Random Permutation

We assess whether our standard errors accurately capture true sampling variation by conducting a randomized placebo test. We randomly permute the timing of CAF II deployment across counties in our sample, preserving the spatial and demographic structure of the dataset while eliminating the true relationship between deployment timing and labor market conditions. We re-estimate the baseline triple-difference model on each placebo dataset, repeating the procedure 500 times.

The distribution of estimated placebo coefficients is shown in Figure A5. For both labor force participation and employment, the empirical distribution of placebo coefficients is centered near zero, and the true point estimates of 0.046 for participation and 0.015 for employment lie in the extreme right tail of their respective placebo distributions, with permutation p-values below 0.01. The nonparametric tests indicate that the findings are not mechanically produced by the panel structure and are not driven by generic unobserved macroeconomic shocks coincident with the 2015 to 2021 deployment window.

C. Alternative Sample Restrictions

Table A11 reports the sensitivity of the estimates to sample composition. Because CAF II primarily targeted underserved areas, one concern is that the effects might be driven by extreme rural outliers with idiosyncratic labor markets. We re-estimate the model dropping the top and bottom 5 percent of counties by population density. The differential coefficient on participation is 3.4 percentage points in the density-restricted sample, somewhat smaller than the full-sample 4.7 percentage points but remaining statistically significant at the one-percent level.

We also restrict the identifying population to ensure the aggregate effect is not driven by a specific subgroup. Excluding individuals with sensory limitations who showed no commute-time response yields a participation differential of 4.6 percentage points. Restricting the sample to individuals with ambulatory limitations alone yields a coefficient of 4.3 percentage points, around the same size as the full-sample estimate. The stability of the effect across these population restrictions indicates that the participation response is not concentrated in a single impairment type but rather extends broadly across the disability population, with larger effects among workers whose impairments most directly raise the costs of geographic search.

D. Sensitivity to Covariates

Table A12 examines coefficient stability under different covariate specifications. The baseline specification without controls yields a participation differential of 4.5 percentage points. The main specification with the full set of demographic and human-capital controls yields 4.7 percentage points. A more stringent specification with county-by-year fixed effects yields 4.0 percentage points. The differential effect is statistically significant at the one-percent level across all specifications and varies within a relatively narrow range of 4.0 to 4.7 percentage points. The pattern indicates that the results are not driven by particular control variables or by particular fixed effects structures.

E. County-Level Aggregation

Table A13 re-estimates the model on county-by-year aggregates constructed from the ACS five-year files as an alternative to individual-level estimation. The differential coefficient on labor force participation is 1.3 percentage points and the differential on employment is 1.0 percentage points, both statistically significant at the one-percent level. The county-level estimates are smaller than the individual-level estimates, consistent with attenuation from aggregating disability prevalence and labor force status to the county level, but confirm that the participation response operates at a geographic scale consistent with infrastructure deployment rather than reflecting individual-level composition. Figure A6 plots the corresponding county-level event study, which shows flat pre-trends and a post-deployment rise consistent with the individual-level dynamics.

F. PUMA-County Crosswalk Quality

Because public ACS microdata identify geography at the PUMA level, the assignment of observations to counties introduces measurement that varies in quality across counties. Table A14 reports the distribution of crosswalk quality and the differential effect estimated separately by quality. Counties that match a PUMA on a one-to-one basis, where the dominant county comprises at least 99.9 percent of the PUMA population, account for 35.8 percent of counties. Dominant-county matches account for 6.2 percent, ambiguous matches for 17.9 percent, and highly probabilistic matches for 40.1 percent. The participation differential is 3.9 percentage points on the one-to-one matched sample and 4.6 percentage points on the full reweighted sample. The effect is positive and significant in both, and the larger full-sample estimate reflects the inclusion of more rural counties where deployment occurred and baseline connectivity was lower.

IX. Economic Magnitudes

We place the estimates in policy context with a cost-benefit calculation as a framework for infrastructure targeting. The calculation reflects extensive-margin gains in employment and intensive-margin gains in hours among employed workers, without quantifying consumer surplus, firm productivity gains, or social benefits beyond labor market outcomes. Therefore, these calculations represent a lower bound on total social returns. We report both a full-sample calculation and a pre-pandemic calculation, summarized in Table A15. The pre-pandemic calculation is more conservative because it excludes 2020 and 2021 observations for which the counterfactual labor supply path cannot be cleanly identified.

CAF II disbursed approximately \$9 billion in subsidies between 2015 and 2021, representing an annualized federal investment of roughly \$1.5 billion. The 81 percent of counties receiving CAF II deployment contain approximately 120 million working-age adults. Assuming a 10 percent prevalence rate of functional limitations among working-age adults, the treated population includes approximately 108 million general-population adults and 12 million workers with disabilities.

The employment differential for workers with disabilities is 1.6 percentage points based on the full-sample specification. The total employment effect for workers with disabilities is the sum of the general-population coefficient (0.2 percentage points) and the differential, yielding 1.8 percentage points. Applied to the 12 million workers with disabilities in treated areas, this translates to approximately 216,000 newly employed workers with disabilities. The total employment effect then is 432,000 new workers.

At a $9 billion federal outlay, the implied cost per job is approximately $20,800. For comparison, the Council of Economic Advisers estimated that the American Recovery and Reinvestment Act fiscal stimulus generated employment at approximately $92,000 per job-year including total GDP effects. The CAF II per-job cost is approximately 23 percent of the ARRA stimulus per-job cost, though direct comparisons are limited by differences in measurement and the nature of the programs.

Applying pre-treatment mean annual earnings of $37,900 for the general population and $28,700 for workers with disabilities, the extensive margin gains translate to approximately $14.4 billion in annual labor market wages. The intensive margin contributions from hours growth among employed workers with disabilities add small additional wage gains given the 1.8 percent intensive-margin response.

Under the pre-pandemic estimates from Table A8, the total employment effect for workers with disabilities is 1.6 percentage points and the general-population effect is statistically indistinguishable from zero, yielding approximately 192,000 new jobs among workers with disabilities and no measurable effect on the general population. At a $9 billion federal outlay, the implied pre-pandemic cost per job is approximately $46,900. Workers with disabilities constitute 10 percent of the working-age population but account for approximately one-third of the differential employment gains generated by CAF II under the full-sample calculation, and essentially all of the measurable gains under the pre-pandemic calculation. The disproportionate share of gains accruing to workers with disabilities indicates that the labor market returns to infrastructure investment depend on the baseline characteristics of the affected population. Areas with higher concentrations of workers facing elevated baseline search costs may generate larger employment responses per dollar of infrastructure investment.

The disability population is one population for which the search friction mechanism can be empirically identified, given the documented elevated baseline search costs and the exogenous variation in deployment timing. The cost-benefit calculation reported here captures the labor market returns attributable to the differential effect on workers with disabilities alone. The total returns to a CAF II expansion that also reached other populations facing elevated search costs would exceed this disability-specific figure, so the calculation is a lower bound on the labor market returns to broadband that operates through reduced search frictions.

These calculations indicate that incorporating labor market conditions and demographic composition into infrastructure investment decisions could improve allocation efficiency. Optimal targeting criteria require additional research and policy analysis beyond the scope of the current paper, but the heterogeneous returns documented here indicate that uniform geographic allocation based solely on connectivity gaps generates labor market returns that vary sharply across population characteristics. The forthcoming BEAD allocation represents an opportunity to test demand-side targeting principles in a setting where the allocation formulas have not yet been finalized.

A Targeting Counterfactual

The heterogeneity estimates imply that a fixed infrastructure budget generates more employment when allocation weights the concentration of high-search-cost residents alongside connectivity gaps. Consider a budget the size of a single BEAD tranche allocated across eligible areas. Under the current rule, funds flow in proportion to connectivity gaps alone. Under a search-cost-weighted rule, the same funds flow toward areas combining connectivity gaps with high concentrations of search-constrained residents, where the differential returns documented in Section VII are largest. The difference in employment generated per dollar measures the efficiency gain from incorporating demand-side characteristics into the allocation formula.

We consider two allocation possibilities to a BEAD-size fixed budget. The connectivity gap serves counties where the unserved people are, and the search-cost rule sends money where the unserved jobless people are. The second rule targets counties by connecting a higher share of workers with disabilities who get a 1.8 percentage point larger employment rate *vis a vis* a 0.2 percentage point increase for the general population. We use pre-treatment working-age population counts by county, and estimate the total jobs generated nation-wide under these two decision rules. Targeting populations with high job-search frictions yields 3,877 additional jobs and reduces the cost per job by 5.8 percent. Although the contemporaneous cost per job exceeds $630,000 under both allocation rules, this static measure does not reflect the durable nature of broadband infrastructure investments. If the estimated employment gains persist over a conservative twenty years service-life, each rule sustains roughly 1.3 million jobs at an implied cost of $31,600-33,600 per job-year. Furthermore, event-study estimates suggest that treatment effects may compound over time rather than remain constant, consistent with gradual adoption and adjustment mechanisms. Therefore, the long-run employment generated per dollar of broadband investment may be substantially larger than implied by static calculations based on contemporaneous effects.

