The Impact of SSA Field Office Closures on Disability Program Participation

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Abstract

This paper estimates the impact of Social Security Administration (SSA) field office closures on participation in federal disability benefit programs. I exploit the uniform, nationwide closure of over 1,200 SSA field offices during the COVID-19 lockdown period as a natural experiment. Using a difference-in-differences framework, I compare changes in the number of newly enrolled disabled beneficiaries across ZIP codes with and without a local SSA office. The results show that, on average, closures reduced the number of disability beneficiaries by 2.3%. The effects are significantly larger in non-metropolitan areas (-9.4%) and in communities with low internet access (-6.65%), suggesting that limited digital infrastructure exacerbated the barriers imposed by the loss of in-person services. These findings provide evidence that in-person administrative access plays a vital role in facilitating disability program enrollment, particularly for vulnerable and digitally underserved populations. The results highlight the risks associated with digital-only service delivery models and emphasize the importance of maintaining physical access points in the design of equitable public service systems.

Keywords: Disability, Social Security programs, Administrative burden.

JEL Classification: I18, I38.

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1 Introduction

Administrative burdens have become a central concern in the design and delivery of public programs. These burdens, comprising learning, compliance, and psychological costs, can deter eligible individuals from participating in social safety net programs. A growing literature highlights how such barriers disproportionately affect marginalized groups, limiting the reach and effectiveness of programs intended to promote social welfare (Giannella et al., 2024; Haeder and Moynihan, 2023; Heinrich et al., 2022; Herd and Johnson, 2024). As governments increasingly digitize public services and expand online enrollment and management systems, a key policy challenge is to understand whether this shift reduces or exacerbates existing access constraints.

Recent trends in public administration reflect growing momentum toward streamlining operations and reducing physical infrastructure through digital service delivery. Proposals to consolidate or close local offices have gained traction, driven by efforts to cut costs, modernize bureaucracies, and respond to shifting user preferences. However, concerns remain that these changes may disproportionately burden individuals with limited digital access or greater support and administrative needs. A notable example of this tension can be seen in the administration of disability benefits.

Disability claimants face significantly higher barriers to benefit enrollment than most other Social Security recipients. The application process for Social Security Disability Insurance (SSDI) is complex, often requiring multiple screenings, medical documentation, and in-person interviews. SSDI eligibility demands extensive administrative navigation, often supported by field office staff. Studying SSDI thus offers a useful lens for understanding how physical access to government services affects program participation, especially for individuals with socioeconomic and health-related vulnerabilities.

This paper investigates how the closure of more than 1,200 Social Security Administration (SSA) field offices during the COVID-19 pandemic affected participation in the SSA federal disability benefit programs. The closures, implemented nationwide in March 2020 as a public health measure, created a natural experiment by abruptly removing in-person access. These closures were not targeted based on local conditions or demographics but applied universally to all SSA field offices; however, the impacts on different groups were not uniform. This setting offers a quasi-experimental opportunity to evaluate the causal effects of losing in-person access on program participation.

To estimate these effects, I construct a panel of ZIP-code-level data from 2016 to 2023, capturing annual changes in the number of enrolled disabled beneficiaries. The identification strategy is a difference-in-differences framework that compares ZIP codes that hosted an SSA field office before the pandemic (treatment group) with ZIP codes that did not have one (control group) in this time period. I supplement this approach with a synthetic difference-in-differences (SDID) estimator, which improves causal identification by adjusting for differential pre-treatment trends, thus creating an arguably better counterfactual comparison for the treated group.

On average, SSA field office closures reduced the number of newly enrolled disabled beneficiaries in treated ZIP codes by approximately 2.3%. These effects are statistically significant across all specifications and robust to the inclusion of state-by-year fixed effects that capture state policy differences at play during this time, and different control groups based on distance to the nearest treated ZIP code.

These effects were not evenly distributed. Non-metropolitan ZIP codes, where residents tend to face limited access to broadband, transportation, and administrative support, experienced a much larger effect, with a decline in beneficiaries of 9.4%. In contrast, metropolitan areas saw smaller reductions of 1.8%, likely because urban residents were better positioned to shift to remote or online application platforms. Further splitting the sample based on internet access explicitly shows that ZIP codes with low internet access experienced even more severe declines. In the lowest-access areas, the estimated effect represents 6.65% decrease in disabled beneficiaries on average. These patterns suggest that digital infrastructure was not a sufficient substitute for in-person support and that the closure of field offices imposed particularly high costs on digitally underserved populations.

This paper builds on several strands of literature. Prior work has examined how changes to Social Security programs affect labor supply, employment, and application behavior (Autor et al. (2019); Burns and Dague (2017); Deshpande (2016b); French and Song (2014); Ne'eman and Maestas (2023b); Powell and Seabury (2018)). Studies have also documented increased SSDI applications during economic downturns (Maestas et al. (2015); Ne'eman and Maestas (2023a)), while the closure of SSA field offices may discourage applications (Deshpande and Li (2019)). However, few studies have used quasi-experimental variation to directly estimate the causal impact of in-person access on disability program participation.