X. Conclusion

This paper documents that the labor market returns to public broadband infrastructure vary sharply with the search-cost characteristics of the population served. We exploit quasi-experimental variation in Connect America Fund Phase II deployment timing, determined by an engineering cost model incorporating terrain slope, soil composition, depth to bedrock, and other geological factors that predict deployment costs but have no direct relationship to labor market conditions. Workers with disabilities serve as an identifying population because they face elevated baseline search costs from transportation barriers, information asymmetries about employer accommodations, and discrimination that increases applications required per offer. These elevated baseline costs are documented in correspondence studies, measurable in administrative survey data, and exogenous to the geological factors that determined deployment timing, providing the cleanest available laboratory for testing whether broadband generates differential labor market responses through search friction reduction.

The empirical findings can be summarized as follows. CAF II deployment increased labor force participation for workers with disabilities by 4.7 percentage points more than the general population, an effect representing a 12.7 percent improvement from the pre-treatment baseline participation rate of 37 percent that exceeds the measured impact of the Americans with Disabilities Act by more than four times. Employment increased by 1.6 percentage points differentially, indicating that the participation gains translated into actual job formation. The extensive-margin response dominates, with the participation differential approximately four times the conditional employment differential, indicating that broadband primarily induced workers into the labor force rather than improving job-finding among those already searching.

The intensive-margin response is small and shifts toward full-time positions. The differential effect on usual weekly hours among employed workers with disabilities is 1.8 percent, while the differential effect on full-time employment is 1.5 percentage points. Workers with disabilities induced into employment by broadband disproportionately enter full-time positions that the search friction reduction made identifiable. This pattern is consistent with workers entering better quality employment that by reducing search costs and improving job matching.

Three empirical patterns address the channel through which broadband expands employment for workers with disabilities. First, workers with disabilities increase telework by 0.8 percentage points less than the general population following deployment. Workers with disabilities exhibit large participation gains but telework gains less than half the general-population response. The negative telework differential is inconsistent with remote work as the primary mechanism. Second, the differential employment effect is uniformly distributed across occupation types. Employment gains are 1.0 percentage points in remote-feasible occupations, 0.9 percentage points in technical and skilled occupations, 1.3 percentage points in coordination-intensive occupations, and 1.2 percentage points in manual labor occupations. The lack of concentration in remote-feasible occupations contradicts the prediction that telework drives the employment response. Workers with disabilities entered manual labor occupations such as construction, food service, manufacturing, and transportation at the same rate they entered remote-feasible occupations such as professional, technical, and administrative positions. Third, commute time reductions concentrate among workers whose disabilities affect physical mobility. Workers with independent living, ambulatory, and cognitive limitations show commute reductions of 0.5 to 0.8 minutes, while workers with vision or hearing impairments show no statistically distinguishable change. The disability-specific pattern of commute responses indicates that broadband enables mobility-constrained workers to identify accessible employers closer to home rather than substituting telework for travel.

The combination of these patterns is consistent with broadband operating through non-telework matching channels. Workers with disabilities who were previously excluded from employment by elevated search costs are enabled to identify suitable employers across the occupation distribution. The mechanism does not operate through remote work, which would predict positive telework differentials, concentrated employment effects in remote-feasible occupations, and uniform commute responses across disability types.

The pandemic period amplified the participation response without altering the underlying mechanism. The pre-pandemic participation differential of 1.6 percentage points expanded to 4.7 percentage points when including the larger pandemic-era response. Effects also vary with local labor market conditions. The participation differential is largest in counties with elevated unemployment, urban geography, and middle income. Effects in low-unemployment, rural, low-income, and high-income areas are smaller or undetectable. The pattern indicates that broadband infrastructure generates the largest returns when it addresses binding connectivity constraints in areas where local labor markets contain both unemployed workers seeking matches and unfilled vacancies that permit match formation.

Several limitations apply to our analysis. First, our mechanism identification relies on differential responses across populations with varying baseline search costs. The evidence indicates that broadband generates large extensive-margin gains for high-search-cost populations through non-telework channels, while the question of whether the small general-population effects operate through similar or different channels remains open. Second, the heterogeneity patterns by local labor market conditions are descriptive rather than experimentally identified, and the policy implications drawn from these patterns require additional research using interventions that vary local conditions independently. Third, the negative differential on broadband subscriptions specifically, alongside the large positive differential on internet subscriptions overall, indicates that workers with disabilities respond to CAF II by adopting entry-level rather than premium internet service, so the labor market mechanism operates through any internet connectivity rather than through high-speed broadband specifically. Fourth, the identifying population is heterogeneous, and while we examine variation by disability type, finer distinctions might reveal additional nuance.

The findings have implications for infrastructure policy that extend beyond the disability population. We use workers with disabilities as an identifying population because their elevated baseline search costs are documented in correspondence studies, measurable in survey data, and exogenous to the geological factors that determined broadband deployment timing. The same mechanism applies to other populations facing elevated search costs from information asymmetries, network gaps, or discrimination. Workers re-entering employment after incarceration face information barriers about which employers will hire applicants with criminal records. Immigrants without local professional networks face information barriers about workplace norms and credential recognition. Displaced workers face information barriers about employers in unfamiliar sectors. Single parents face information barriers about employer scheduling flexibility. Older workers face information barriers about age-inclusive workplaces. The mechanism we identify operates through identification of suitable employers rather than through spatial substitution, and the mechanism applies wherever the binding constraint on employment is information about suitable workplaces rather than physical capacity to reach them. We frame these extensions as testable predictions rather than findings, since the present design identifies the mechanism only for workers with disabilities, and we leave estimation for these additional populations to future research.

For federal infrastructure programs, the implications are concrete. First, broadband generates labor market returns through mechanisms other than remote work, with benefits extending across the occupation distribution rather than concentrating in telework-amenable positions. Targeting strategies should consider which populations face the most binding search constraints, not only which populations are positioned for telework. The disability population shows a large participation response in counties where the general population shows none, and other search-constrained populations should show comparable differential responses to infrastructure that reduces information costs. Second, returns depend on local labor market conditions. Effects concentrate in areas where elevated unemployment indicates the presence of workers seeking matches, urban areas with employer density supporting many potential matches, and middle-income areas combining connectivity gaps with employer density that permits match formation. The BEAD program allocates $42.5 billion primarily based on connectivity gaps, with limited consideration of labor market conditions or population characteristics. Layering labor market criteria and demand-side population characteristics onto this targeting could improve allocation efficiency. Third, employment benefits may require complementary conditions. Low-income rural areas showed limited responses despite presumably large connectivity gaps, indicating that infrastructure alone may be insufficient absent complementary local economic opportunity and employer density.

References

Acemoglu, D., & Angrist, J. D. (2001). Consequences of employment protection? The case of the Americans with Disabilities Act. *Journal of Political Economy*, *109*(5), 915-957.

Ameri, M., Schur, L., Adya, M., Bentley, F. S., McKay, P., & Kruse, D. (2018). The disability employment puzzle: A field experiment on employer hiring behavior. *Ilr Review*, *71*(2), 329-364.

David, H. (2001). Wiring the Labor Market. *Journal of Economic Perspectives*, *15*(1).

Autor, D. H., & Duggan, M. G. (2003). The rise in the disability rolls and the decline in unemployment. *The Quarterly Journal of Economics*, *118*(1), 157-206.

Baldwin, M. L., & Johnson, W. G. (2000). Labor market discrimination against men with disabilities in the year of the ADA. *Southern Economic Journal*, *66*(3), 548-566.

Bhuller, M., Ferraro, D., Kostøl, A. R., & Vigtel, T. C. (2023). *The internet, search frictions and aggregate unemployment* (No. w30911). National Bureau of Economic Research.

Borusyak, K., Jaravel, X., & Spiess, J. (2024). Revisiting event-study designs: robust and efficient estimation. *Review of Economic Studies*, *91*(6), 3253-3285.

Bound, J., & Burkhauser, R. V. (1999). Economic analysis of transfer programs targeted on people with disabilities. *Handbook of labor economics*, *3*, 3417-3528.

Council of Economic Advisers. (2009). Estimates of Job Creation from the American Recovery and Reinvestment Act of 2009. Washington, DC: Executive Office of the President.

De Chaisemartin, C., & d'Haultfoeuille, X. (2023). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. *The econometrics journal*, *26*(3), C1-C30.

Dettling, L. J. (2017). Broadband in the labor market: The impact of residential high-speed internet on married women's labor force participation. *Ilr Review*, *70*(2), 451-482.

Diamond, P. A. (1982). Wage determination and efficiency in search equilibrium. *The Review of Economic Studies*, *49*(2), 217-227.

Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home?. *Journal of Public Economics*, *189*, 104235.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254-277.

Hansen, S., Lambert, P. J., Bloom, N., Davis, S. J., Sadun, R., & Taska, B. (2023). *Remote work across jobs, companies, and space* (No. w31007). National Bureau of Economic Research.

Hjort, J., & Poulsen, J. (2019). The arrival of fast internet and employment in Africa. *American Economic Review*, *109*(3), 1032-1079.

Kroft, K., & Pope, D. G. (2014). Does online search crowd out traditional search and improve matching efficiency? Evidence from Craigslist. *Journal of Labor Economics*, *32*(2), 259-303.

Kuhn, P., & Mansour, H. (2014). Is internet job search still ineffective?. *The Economic Journal*, *124*(581), 1213-1233.

Kuhn, P., & Skuterud, M. (2004). Internet job search and unemployment durations. *American Economic Review*, *94*(1), 218-232.

Maestas, N., Mullen, K. J., & Strand, A. (2013). Does disability insurance receipt discourage work? Using examiner assignment to estimate causal effects of SSDI receipt. *American economic review*, *103*(5), 1797-1829.

Marinescu, I., & Rathelot, R. (2018). Mismatch unemployment and the geography of job search. *American Economic Journal: Macroeconomics*, *10*(3), 42-70.

Mortensen, D. T. (1982). The matching process as a noncooperative bargaining game. In *The economics of information and uncertainty* (pp. 233-258). University of Chicago Press.

Nazareno, L., Jose, J., & Hart, G. (2025). Wired and working? An evaluation of broadband expansion in Rural America. *Telecommunications Policy*, 103074.

Pissarides, C. A. (1985). Short-run equilibrium dynamics of unemployment, vacancies, and real wages. *The American Economic Review*, *75*(4), 676-690.

Rupasingha, A., Pender, J., & Dinterman, R. (2025). Impacts of the USDA broadband initiatives program on employment and telework: Evidence from confidential American community survey microdata. *Telecommunications Policy*, 103102.

Stevenson, B. (2008). *The Internet and job search* (No. w13886). National Bureau of Economic Research.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175-199.

Zuo, G. W. (2021). Wired and hired: Employment effects of subsidized broadband Internet for low-income Americans. *American Economic Journal: Economic Policy*, *13*(3), 447-482.

Tables

Table 1. Summary Statistics

	No Disability	Disability	Difference
		Panel A. Demographics	
Age	40.27	47.26	-6.985***
Female	0.51	0.48	0.028***
White	0.81	0.78	0.029***
College degree	0.33	0.16	0.163***
		Panel B. Labor Market	
Labor force participation	0.77	0.38	0.389***
Employment	0.93	0.85	0.078***
Annual earnings ($)	37.95	28.74	9.20***
Weekly hours	31.39	14.54	16.851***
Full-time	0.63	0.28	0.355***
Telework	0.04	0.05	-0.006***
		Panel C. Technology Access	
Internet subscription	0.86	0.73	0.133***
Broadband	0.82	0.80	0.023***
Computer ownership	0.86	0.73	0.129***
Observations	31,394,874	3,876,847	

Notes: Means for pre-treatment period (2006-2014). Sample includes individuals ages 16-64 not residing in group quarters. Earnings, hours, and telework conditional on employment.

Table 2. Broadband Deployment Effects on Technology Access and Labor Supply

	(1)	(2)	(3)	(4)	(5)
	Broadband	LFP	Empl	Log Hrs	Full-Time
	Panel A. General Population Effects				
General Population	0.010***	0.001	0.002**	-0.001	0.001
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
	Panel B. Differential Effects				
General Population	0.012***	-0.001	0.001	-0.002	0.000
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Differential (PWD)	-0.009***	0.047***	0.016***	0.018***	0.015***
	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)
Observations	39.1M	70.9M	50.7M	46.8M	46.8M
Baseline Mean (PWD)	0.80	0.37	0.87	37.44	0.73

Notes: All specifications include county and year fixed effects and individual controls for age, education, race, sex, and marital status. Panel A shows effects from a regression on the general population. Panel B shows effects from a regression with a triple-difference interaction between deployment and disability. Estimates are weighed by county and personal weights. Standard errors clustered at county level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 3. Internet Adoption by Service Tier

	(1) Broadband	(2) Low-Speed Internet
Deployment x Low tier	0.0179***	-0.0205***
	(0.0057)	(0.0049)
Deployment x Mid tier	0.0134***	-0.0162***
	(0.0046)	(0.0041)
Deployment x High tier	0.0106***	-0.0155***
	(0.0032)	(0.0029)
Deployment x Low x Disability	-0.0073*	0.0183***
	(0.0039)	(0.0034)
Deployment x Mid x Disability	-0.0075**	0.0179***
	(0.0031)	(0.0027)
Deployment x High x Disability	-0.0099***	0.0209***
	(0.0014)	(0.0013)
Observations	39071750	42863635
R-squared	0.05	0.04
Outcome Mean (PWD)	0.75	0.20

Notes: CAF II effect on connectivity by county PRE-CAF (Dec-2015) speed tier (tercile). Speed tier data is sourced from the FCC F477 forms. Each column includes a triple-difference regression with county, year, and age fixed effects. Broadband is equivalent to high-speed subscription; and Low-Speed Internet represents internet without broadband (entry tier; no-internet households). Standard errors clustered at the county level. * p<0.10 ** p<0.05 *** p<0.01.

Table 4. Mechanism Tests: Telework, Occupation, Search Intensity, and Commute

	(1)	(2)	(3)	(4)	(5)
	Panel A. Intermediate Outcomes				
	Telework	Search Intensity	Migration (State)	Migration (Local)	
General Population	0.017***	-0.000	-0.000	-0.008***	
	(0.003)	(0.000)	(0.000)	(0.002)	
Differential (PWD)	-0.008***	-0.000	-0.001***	-0.006***	
	(0.001)	(0.000)	(0.000)	(0.001)	
Prediction Test	S1: ✓	S3: ✓			
Baseline (PWD)	0.07	0.99	0.02	0.13	
	Panel B. Employment by Occupation Type				
	Remote-Feasible	Tech/ Skill	Coord-ination	Manual Labor	
General Population	0.001**	0.001	0.003**	0.001	
	(0.001)	(0.001)	(0.001)	(0.002)	
Differential (PWD)	0.010***	0.009***	0.013***	0.012***	
	(0.001)	(0.002)	(0.002)	(0.002)	
Prediction Test	R2: ✗	S2: ✓	S2: ✓	S2: ✓	
Baseline (PWD)	0.92	0.94	0.89	0.87	
	Panel C. Commute by Disability Type (minutes)				
	Cognitive	Ambulatory	Indep. Living	Vision	Hearing
Deployment Effect	-0.545***	-0.648***	-0.842***	-0.096	0.178
	(0.209)	(0.240)	(0.299)	(0.259)	(0.233)
Baseline (PWD)	24.12	24.68	23.70	25.37	26.29

Notes: Panel A: Telework is indicator for working primarily from home; Search is indicator for active job search among unemployed. Panel B: Occupation categories follow Dingel and Neiman (2020). Remote-feasible includes computer, education, legal, business, management, arts, office support occupations, and architecture and engineering occupations. Tech/Skill intensive occupations include management, business, computer, architecture and engineering, sciences, legal, and healthcare. Coordination occupations are social services, healthcare support, protective service, sales, office support, and transportation. Manual Labor includes construction, food service, production, transportation. Panel C: Commute sample restricted to employed workers. All specifications include county and year fixed effects. Standard errors clustered at county level. * p<0.10, ** p<0.05, *** p<0.01.

Table 5. Robustness to Alternative Explanations

	(1) Baseline	(2) +Benefits	(3) +Industry
CAF 2 x Disability (differential)	0.0469***	0.0174***	0.0485***
	(0.0027)	(0.0018)	(0.0028)
CAF 2 Deployment	-0.0029***	-0.0001	-0.0043***
	(0.0010)	(0.0010)	(0.0009)
Disability	-0.3407***	-0.2065***	-0.3419***
	(0.0013)	(0.0009)	(0.0014)
Observations	70938632	70938632	58108289
R-squared	0.20	0.25	0.20
Outcome Mean (PWD)	0.38	0.38	0.38

Notes: Dependent variable is labor force participation. Columns show differential effect in regressions controlling for social benefits (2) and industry location quotients (3). Social Benefits include Social Security Income, Supplemental Security Income, and Public Assistance Income. Location Quotients are built with county-level industry employment in the Quarterly Census of Employment and Wages for private firms $LQ_{cit} = {}^{E_{cit}}/_{E_{ct}} / {}^{E_{it}}/_{E_t}$. All specifications include baseline controls, county and year fixed effects. Standard errors clustered at county level. * p<0.10, ** p<0.05, *** p<0.01.