This study makes three key contributions. First, it provides new causal evidence on how disruptions to administrative services influence participation in federal disability programs. Second, it highlights the role of digital inequality in shaping the effectiveness of remote service delivery, demonstrating how limited internet access can compound the exclusionary effects of service disruptions. Third, it contributes to the literature on administrative burdens by showing that eliminating local service infrastructure, even temporarily, can significantly reduce program participation, despite the availability of remote alternatives.

These findings carry important implications for policy. While digital platforms may improve efficiency for some users, the results suggest that eliminating physical access points creates substantial barriers for vulnerable populations. Policymakers weighing the consolidation or closure of local offices must consider the distributional consequences of such decisions. Until digital systems are universally accessible and capable of supporting complex administrative needs, preserving in-person services remains essential to maintaining equitable access to the social safety net.

2 Literature Review

In exploring disability programs, the existing literature has extensively examined their effectiveness and the impact of policy changes on labor supply decisions, employment and earnings statuses, and parental behavior. Additionally, research has focused on the determinants of applying for federal disability programs, particularly considering state-level Medicaid requirements.

The relationship between economic conditions and disability applications has been well-documented. For instance, Maestas et al. (2015) found that SSDI applications are responsive to changes in unemployment. Using a log-linear model, they estimate that a one percentage point increase in the unemployment rate leads to a 1.3 percent increase in applications. Based on this estimate, the five percentage point rise in unemployment observed during the Great Recession would correspond to an approximate 6.7 percent increase in SSDI applications. This finding suggests that adverse economic conditions significantly influence application trends and aligns with the broader literature showing that individuals are more likely to seek disability benefits as a form of financial support during downturns. However, Deshpande and Li (2019) highlighted a mitigating factor: the closure of SSA field offices, which decreased application volume by 10 percent and recipients by 16 percent in affected areas. This suggests that accessibility to application facilities is essential, particularly during economic crises.

The COVID-19 pandemic introduced unique dynamics in the labor market for individuals with disabilities. According to Ne'eman and Maestas (2023b), while initial employment losses were comparable between disabled and non-disabled individuals, the subsequent recovery in 2021-2022 saw a faster employment growth rate among disabled individuals. This was largely driven by increased participation in teleworkable, essential, and non-frontline occupations. These findings imply that the shift towards more flexible and remote work environments may have inadvertently benefited disabled workers, offering new opportunities for labor market integration.

Medicaid expansion has played a significant role in shaping disability program participation. Ne'eman and Maestas (2023a) observed a notable increase in SSDI participation among individuals with specific disabilities post-Medicaid expansion. However, findings on SSI participation were inconclusive, highlighting the complexity of health policy impacts on different disability programs. Additionally, Burns and Dague (2017) noted a 7 percent decline in Supplemental Security Income (SSI) participation following Medicaid expansion, suggesting that increased health coverage access might reduce reliance on SSI benefits. These studies collectively suggest that health insurance availability can influence the decision to apply for disability benefits, although the effects vary across programs and populations.

Application costs are a critical factor in disability program participation. Deshpande and Li (2019) used SSA field office closures to demonstrate that reduced accessibility significantly decreases application volumes. Similarly, Foote et al. (2019) showed that lowering transaction costs through online applications increased SSDI applications, demonstrating that administrative design directly shapes participation. The long-term effects of disability program participation and welfare policy changes have been explored in several studies. Deshpande (2016a) found that removing youth from SSI at age 18 leads to reduced earnings in adulthood, suggesting that early access to disability benefits can have lasting economic impacts. Moreover, Deshpande and Mueller-Smith (2022) demonstrated that removing SSI benefits for youth increased criminal charges and incarceration rates, highlighting unintended negative consequences of welfare policy changes.

The impact of disability insurance on labor supply decisions is also well-documented. French and Song (2014) and Autor et al. (2019) both employed instrumental variable approaches to show that receiving disability benefits decreases labor force participation and earnings. However, the extent of this impact varies, with older individuals, college graduates, and those with mental illness experiencing a less pronounced decline.

Disabled individuals face significant employment barriers and adverse economic outcomes, as shown in numerous studies. McKinney and Swartz (2021) identified employer biases as a major barrier to employment for disabled individuals. Similarly, Bratsberg et al. (2013) and Meyer and Mok (2019) linked job losses and increased disability insurance claims to negative economic outcomes such as poverty and reduced earnings.

These findings emphasize the persistent challenges faced by disabled individuals in the labor market and the need for targeted interventions.

As for administrative burdens, Giannella et al. (2024), Homonoff and Somerville (2021), and Gray (2019) show that procedural denials, recertification costs, and other participation hurdles deter enrollment in safety net programs, while such barriers also impose substantial costs on families and children (Arbogast et al., 2022; Heinrich et al., 2022). Evidence further indicates that these barriers are not experienced equally: racial and socioeconomic disparities shape who is most burdened (Haeder and Moynihan, 2023; Herd and Johnson, 2024), with long-term implications for inequality given the documented benefits of early access to safety nets (Hoynes et al., 2016). Synthesizing this literature, Herd and Moynihan (2023) emphasize that administrative burdens systematically constrain the effectiveness of social protection programs by disproportionately limiting access for marginalized groups.

While the existing literature offers rich insights into the determinants of disability program participation, highlighting the roles of economic conditions, policy design, and individual-level application costs, less is known about how institutional access constraints shape participation in practice. In particular, the administrative infrastructure through which benefits are delivered remains understudied. The closure of SSA field offices during the COVID-19 period presents a rare opportunity to examine the causal role of physical access in shaping program uptake. This study addresses that gap by leveraging the abrupt, nationwide removal of in-person services as a natural experiment. By doing so, it shifts attention from individual behavior to institutional barriers, offering new evidence on how administrative disruptions affect participation in federal disability programs, especially for populations with limited digital access and greater reliance on local service infrastructure.

3 Background

The Social Security Disability Insurance (SSDI) program provides monthly benefits to individuals who are unable to engage in substantial gainful activity due to a severe and long-lasting health condition. Eligibility is based on two dimensions: a sufficient history of covered employment with recent contributions to Social Security, and medical criteria requiring evidence of an impairment expected to last at least twelve months or result in death. To evaluate SSDI applications, the SSA uses a five-step sequential process. This process considers whether the applicant is currently working, whether the condition is severe, whether it meets the SSAs official listings of impairments, and, if not, whether the individual can perform past work or adjust to alternative employment (Social

Security Administration, 2023).

Applications begin at local field offices, where staff verify non-medical eligibility factors such as age and work history. Claims are then transferred to state Disability Determination Services (DDS), where disability examiners and medical consultants review medical evidence, request additional documentation, or order consultative examinations. This two-stage structure is intended to ensure consistency in both administrative and medical determinations (Social Security Administration, 2023).

The COVID-19 pandemic introduced an unprecedented disruption. On March 17, 2020, SSA closed more than 1,200 field offices to the public, halting nearly all in-person services (U.S. Government Accountability Office, 2022). While applications could still be filed online, by mail, or over the phone, the sudden loss of in-person intake altered the way claimants interacted with the agency. SSA expanded remote options, including publishing local telephone numbers, enhancing the *my Social Security* portal, and introducing limited telehealth consultative examinations. Despite these adjustments, in-person services did not fully resume until April 2022 (Social Security Administration, 2023; U.S. Government Accountability Office, 2022). Appendix Figure A1 traces this operational timeline.

Because of the closures, states processed 119 fewer SSDI initial claim determinations per month, while pending caseloads increased by more than 650 cases on average. Applications for reconsiderations, which allow individuals to appeal an initial assessment, rose by about 40, and applications for continuing disability reviews increased by nearly 150 (see Appendix Figure A2 and Table A1. A preliminary analysis for SSDI claims at the state-level before and after the closures[1] shows statistically significant increases in pending cases alongside declines in determinations and allowances (see Table A2 in the Appendix). Despite efforts to expand remote service options, including phone lines and online applications, the closure of field offices was associated with notable disruptions to the flow of applications and decisions.

This context motivates a ZIP-code-level analysis. While the closures were nationwide, local dependence on field offices varied substantially. Geographic variation in the presence of SSA offices creates an opportunity to identify how losing physical access affected disability program participation.

[1] I implement a two-way fixed effect regression, following this equation with monthly data from SSA State Monthly Workload Data from January 2015 to January 2024: $Y_{st} = \alpha_s + \gamma_t + \beta \cdot \text{SSAClosure}_t + \varepsilon_{st}$, where Y_{st} denotes the outcomes of interest in state s and month-year t, including applications, pending cases, determinations, and allowances. The variable SSAClosure_{st} is a binary indicator equal to one during the SSA field office closure period (March 2020 to April 2022). State fixed effects α_s control for time-invariant heterogeneity across states, while month-year fixed effects γ_t absorb national time trends and seasonality.

4 Data

To capture local variation in disability program participation and identify causal effects of SSA field office closures, I used the ZIP-code counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries, published annually by the SSA. This data provides annual totals of program recipients by geographic unit and benefit type. The analysis is restricted to ZIP codes in the contiguous United States, excluding Hawaii, Alaska, U.S. territories, and island areas due to their distinct geographic and administrative structures.

The analysis focuses exclusively on disabled beneficiaries, excluding those receiving retirement or survivor benefits. I construct a balanced panel of ZIP-code-level observations from 2015 to 2023 and compute the annual change in the number of disabled beneficiaries as a proxy for new benefit approvals. This structure supports a difference-in-differences framework comparing ZIP codes that hosted a local SSA field office before the pandemic (treated) to those that did not have one (control) [2], leveraging geographic variation in access to in-person services prior to COVID-19. To identify treated ZIP codes, I used the SSAs public list of current field office addresses and matched them to ZIP codes.