Table 6. Labor Force Participation Effects by Local Labor Market Conditions

	(1)	(2)	(3)
	Panel A. By County Unemployment Rate		
	Low (Bottom Tercile)	Medium (Middle)	High (Top Tercile)
Differential (PWD)	0.002	0.019***	0.018***
	(0.007)	(0.003)	(0.003)
	Panel B. By Urbanicity		
	Rural	Urban	
Differential (PWD)	-0.000	0.015***	
	(0.002)	(0.003)	
	Panel C. By County Income Level		
	Low (Bottom Tercile)	Middle (Middle)	High (Top Tercile)
Differential (PWD)	-0.003	0.017***	-0.002
	(0.004)	(0.003)	(0.003)

Notes: Dependent variable is labor force participation. Columns show differential effect (Post × Disability) within each subsample. Panel A stratifies by pre-treatment county unemployment rate tercile. Panel B stratifies by rural/urban classification. Panel C stratifies by pre-treatment county median household income tercile. All specifications include county and year fixed effects. Standard errors clustered at county level. * p<0.10, ** p<0.05, *** p<0.01.

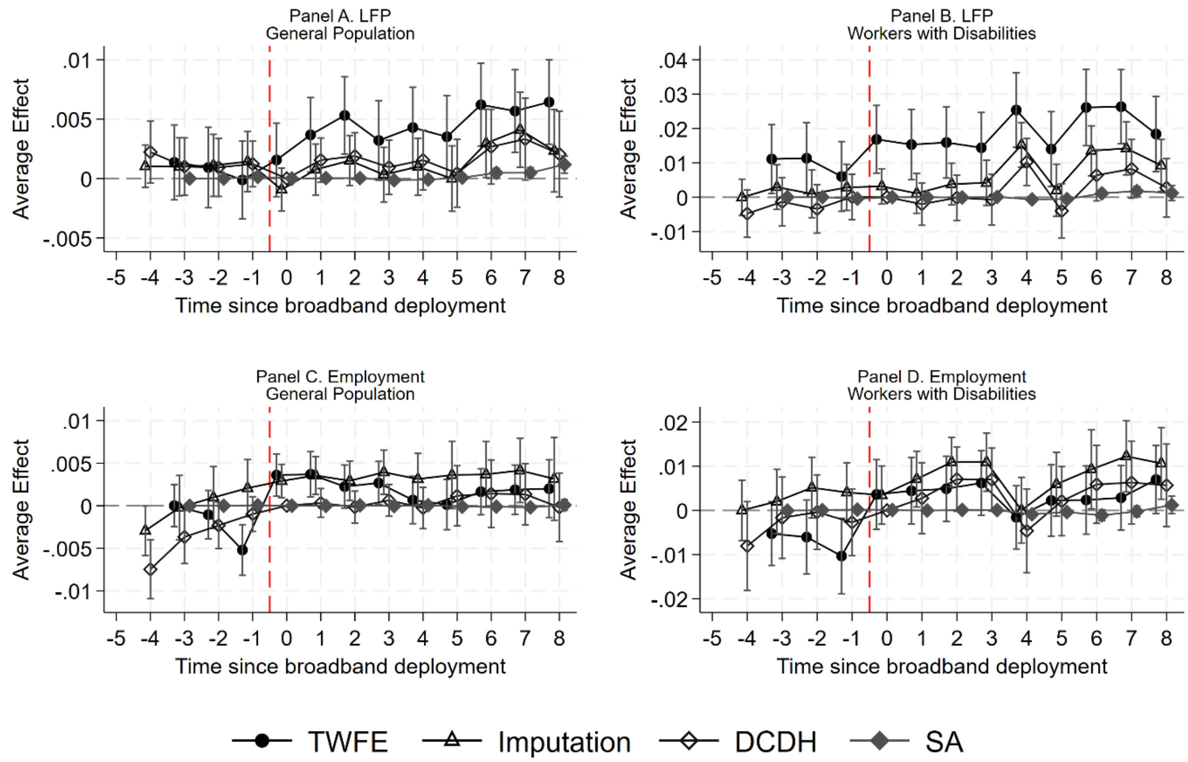
Table 7. Employment Returns Under Alternative Allocation Rules

	Connectivity-Gap Allocation	Search-Cost-Weighted Allocation
Jobs generated	63,250	67,127
Cumulative job-years (20yr)	1,265,000	1,342,540
Upfront cost per job	$671,149	$632,385
Cost per job-year	$33,557	$31,619

Notes: Each column applies a fixed infrastructure budget of $42.45 billion (the size of the federal BEAD program) which connects N = 15,160,714 previously unserved people at an assumed constant cost of $2,800 per connection ($42.45B divided by $2,800 = 15,160,714), allocated across the 3033 counties with a positive December 2015 connectivity gap. The connectivity-gap rule distributes funds in proportion to each county's unserved population; the search-cost rule distributes funds in proportion to each county's unserved population of workers with disabilities, who face the highest job-search frictions. Per-connection cost is held constant across counties, so the difference between rules reflects demand-side targeting alone, not cost variation. Jobs generated is the steady-state annual increase in employment, computed county by county as connected population times a disability-share-weighted employment effect ($N \times [s \times 0.018 + (1 - s) \times 0.002]$, where 0.018 (workers with disabilities) and 0.002 (general population) are the employment effects from Table 2 and s is the disability share of the connected population. The two rules aggregate to a population-weighted disability share of 13.6 percent (63,250 jobs) versus 15.2 percent (67,127 jobs). Cumulative job-years equal annual jobs generated times a 20-year infrastructure service life. Upfront cost per job equals the $42.45 billion budget divided by annual jobs generated; cost per job-year equals the budget divided by cumulative job-years. All figures are undiscounted.

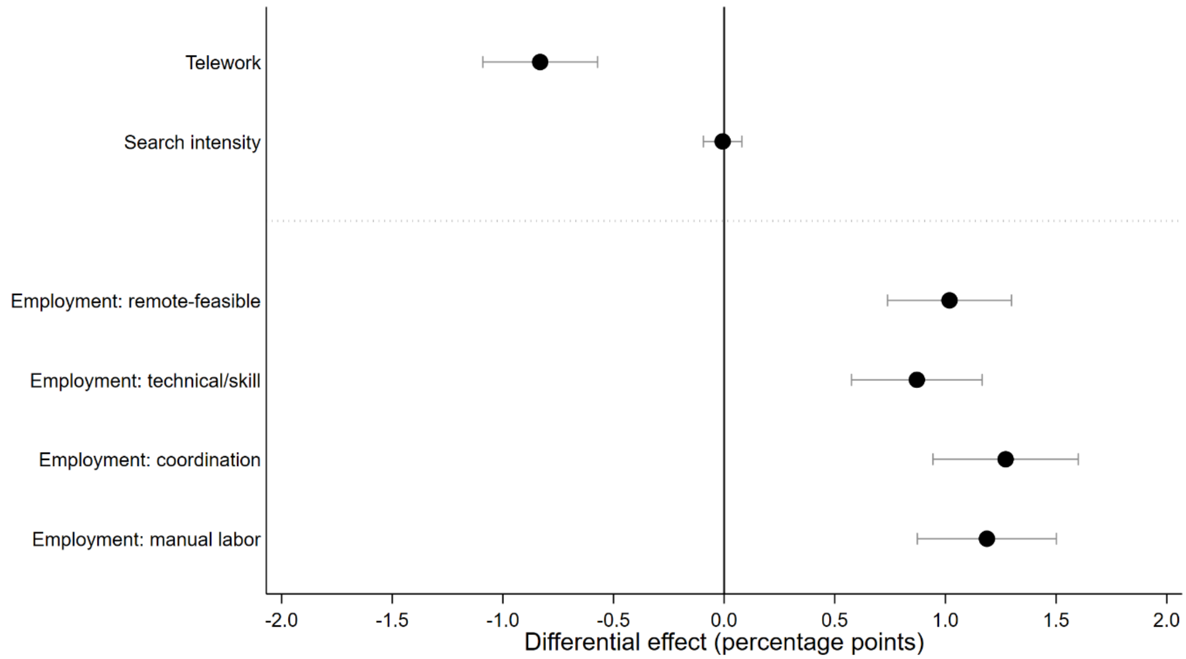
Figures

Figure 1: Event Study Estimates: Labor Force Participation and Employment



Notes: Event time 0 is year of CAF II deployment. Four estimators shown: two-way fixed effects (TWFE), imputation estimator in Borusyak et al. (2024), De Chaisemartin and D'Haultfoeuille (2023), and Sun and Abraham (2021). Whiskers indicate 95 percent confidence intervals based on standard errors clustered at county level. Sample includes individuals ages 16-64 from ACS 2006-2024.

Figure 2. Mechanism Tests: Differential Effects for Workers with Disabilities



Notes: Coefficients show differential effects (Post × Disability interaction) from specifications including county and year fixed effects and individual controls. Horizontal bars indicate 95 percent confidence intervals. Telework and Search Intensity from Table 3 Panel A. Occupation effects from Table 3 Panel B.