I use ZIP-code-level data because, first, they offer finer spatial resolution than state-level claims data, allowing identification of geographic patterns in program participation. Second, unlike administrative claims data, which reflect submitted applications, these data measure realized participation by counting individuals who successfully entered the disability rolls. The annual change in the number of disabled beneficiaries thus serves as a credible proxy for program entry.

To account for differences in population size across ZIP codes, I compute the annual change in disabled beneficiaries per 100,000 residents. The population denominator is drawn from the ACS 5-Year Estimates at the ZIP-code level. This per capita transformation ensures comparability across areas of different sizes and prevents larger ZIP codes from disproportionately influencing the results. It also supplements the analysis by offering a normalized metric of program growth.

Because physical proximity may interact with rural remoteness in shaping program access, I classify ZIP codes as metropolitan or non-metropolitan using the 2020 ZIP Code

[2]The control group is defined as ZIP codes that did not have a Social Security Administration (SSA) field office within the sample period of 2016 to 2023, based on the current list of field offices. Some ZIP codes may have hosted an office in the past but experienced closures prior to 2016. Publicly available data document office closures before the sample period (Deshpande and Li, 2019), but it is not possible to determine whether additional closures occurred between 2016 and 2023. Therefore, the assumption is that the control group never had an SSA field office during the sample period.

Tabulation Area (ZCTA) to county crosswalk. ZIP codes are assigned the metro status of the county where the majority of their land area falls. Although some ZIP codes span both types, excluding these ambiguous cases would result in considerable sample loss. Since classification is based on majority overlap, any misclassification is limited and unlikely to introduce systematic bias.

To control for socioeconomic differences, I merge in a set of local characteristics from the American Community Survey (ACS) 5-Year Estimates. These include total population, the share of residents living below the poverty line, unemployment rate, mean income, and educational attainment, disaggregated into the shares with a high school diploma, some college, an associate degree, or a bachelors degree. Population density is calculated as the total population divided by land area.

In addition, I include several measures of internet access to assess whether broadband availability moderated the effect of field office closures. Specifically, I use the percentage of households with internet subscriptions from the ACS 5-Year Estimates (2017-2023) and the ACS 1-Year Estimates. The 2020 ACS 1-Year Estimates were not released due to pandemic-related disruptions that compromised data quality. I interpolate the missing value as the average of 2019 and 2021.

I also incorporate county-level data on broadband provider coverage from the Federal Communications Commission (FCC), available through 2021. While this measure reflects provider availability rather than actual household connectivity, it serves as a useful robustness check. The FCC data are known to overstate coverage (Grubesic (2012)). To improve interpretability, I calculate the number of broadband providers relative to county population as a proxy for provider density. Although this is the weakest of the internet measures, it offers an alternative specification for sensitivity tests.

Finally, I construct binary indicators for high internet access based on whether a ZIP codes internet subscription value exceeds the sample median value in each measure. These variables support heterogeneity analysis by digital connectivity, a relevant dimension of modern service delivery. Rural areas with limited broadband adoption are particularly vulnerable to the impacts of field office closures, as they lose access to physical services while facing constraints in using online alternatives.

Table 1 presents summary statistics for the full sample, ZIP codes with an SSA field office before closure, and ZIP codes without one. On average, ZIP codes with a field office experienced larger declines in the annual change of disabled beneficiaries, both in absolute terms and per capita, than those without. These ZIP codes also tend to be more urban, with higher populations, greater density, slightly higher unemployment rates, and lower average incomes.

Table 1: Summary Statistics for ZIP Codes with SSA Office, without SSA Office, and Full Sample.

	All ZIP Codes in Sample	ZIP Codes with SSA Field Office Pre-Closure	ZIP Codes without SSA Field Office	Difference in Means
	Mean (SD)	Mean (SD)	Mean (SD)	p-value
Disabled Beneficiaries	256.4	875.2	232.3	0.000
	(350.8)	(473.4)	(321.8)	
Annual Change in Disabled Beneficiaries	-5.769	-20.63	-5.188	0.000
	(18.79)	(29.37)	(18.01)	
Annual Change in Disabled Beneficiaries per 100,000 Population	-72.03	-86.66	-71.45	0.199
	(1,460)	(301.5)	(1,487)	
Annual Change in Disabled Beneficiaries in Metro Areas	-8.450	-21.90	-7.741	0.000
	(23.51)	(31.17)	(22.82)	
Annual Change in Disabled Beneficiaries in Non-Metro Areas	-2.512	-17.53	-2.175	0.000
	(9.722)	(23.73)	(8.878)	
ZIP Code Characteristics				
Population	10,669	32,252	9,826	0.000
	(15,133)	(17,496)	(14,391)	
Population Density	1,285	3,712	1,190	0.000
	(5,048)	(8,950)	(4,807)	
% People living below the poverty line	9.854	12.94	9.734	0.000
	(9.061)	(7.975)	(9.080)	
Mean Income	81,205	76,622	81,384	0.000
	(36,987)	(26,812)	(37,317)	
Unemployment Rate	5.629	6.646	5.589	0.000
	(5.163)	(3.387)	(5.216)	
% High School Graduate	28.47	25.75	28.58	0.000
	(11.90)	(7.945)	(12.02)	
% Some College	16.29	16.02	16.30	0.003
	(8.530)	(7.146)	(8.579)	
% Associate Graduate	11.59	11.76	11.58	0.029
	(7.257)	(6.420)	(7.287)	
% College Graduate	13.41	15.29	13.34	0.000
	(9.661)	(8.319)	(9.702)	
% of Internet Subscription (ACS 5-Year Estimates)*	81.16	82.78	81.09	0.000
	(8.628)	(7.924)	(8.648)	
% of Internet Subscription (ACS 1-Year Estimates)*	87.78	87.34	87.81	0.000
	(5.971)	(6.122)	(5.961)	
% Broadband Providers (FCC)*	66.43	71.27	66.24	0.000
	(15.33)	(13.23)	(15.37)	
High Internet Access (Above-Median ACS 5-Year Estimates)	0.500	0.597	0.496	0.000
	(0.500)	(0.490)	(0.500)	
High Internet Access (Above-Median ACS 1-Year Estimates)	0.501	0.477	0.502	0.000
	(0.500)	(0.500)	(0.500)	
High Internet Access (Above-Median Broadband Providers (FCC))	0.500	0.670	0.494	0.000
	(0.500)	(0.470)	(0.500)	
Observations	231,888	8,720	223,168	