ONLINE APPENDIX

Table A1. Correlation between CAF II Deployment Year and Pre-Treatment County Characteristics

	(1)	(2)	(3)	(4)	(5)	(7)	(8)	(9)
						Employment Share		
	Population	Median income	Poverty rate	Unempl. rate	Manufacture	Transport.	Information	Professional
2010	-1280.30**	-873.20**	0.004	0.001	-0.012	-0.001	0.000	-0.013
	(518.09)	(347.45)	(0.006)	(0.001)	(0.013)	(0.002)	(0.001)	(0.010)
2011	1833.19***	-1158.70***	-0.006***	-0.003***	0.005***	-0.007***	-0.003***	0.001
	(252.83)	(129.05)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
2015	143.45	-569.44***	0.001	-0.001*	0.002	0.000	-0.001**	0.001
	(392.90)	(141.33)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
2016	1337.00**	-937.48***	0.001	-0.003***	-0.000	0.001	-0.001	-0.001
	(605.82)	(158.76)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)
2017	-1451.38***	-529.22***	0.001	-0.001	0.002	0.000	-0.001	-0.001
	(266.63)	(159.71)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)
2018	-1407.04***	-66.02	-0.000	-0.003*	0.005	-0.002	-0.002**	-0.001
	(280.43)	(271.97)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
2019	-950.25***	-236.09	-0.000	-0.002*	0.004	-0.000	-0.001	0.000
	(347.31)	(190.30)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
2020	939.44	150.25	0.001	0.000	0.014*	-0.002	-0.002	-0.002
	(1164.25)	(389.41)	(0.002)	(0.002)	(0.008)	(0.003)	(0.001)	(0.003)
2021	-1166.13**	155.01	0.006	0.005	-0.016	0.001	0.003	-0.058
	(477.38)	(683.83)	(0.004)	(0.005)	(0.012)	(0.004)	(0.003)	(0.047)
Observations	3141	3141	3141	3141	3141	3141	3141	3141
R-squared	0.02	0.02	0.00	0.00	0.00	0.00	0.01	0.02

Notes: Independent variable is deployment year. Dependent variables are 2010-2014 changes in county characteristics from the 5-YR ACS. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A2. CAF II Broadband Rollout

Deployment Year	Counties	County (%)	Mean download speed (Mbps)	Mean upload speed (Mbps)
2005	2	0	10	1
2011	1	0	10	1
2015	800	25	12	2
2016	484	15	12	2
2017	643	20	12	2
2018	144	5	16	3
2019	366	12	33	8
2020	73	2	10	1
2021	21	1	10	1
Never treated	610	19		
Counties	3144			

Notes: The table displays the deployment year of broadband funded by the Connect America Fund Phase II program. The program started in 2015 and finalized in 2021. Counties treated before 2015 had early deployment, but providers filed for funding in 2015.

Table A3. Device Gap: all households vs laptop-owning households

	(1) Broadband: All	(2) Broadband: Laptop HH
CAF 2 x Disability (differential)	-0.0093***	-0.0066***
	(0.0013)	(0.0010)
CAF 2 Deployment	0.0115***	0.0067***
	(0.0028)	(0.0026)
Disability	-0.0097***	-0.0036***
	(0.0007)	(0.0006)
Observations	39114161	35164648
R-squared	0.05	0.04
Outcome Mean (PWD)	0.75	0.81

Notes: The table tests the connectivity regression in a sample of households that own a laptop. The estimates test whether the negative differential in broadband connectivity reflects household-level device access. All regressions include county, year, and age fixed effects. Standard Errors clustered by county in parenthesis. Column 3 (Laptop HH) restrict the sample to households that own a laptop. * p<0.10 ** p<0.05 *** p<0.01.

Table A4. Effect of CAF II on Employment by Dingel-Neiman (2020) Occupation Category

	(1) Telework-feasible	(2) Physical-presence	(3) In-person service
CAF II Deployment	0.0015**	0.0016	0.0015
	(0.0007)	(0.0015)	(0.0011)
Disability	-0.0502***	-0.0686***	-0.0663***
	(0.0006)	(0.0007)	(0.0011)
Differential	0.0102***	0.0124***	0.0138***
	(0.0014)	(0.0014)	(0.0020)
Observations	20367220	21557990	8180341
R-squared	0.02	0.04	0.04
Baseline mean (PWD)	0.92	0.88	0.89

Dependent variable: employment. Telework-feasible = SOC major groups with Dingel-Neiman telework share >= 0.50 (groups 11, 13, 15, 17, 19, 23, 25, 27, 43). Physical-presence = healthcare practitioners/support, food prep, building/grounds, farming/fishing, construction, installation, production, transportation (29, 31, 35, 37, 45, 47, 49, 51, 53). In-person service = community/social, protective service, personal care, sales (21, 33, 39, 41). Standard errors clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01

Table A5. Labor Force Participation Effects by Type of Disability

	(1) All disabilities	(2) Cognitive	(3) Ambulatory	(4) Self-Care	(5) Indep Living	(5) Vision	(6) Hearing
Deployment	0.006*** (0.002)	0.009*** (0.003)	0.006*** (0.002)	0.005** (0.003)	0.008*** (0.002)	0.008** (0.004)	0.002 (0.003)
Observations	9078641	2657533	4454062	1614941	3180980	1482536	1729248
R-squared	0.11	0.07	0.07	0.06	0.08	0.15	0.15
Baseline Mean	0.38	0.21	0.27	0.16	0.19	0.42	0.54

Notes: Each coefficient is estimated in a subsample conditional on each disability type. Disability types not mutually exclusive. All specifications include county and year fixed effects. Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A6. Labor Force Participation Effects by Education Level

	(1) HS Dropout	(2) HS Degree	(3) BA+
General Population	0.000	-0.001	-0.002**
	(0.002)	(0.001)	(0.001)
Differential (PWD)	0.018***	0.045***	0.052***
	(0.004)	(0.003)	(0.003)
Observations	6331784	52149552	22035157
R-squared	0.21	0.14	0.11
Baseline Mean (PWD)	0.53	0.77	0.84

Notes: All specifications include county and year fixed effects. Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A7. Labor Force Participation Effects by Age Group

	(1) 16-24 Years Old	(2) 25-34 Years Old	(3) 35-44 Years Old	(4) 45-54 Years Old	(5) 55-65 Years Old
General Population	-0.005***	-0.003*	-0.001	-0.004***	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Differential (PWD)	0.026***	0.049***	0.060***	0.052***	0.013***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
Observations	12.4M	12.6M	13.4M	15.4M	18.5M
R-squared	0.21	0.11	0.13	0.18	0.18
Baseline Mean (PWD)	0.40	0.47	0.44	0.41	0.31

Notes: All specifications include county and year fixed effects. Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A8. Period Comparison: Pre-Pandemic vs. Full Sample vs. Post-2019

	(2) Broadband	(3) LFP	(4) Empl	(5) Log Hrs	(6) Full-Time
	Panel A. Pre-Pandemic (<2020)				
CAF II Deployment	0.0118***	-0.0009	0.0022**	-0.0020*	-0.0007
	(0.0026)	(0.0011)	(0.0011)	(0.0012)	(0.0015)
Disability	-0.0073***	-0.3478***	-0.0780***	-0.0978***	-0.0961***
	(0.0007)	(0.0013)	(0.0008)	(0.0012)	(0.0010)
Differential	-0.0185***	0.0160***	0.0153***	0.0010	0.0016
	(0.0017)	(0.0026)	(0.0015)	(0.0028)	(0.0025)
Observations	23981491	53544317	38325599	35217144	35217144
Baseline mean	0.75	0.37	0.87	37.05	0.72
	Panel B. Full Sample				
CAF II Deployment	0.0115***	-0.0029***	0.0015	-0.0018	0.0001
	(0.0028)	(0.0010)	(0.0012)	(0.0015)	(0.0018)
Disability	-0.0097***	-0.3407***	-0.0749***	-0.0940***	-0.0925***
	(0.0007)	(0.0013)	(0.0007)	(0.0011)	(0.0009)
Differential	-0.0093***	0.0469***	0.0158***	0.0181***	0.0152***
	(0.0013)	(0.0027)	(0.0012)	(0.0019)	(0.0016)
Observations	39114161	70938632	50758997	46877371	46877371
Baseline mean	0.75	0.72	0.94	36.99	0.72
	Panel C. Post-2019 (year > 2019)				
CAF II Deployment	0.0013	-0.0038	-0.0020	0.0039*	0.0025
	(0.0055)	(0.0054)	(0.0032)	(0.0022)	(0.0030)
Disability	-0.0157***	-0.3076***	-0.0601***	-0.0777***	-0.0779***
	(0.0011)	(0.0022)	(0.0011)	(0.0016)	(0.0015)
Differential	0.0004	0.0353***	0.0015	0.0102***	0.0083***
	(0.0016)	(0.0040)	(0.0018)	(0.0025)	(0.0024)
Observations	15132670	17394315	12433398	11660227	11660227
Baseline mean	0.76	0.40	0.90	36.82	0.72

Notes: All specifications include county and year fixed effects and individual controls for age, education, race, sex, and marital status. County-level household technology access is only available for the general population. Estimates are weighted by population size. Standard errors clustered at county level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A9. Main Results in Pre-Pandemic Sample (2006-2019)

	(1)	(2)	(3)	(4)
	Panel A. Main Effects			
	Broadband	LFP	Empl	
General Population	0.012***	-0.001	0.002**	
	(0.003)	(0.001)	(0.001)	
Differential (PWD)	-0.019***	0.016***	0.015***	
	(0.002)	(0.003)	(0.002)	
Observations	23.9M	53.5M	38.3M	
	Panel B. Mechanisms			
	Telework	Search Intensity		
General Population	0.002***	-0.000		
	(0.001)	(0.000)		
Differential (PWD)	-0.001	0.001		
	(0.001)	(0.000)		
Observations	35.0M	2.1M		
	Panel C. Employment by Occupation Type			
	Tech/Skill	Remote-Feasible	Coordination	Manual Labor
General Population	0.001	0.002***	0.003***	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Differential (PWD)	0.013***	0.013***	0.014***	0.013***
	(0.003)	(0.002)	(0.002)	(0.003)
Observations	9.3M	15.1M	8.7M	11.8M

Notes: The sample is restricted to observations before 2020. All specifications include county and year fixed effects and individual controls for age, education, race, sex, and marital status. Panel A shows effects on household technology access and labor market effects. Panel B shows effects on the main mechanisms (telework and search intensity). Panel C shows employment effects in subsamples by occupation type. Estimates are weighed by county and personal weights. Standard errors clustered at county level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A10. Interactions with the COVID-19 Pandemic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Broad-band	LFP	Empl	Log Hours	Full-Time	Telework	Search Intensity
Differential (PWD)	-0.011***	0.047***	0.021***	0.018***	0.016***	-0.007***	-0.000
	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)
Differential x COVID-19	0.013***	-0.017***	-0.027***	-0.013***	-0.013***	0.014***	0.001
	(0.002)	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)	(0.001)
Observations	39.1M	70.9M	50.7M	46.8M	47.6M	46.6M	26.6M

Notes: The COVID-19 dummy indicates years 2020 and 2021. All specifications include county and year fixed effects and individual controls for age, education, race, sex, and marital status. Estimates are weighed by county and personal weights. Standard errors clustered at county level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A11. Estimates with Sample Restrictions

	(1) LFP	(2) Employment
	Panel A. Baseline	
CAF II Deployment	-0.003**	0.001
	(0.001)	(0.001)
Disability	-0.341***	-0.075***
	(0.001)	(0.001)
Differential Effect	0.047***	0.016***
	(0.003)	(0.001)
Observations	70938632	50758997
R-squared	0.20	0.05
	Panel B. Excluding Density Extremes	
CAF II Deployment	-0.003***	0.003**
	(0.001)	(0.001)
Disability	-0.333***	-0.077***
	(0.002)	(0.001)
Differential Effect	0.034***	0.020***
	(0.003)	(0.001)
Observations	-0.003***	0.003**
R-squared	(0.001)	(0.001)
	Panel C. Excluding Sensory Impairment	
CAF II Deployment	-0.001	0.002
	(0.001)	(0.001)
Disability	-0.397***	-0.097***
	(0.001)	(0.001)
Differential Effect	0.046***	0.019***
	(0.003)	(0.002)
Observations	67826181	49208687
R-squared	0.20	0.05
	Panel D. Ambulatory Impairment Only	
CAF II Deployment	0.000	0.002**
	(0.001)	(0.001)
Disability	-0.540***	-0.124***
	(0.001)	(0.001)
Differential Effect	0.043***	0.006*
	(0.002)	(0.003)
Observations	65040971	47905739
R-squared	0.20	0.05

Notes: All models include year and county fixed effects. Standard Errors are clustered at the county level. Panel A includes the main specification with the full sample. Panel B drops counties in bottom/top ventile of population density. Panel C excludes individuals with any sensory limitation. Panel D restricts disability group to ambulatory limitations. * p<0.10, ** p<0.05, *** p<0.01

Table A12. Sensitivity to Covariates

	(1) Baseline	(2) Main	(3) Interaction
	Panel A. LFP, General Population		
CAF 2 Deployment	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)
	Panel B. LFP, Differential Effects		
CAF 2 Deployment	-0.002*	-0.003***	-0.002*
	(0.001)	(0.001)	(0.001)
Disability	-0.370***	-0.341***	-0.325***
	(0.002)	(0.001)	(0.001)
Interaction	0.045***	0.047***	0.040***
	(0.003)	(0.003)	(0.003)
	Panel C. Empl., General Population		
CAF 2 Deployment	0.002*	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
	Panel D. Empl., Differential Effects		
CAF 2 Deployment	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Disability	-0.079***	-0.075***	-0.074***
	(0.001)	(0.001)	(0.001)
Interaction	0.015***	0.016***	0.015***
	(0.001)	(0.001)	(0.001)
Observations	70.9-50.7M	70.9-50.7M	70.9-50.7M
Controls	N	Y	Y
FEs	Y	Y	Interaction

Notes: The baseline specification consists of the treatment variable, county and year fixed effects. The main specification includes the full set of controls and fixed effects. The third specification includes the interaction between county and year fixed effects. Estimates are weighed by county and personal weights. Standard errors clustered at county level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A13. County-Level Results Using ACS 5-Year Estimates

	(1)	(2)	(3)	(4)
	Internet	Broadband	LFP	Empl
General Population	0.005***	0.006***	-0.006***	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Differential (PWD)			0.013***	0.010***
			(0.002)	(0.002)
Observations	21993	21993	75391	75391
Baseline Mean (PWD)			0.42	0.36

Notes: All specifications include county and year fixed effects and individual controls for age, education, race, sex, and marital status. County-level household technology access is only available for the general population. Estimates are weighted by population size. Standard errors clustered at county level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A14. PUMA-County Crosswalk Quality

	(1)	(2)	(3)
	Panel A. Crosswalk quality distribution		
		Counties (%)	
1:1 Ratio (p2c ≥ 0.999)		35.79	
Dominant County (0.50 ≤ p2c < 0.999)		6.21	
Ambiguous (0.20 ≤ p2c < 0.50)		17.89	
Highly Probabilistic (p2c < 0.20)		40.09	
	Panel B. Differential coefficient by mapping quality		
	Baseline	1:1 Mapping	Dominant County
CAF II Deployment	-0.0029***	-0.0051***	-0.0050***
	(0.0010)	(0.0012)	(0.0012)
Disability	-0.3407***	-0.3369***	-0.3371***
	(0.0013)	(0.0019)	(0.0019)
Differential	0.0469***	0.0392***	0.0395***
	(0.0027)	(0.0028)	(0.0028)
Observations	70938632	25394547	25479094
R-squared	0.20	0.20	0.20

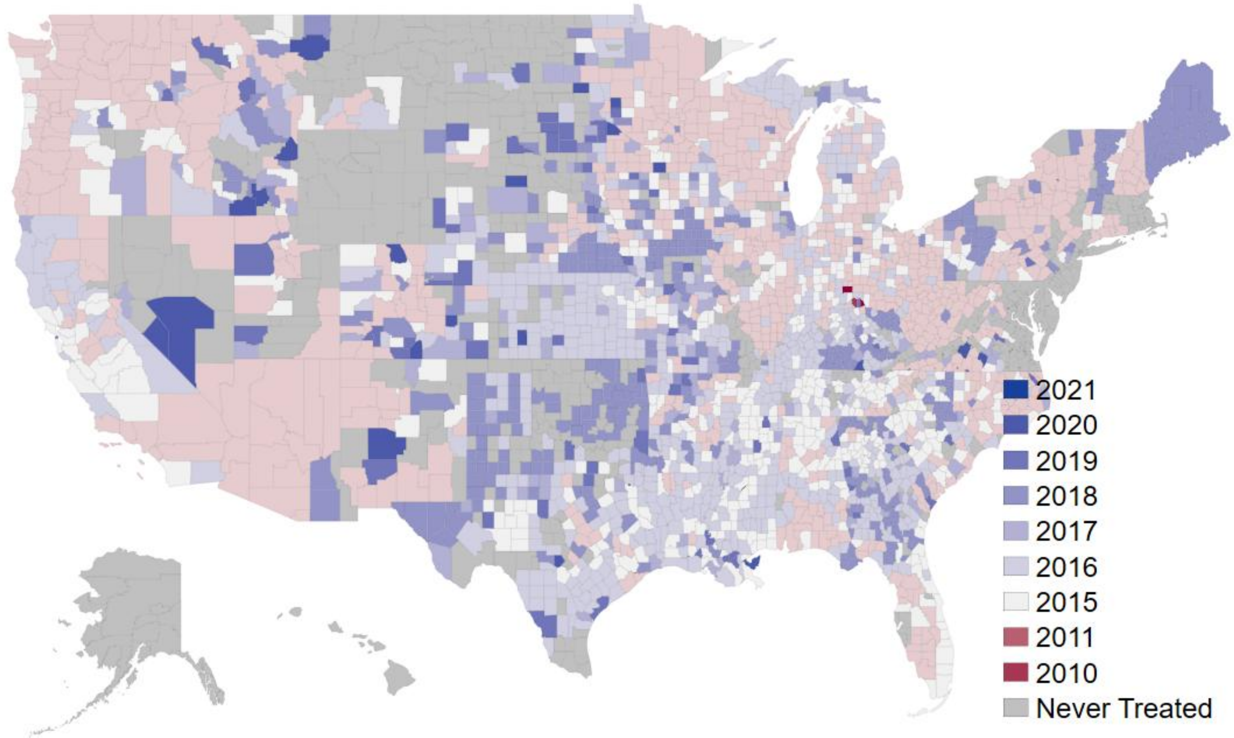
Notes: The table shows Labor Force Participation estimates on various samples depending on the PUMAS-county crosswalk quality. Panel A presents the distribution of counties based on four types: one-to-one matches are cases where a PUMA lies within a given county; dominant-county matches are cases where the majority of the PUMA's population lives in one county; ambiguous matches are cases where no county accounts for a majority of the PUMA; and highly probabilistic matches are cases where the PUMA population is split across many counties. Panel B displays the Labor Force Participation estimates on the baseline regression with the full-sample, including all crosswalk quality types (Column 1), on counties that are only near perfect matches (Column 2), and on dominant counties (Column 3).