Notes: The full sample is based on ZIP-code-level data for Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries published annually by the Social Security Administration (SSA), covering the period from 2016 to 2023. ZIP Codes with SSA Field Office Pre-Closure refers to ZIP codes that had a physical SSA field office prior to the COVID-19 pandemic and experienced temporary closures between 2020 and 2022. ZIP code characteristics are primarily drawn from the American Community Survey (ACS) 5-Year Estimates. The p-value column reports the test for the difference in means between treated and control ZIP codes (two-sample t-test). Variables marked with an asterisk (*) are not available for the full sample period. Specifically, the percentage of internet subscriptions from the ACS 5-Year Estimates is available from 2017 to 2023. The ACS 1-Year Internet Subscription Estimates cover 2016 to 2023, though 2020 data were not published; the 2020 value was interpolated as the average of 2019 and 2021. Broadband provider coverage data from the Federal Communications Commission (FCC) is available through 2021.

Figure A4 in the Appendix displays the national distribution of SSA field office locations. Together, these descriptive statistics support a ZIP-code-level research design that accounts for the spatial distribution of in-person access and enables identification of causal effects based on local variation in service availability.

5 Empirical Strategy

To identify the causal effects of SSA field office closures, I use a panel of ZIP-code-level annual changes in the number of disabled OASDI beneficiaries. This analysis leverages local variation in office presence before the pandemic within a difference-in-differences framework. ZIP codes that hosted an SSA office before 2020 comprise the treatment group, while those that never hosted an office within the sample period serve as the control group. The identifying assumption is that, absent the closures, trends in disability benefit participation would have evolved similarly in both the treatment and control groups (parallel trends assumption).

The core hypothesis motivating this analysis is that individuals residing in ZIP codes with an SSA office may have relied more heavily on in-person services for accessing disability benefits. The sudden closure of local offices during the COVID-19 pandemic could have imposed significant barriers in these areas, potentially reducing application activity and limiting program participation. In contrast, ZIP codes that never hosted an SSA field office would have been less dependent on in-person interactions and may be better positioned to continue engagement through remote channels.

The nationwide and uniformly implemented closure of SSA field offices during the COVID-19 pandemic presents a rare opportunity to study the causal effects of disrupting access to administrative services. Unlike targeted policy reforms, this shutdown was applied equally to all field offices, regardless of local conditions or service demand. Because the SSA closures were triggered by a national public health emergency rather than endogenous local decisions, treatment assignment is plausibly exogenous to ZIP code-level characteristics that influence disability benefit participation. This exogenous variation supports a difference-in-differences identification strategy and enables a quasi-experimental framework to estimate the impact of losing physical service access. In this context, the pandemic-induced office closures serve as a natural experiment to evaluate how constraints on in-person access affect the take-up of federal social safety net programs.

The model is specified as:

$$Y_{zt} = \alpha_z + \gamma_t + \delta \cdot \text{Treatment}_z \times \text{Post}_t + \mathbf{X}_{zt}\Gamma + \varepsilon_{zt} \tag{1}$$

where Y_{zt} is the annual change in the number of disabled beneficiaries in ZIP code z and year t, which serves as a proxy for new benefit approvals and program entry. ZIP-code fixed effects α_z account for time-invariant local factors, and year fixed effects γ_t absorb time trends and seasonality. The interaction term $\text{Treatment}_z \times \text{Post}_t$ captures the differential change in the outcome for ZIP codes with an SSA office following the closures, representing the average treatment effect on the treated (ATET). Covariates $\mathbf{X}_{zt}$ include the unemployment rate, poverty rate, income, and educational attainment from the ACS.