Table A15. Cost-Benefit Calculation of CAF II Labor Market Returns

Component	Full Sample	Pre-Pandemic
Total federal outlay, 2015 to 2021 ($)	9.0	
Annualized federal investment ($)	1.5	
Treated working-age population (million)	120	120
New jobs, general population	216,000	0
New jobs, workers with disabilities	216,000	192,000
Total new jobs	432,000	192,000
Implied cost per job ($)	20,833	46,875
Annual wage gains, extensive margin ($ billion)	14.4	5.5
ARRA stimulus cost per job-year (comparison, $)	92,000	

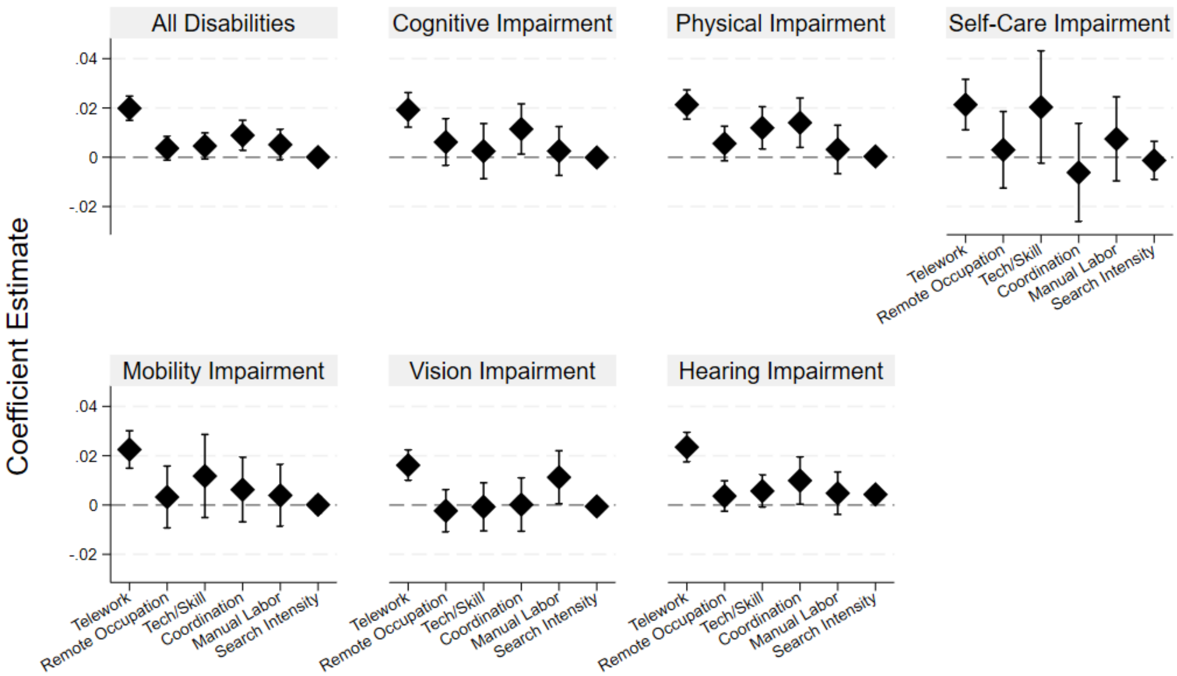
Notes: Employment effects applied to the full-sample treated working-age population are 0.2 percentage points for the general population and 1.8 percentage points for workers with disabilities (Table 2). Pre-Pandemic estimates are zero for the general population and 1.6 for workers with disabilities (Table A8). The treated population assumes 81 percent of counties treated, approximately 120 million working-age adults, and a 10 percent prevalence of functional limitations. Wage gains apply pre-treatment mean annual earnings of $37,900 for the general population and $28,700 for workers with disabilities. The ARRA comparison is from the Council of Economic Advisers (2009) and includes total GDP effects rather than wages alone. The calculation excludes consumer surplus, firm productivity, and non-labor-market benefits and represents a lower bound on total social returns.

Figure A1. Geographical Distribution of CAF II Rollout



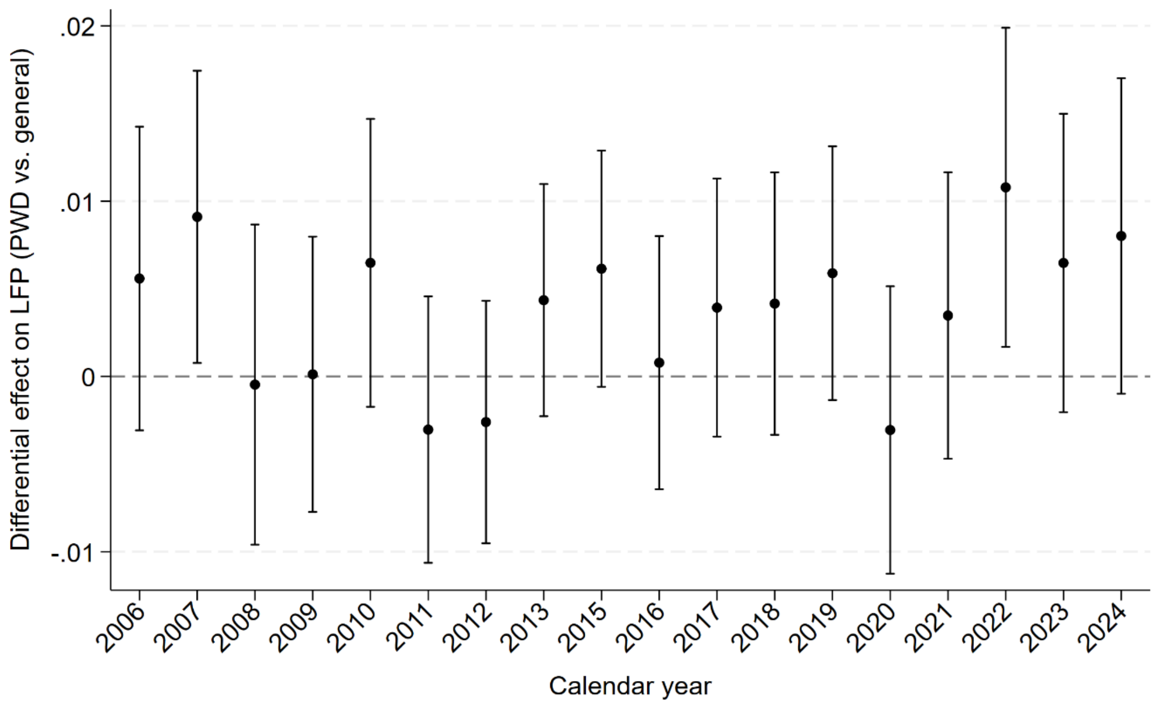
Note: The map plots the geographic distribution of CAF II by treatment year across counties.