To examine the evolution of the treatment effect over time, I also estimate event-style regressions that compare annual outcomes relative to the 2019 baseline. This allows both a visual inspection of pre-treatment trends and an assessment of the persistence or dissipation of the treatment effect after offices reopened in 2022.

The event-style specification is:

$$Y_{zt} = \alpha_z + \gamma_t + \beta \cdot \text{Treatment}_z + \sum_{k \neq 2019} \delta_k \cdot (\text{Treatment}_z \times \mathbb{1}_{\{t=k\}}) + \mathbf{X}_{zt}\Gamma + \varepsilon_{zt} \tag{2}$$

where δ_k captures year-specific effects relative to 2019, the omitted base year. The coefficients for pre-2020 years (2016 to 2018) are used to test for pre-trends with the assumption that these trends would have continued in the absence of treatment. Coefficients from 2020 onward trace the trajectory of the treatment effect after closures, including any persistent or recovering trends once offices reopened in 2022.

This design tests the hypothesis that the most pronounced effects of office closures may occur in 2020 and 2021, during the period of complete suspension of in-person services. If access to local SSA offices played a critical role in facilitating benefit participation, one would expect to observe a decline during these years, followed by a partial or full recovery after in-person operations resumed in 2022. A return to pre-pandemic participation levels would be consistent with the interpretation that reduced access (rather than underlying trends or demand shifts) drove the observed changes.

All regressions are estimated with standard errors clustered at the ZIP code level. Specifications were tested both with and without population weights and with and without controlling for population density. Weighting by population ensures that larger ZIP codes, which represent more individuals, have a proportionally greater influence on the estimated effects. This reduces the influence of sparsely populated ZIP codes that may have noisier data. Controlling for population density adjusts for urban areas and service infrastructure differences, which may affect both access to services and reliance on SSA field offices.

To strengthen the identification strategy and address concerns about potential violations of the parallel trends assumption, I additionally implement the Synthetic Difference-in-Differences (SDID) framework proposed by Arkhangelsky et al. (2021). This method combines the strengths of traditional difference-in-differences and synthetic control by constructing weighted averages of untreated ZIP codes and time periods that closely match the pre-treatment outcome trajectories of treated ZIP codes.

The SDID estimator is used to estimate the average causal effect of exposure to SSA field office closures, denoted by $\hat{\tau}_{\text{sdid}}$. The method assigns unit weights to untreated ZIP codes that match treated units based on pre-treatment trends and time weights that balance pre- and post-treatment periods. These weights are then applied within a weighted two-way fixed effects regression that accounts for unobserved unit-level and time-level heterogeneity.

Let Y_{zt} denote the annual change in the number of disabled beneficiaries for ZIP code z in year t, and let $C_{zt} \in \{0, 1\}$ be a binary indicator equal to one for ZIP codes that experienced a field office closure starting in 2020, and zero otherwise. The SDID estimator without covariates is defined as:

$$(\hat{\tau}_{\text{sdid}}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg \min_{\tau,\mu,\alpha,\beta} \sum_{z=1}^{N} \sum_{t=1}^{T} \left(Y_{zt} - \mu - \alpha_z - \beta_t - C_{zt}\tau\right)^2 \hat{\omega}_z \hat{\lambda}_t \tag{3}$$

where $\hat{\omega}_z$ and $\hat{\lambda}_t$ are ZIP code and year weights, respectively, selected to minimize differences in pre-treatment outcomes across treated and control ZIP codes and across time. Fixed effects α_z and β_t absorb time-invariant ZIP-code characteristics and time-specific shocks common to all units.

To account for time-varying covariates, I follow the residualization approach recommended by Arkhangelsky et al. (2021). Specifically, I first regress the outcome on observed covariates and compute the residuals:

$$Y_{zt}^{\text{res}} = Y_{zt} - X_{zt}'\hat{\gamma} \tag{4}$$

where X_{zt} includes time-varying controls such as the unemployment rate, share of the population below the poverty line, income, educational attainment, and population density. The SDID estimator is then applied to these residuals to estimate the treatment effect net of observed covariates:

$$(\hat{\tau}_{\text{sdid}}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg\min_{\tau,\mu,\alpha,\beta} \sum_{z=1}^{N} \sum_{t=1}^{T} \left(Y_{zt}^{\text{res}} - \mu - \alpha_z - \beta_t - C_{zt}\tau\right)^2 \hat{\omega}_z \hat{\lambda}_t \tag{5}$$

This approach allows me to isolate the average causal effect of exposure to SSA office closures, while preserving the robust counterfactual construction that accounts for latent confounding factors. Statistical inference is conducted using a nonparametric bootstrap procedure, which resamples ZIP codes with replacement. For each iteration, the treatment effect is re-estimated, allowing for the construction of valid confidence intervals that account for serial correlation and panel dependence.

To assess whether the impact of SSA field office closures varied across regional and infrastructural contexts, I implemented a series of heterogeneity analyses and robustness checks. First, I estimate the main specification separately for metropolitan and non-metropolitan ZIP codes. This stratification tests whether residents in rural areas, who typically face more limited access to broadband infrastructure, digital literacy, and transportation, experienced more pronounced declines in benefit participation due to their greater reliance on in-person administrative services. The results from this analysis speak to potential disparities in how remote service delivery affects different geographic communities (see Appendix section A.1).

Second, I conducted a distance-based sensitivity analysis to assess the robustness of the control group and examine potential spatial spillover effects. ZIP codes located within five miles of a treated ZIP code are excluded to avoid contamination, and the remaining untreated ZIP codes are divided into distance bands: 5-10 miles, 10-20 miles, and more than 20 miles from the nearest treated ZIP. This approach allows me to test whether treatment effects grow stronger when comparing treated areas to control units located farther away, where reliance on the same field office would have been less likely. If geographic proximity to SSA offices influenced service usage before the pandemic, more distant control groups should yield cleaner comparisons and larger estimated effects (see Appendix section A.2).

To further account for confounding policy variation, I also included a specification with state-by-year fixed effects, which absorb differential pandemic-related responses across states and over time (see Appendix section A.3).

Finally, I test for a key mechanism by examining whether local internet access moderated the impact of SSA office closures. Using county-level data on broadband availability, I estimated treatment effects separately for high-access and low-access areas. This analysis is motivated by the idea that residents in low-connectivity ZIP codes may have faced greater difficulty transitioning to remote SSA service options during the pandemic. If digital infrastructure is a relevant constraint, then office closures should have led to larger declines in program participation in these digitally underserved communities (for more details, see Appendix section A.4).

6 Results

The results come from the causal inference methods applied to ZIP-code-level annual changes in the number of disabled beneficiaries, which serve as a proxy for newly approved applicants and program participation. The analysis leverages a quasi-experimental setting created by the pandemic-induced closures of SSA field offices, comparing areas with and without local office access prior to the pandemic. The results provide evidence on the average treatment effect on the treated, as well as the timing and persistence of these effects over time.

By using ZIP codes that never hosted an SSA office as a comparison group, the analysis relies on a more stable and credible counterfactual. The models exploit spatial variation in field office presence and temporal variation before and after the closures, allowing for a more precise estimate of how access constraints affected participation in federal disability programs during the pandemic. This approach isolates the role of in-person administrative access in shaping benefit uptake.

Table 2 reports the main findings from the ZIP-code-level analysis of SSA field office closures, estimated using both the difference-in-differences (DID) and synthetic difference-in-differences (SDID) frameworks. Across all DID specifications, ZIP codes served by a field office that closed during the pandemic experienced a statistically significant decline in the number of new disabled beneficiaries relative to ZIP codes that never hosted a local SSA office.

The estimated treatment effects are consistently negative and statistically significant at the 1 percent level across all model variations. The point estimates become more stable and precise when models are weighted by population and include controls for population density, which account for differences in ZIP code size and geographic coverage. Column (5) adds the county-level mortality rate as a control variable to account for differences in death rates and to rule out the possibility that the decline in the outcome is driven by higher mortality among disabled individuals rather than by reduced approvals, which is the proxy used in this analysis.[3] Column (6) presents the SDID estimate, which is slightly larger in magnitude and remains highly significant.

Table 2: Effect of SSA Field Office Closures on Disabled Beneficiaries.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment x Post	-9.577***	-4.291***	-4.315***	-4.291***	-4.444***	-5.523***
	(0.616)	(0.775)	(0.777)	(0.775)	(0.776)	(0.808)
% relative to control mean (pre-treat.)	-3.9%	-1.8%	-1.8%	-1.8%	1.8%	-2.3%
Observations	231,888	231,888	231,888	231,888	229,712	231,888
R-squared	0.324	0.298	0.297	0.298	0.311	-
Weighted by population	No	No	Yes	Yes	Yes	No
Control for population density	No	Yes	No	Yes	Yes	Yes
Control for mortality rate	No	No	No	No	Yes	No
Method	DID	DID	DID	DID	DID	Synthetic DID

Notes: Standard errors in parentheses. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The outcome variable is the annual change in disabled beneficiaries. The sample period spans 2016 to 2023. All regressions include ZIP code and year fixed effects, with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. Median household income is also included. Column (5) additionally controls for the county-level mortality rate, which comes from the Provisional Mortality Statistics - Center for Disease Control and Prevention (CDC). Effect sizes are expressed as a percentage of the pre-treatment control group mean of the dependent variable. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1 compares the average treatment effects estimated using DID and SDID approaches. The left panel presents the DID estimates with controls included but without population weighting. The right panel displays the SDID estimates, which use data-driven weights to better align the pre-treatment trajectories of treated and control ZIP codes. The gray shaded areas represent the weights assigned across years, with the SDID estimator placing more weight on observations from 2018 to construct a better counterfactual. In contrast, the DID estimator treats all pre-period observations equally.

[3]County-level mortality data are not available for all counties over the sample period, which reduces the number of observations. Because results remain consistent, the main analysis proceeds without this control in subsequent specifications.