Figure A2. Mechanism Tests by Disability Type



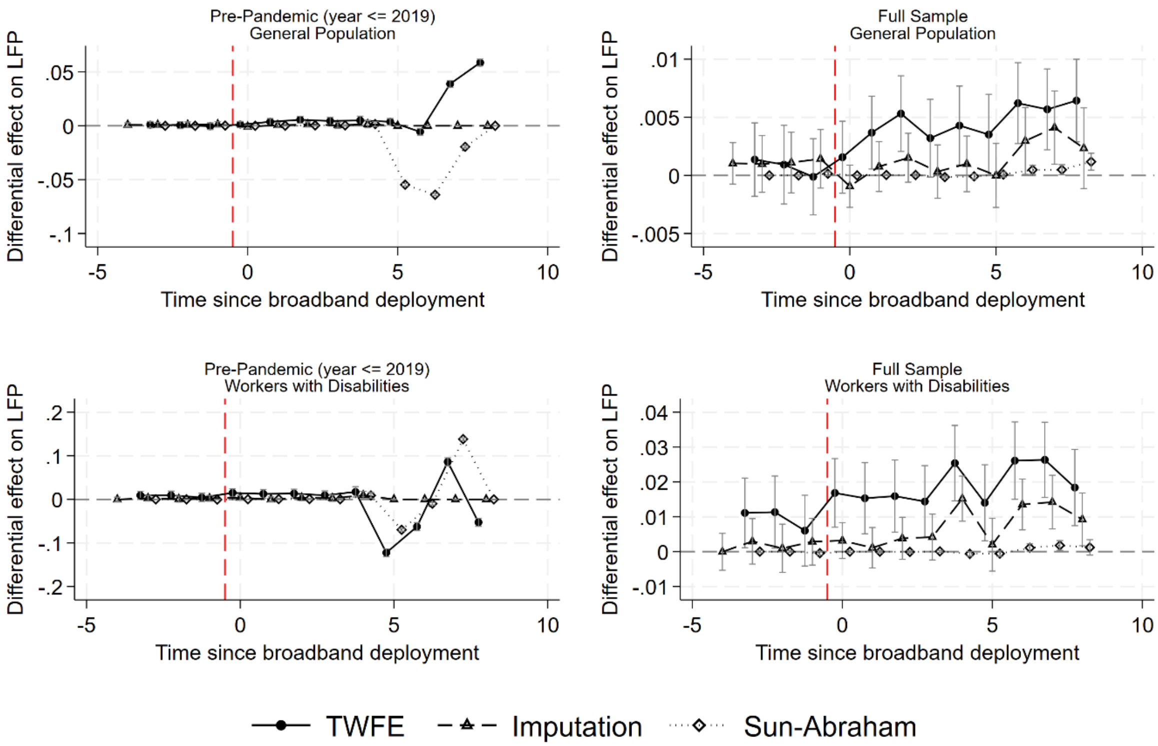
Notes: Coefficients show the CAF II coefficient from specifications including county and year fixed effects and individual controls. Horizontal bars indicate 95 percent confidence intervals.

Figure A3. Year-by-Year Differential Effect on Labor Force Participation



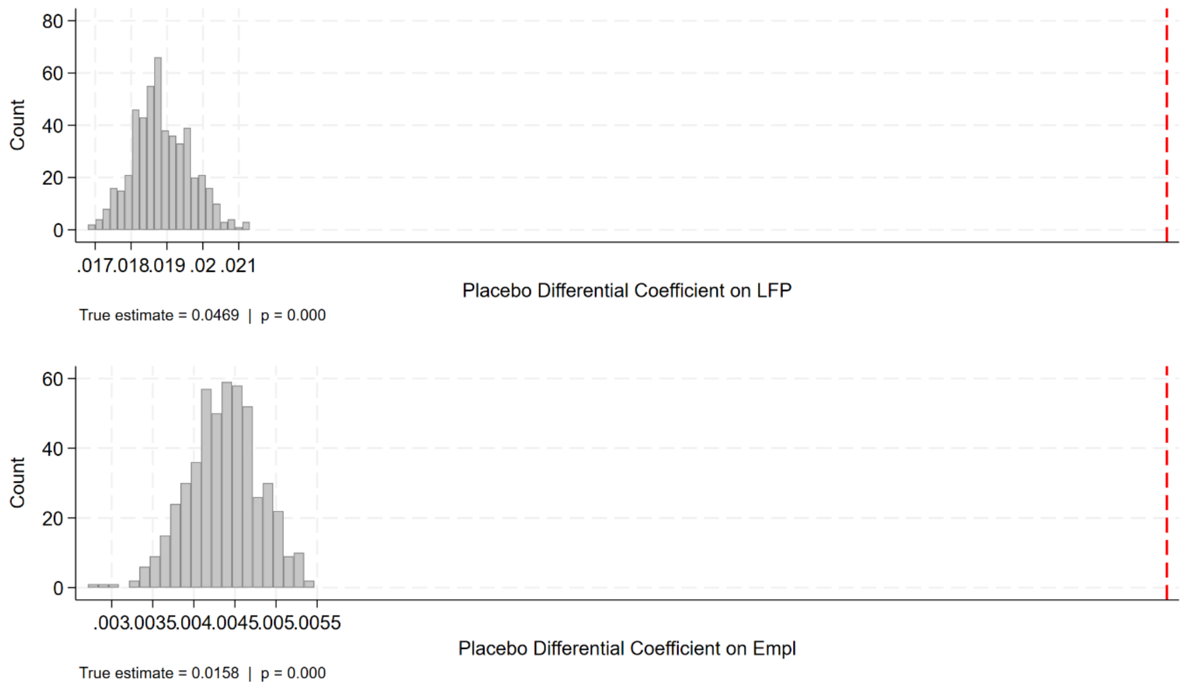
Notes: Coefficients show the CAF II differential coefficient interacted by year. Baseline year is 2014. The specification includes controls, county fixed effects, and year fixed effects. Standard errors are clustered at the county level.

Figure A4. Event Study Split by Pre-Pandemic vs. Full Sample



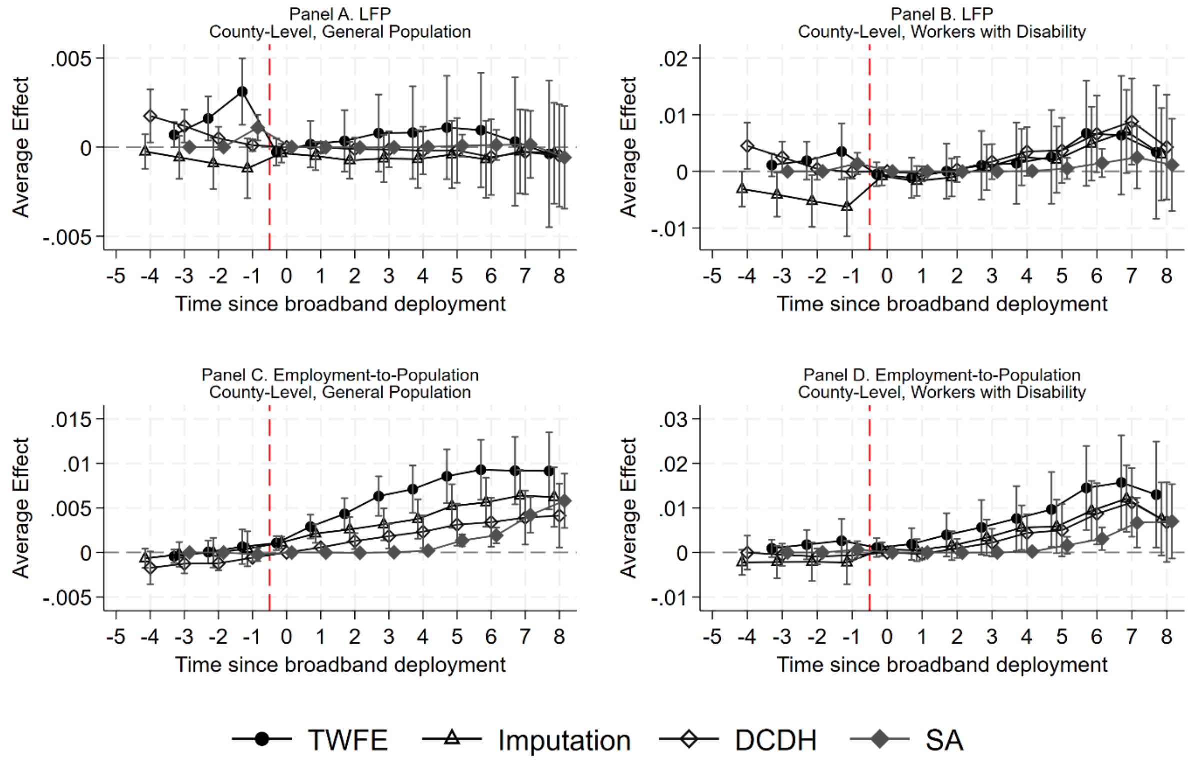
Notes: Event time 0 is year of CAF II deployment. Three estimators shown: two-way fixed effects (TWFE), imputation estimator in Borusyak et al. (2024), and Sun and Abraham (2021). Whiskers indicate 95 percent confidence intervals based on standard errors clustered at county level.

Figure A5. Estimates from Placebo Rollout Assignment Test



Notes: Coefficients show the CAF II differential coefficient from specifications with randomly assigned rollout timing and treatment across counties ($N = 500$ iterations). Rollout timing is randomly assigned following the true distribution of treatment years.

Figure A6. Event Study Estimates in County-level Data



Notes: Event time 0 is year of CAF II deployment. Four estimators shown: two-way fixed effects (TWFE), imputation estimator in Borusyak et al. (2024), De Chaisemartin and D'Haultfoeuille (2023), and Sun and Abraham (2021). Whiskers indicate 95 percent confidence intervals based on standard errors clustered at county level. Sample includes individuals ages 16-64 from the 5-Year ACS 2006-2024.