Figure 1: Effect of SSA Field Office Closures on Disabled Beneficiaries (SDID Estimates).

Notes: This figure presents synthetic difference-in-differences estimates of the impact of SSA field office closures on the annual change in the number of disabled beneficiaries. The sample period spans 2016 to 2023. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include population density, the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The red vertical line denotes the onset of SSA field office closures. The shaded area at the bottom of the figure reflects the sample weights used to construct the synthetic control group. All estimates are statistically significant at the 1 percent level.

The estimated treatment effect is larger in magnitude under the DID model compared to the SDID model, consistent with the possibility that the unweighted DID specification may overstate the impact by not accounting for differences in population size and different pre-trends (which can be seen in Figure 1). As shown in Table 2, the inclusion of population weights and control for population density improves the precision and stability of the DID estimates. This comparison highlights the robustness of the negative effect across identification strategies.

The decline in disability program participation may vary in both magnitude and persistence across years. Figure 2 presents annual treatment effects relative to the 2019 pre-closure baseline. The first vertical line marks the onset of the closure period in 2020, while the second corresponds to the post-reopening period following the full resumption of in-person services in April 2022. The figure confirms that pre-trends hold before 2020, followed by a sustained decline in the number of newly enrolled disabled beneficiaries from 2020 through 2022. A partial recovery is observable in 2023, consistent with the reopening of in-person administrative access, which can also be observed in Figure 1.

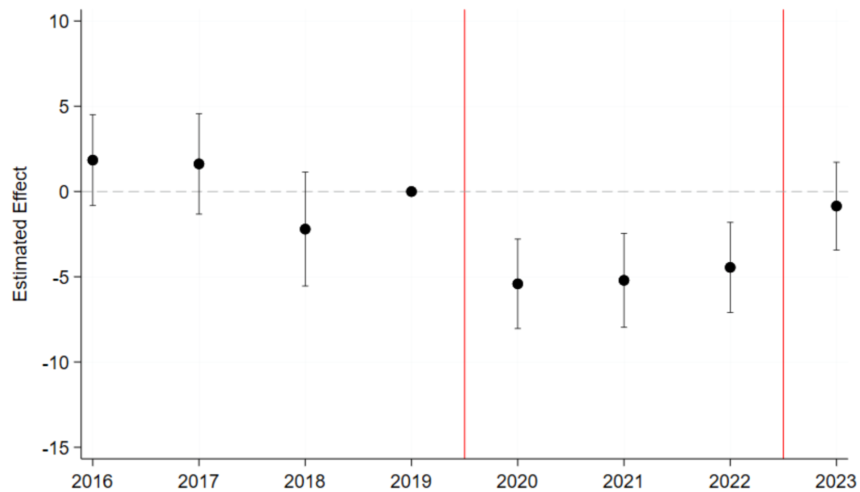


Figure 2: Annual Treatment Effects on Disabled Beneficiaries.

Notes: This figure presents the annual treatment effects of the impact of SSA field office closures on the annual change in the number of disabled beneficiaries, estimated from an event-style regression. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The sample period spans 2016 to 2023. All regressions are weighted by population and include ZIP code and year fixed effects, with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include population density, the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. The red vertical line between 2019 and 2020 marks the onset of SSA field office closures, while the line between 2022 and 2023 marks their reopening.

These results are consistent with a setting in which in-person administrative services play a critical role in facilitating disability benefit applications. The observed rebound in 2023 further supports the interpretation that access constraints were a key driver of the participation decline during the closure period. In sum, the closure of SSA field offices, on average, reduced the number of newly enrolled disabled beneficiaries by approximately four to five individuals per ZIP code per year, relative to ZIP codes without an SSA office. This result represents a 2.3% reduction in the number of disabled beneficiaries relative to the control group's pre-treatment average[4].

Additionally, to further account for differences in ZIP code population size, Appendix Table A3 and Figure A5 reports these effects in per capita terms, confirming the direction and significance of the results.

[4]The control group's pre-closure average was 243.8 disabled beneficiaries in the program.

6.1 Heterogeneous Effects

Table 3 reports estimates from the DID and SDID models, disaggregated by metropolitan and non-metropolitan ZIP codes. This heterogeneity analysis is motivated by the expectation that non-metro areas may be more vulnerable to access disruptions due to limited broadband infrastructure, lower levels of digital literacy, and greater reliance on in-person public services. If field offices serve as a more critical access point in rural communities, closures would be expected to produce a larger decline in program participation in those areas.

The results confirm this hypothesis. The estimated treatment effects are consistently larger in non-metro ZIP codes than in metro ZIP codes across all model specifications, indicating that the impact of closures was more pronounced where alternative access channels were limited.

Table 3: Effect of SSA Field Office Closures on Disabled Beneficiaries: Metro and Non-Metro.

	Metro			Non-metro		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment x Post	-3.166***	-3.132***	-6.331***	-10.421***	-10.449***	-10.552***
	(0.906)	(0.903)	(0.863)	(1.337)	(1.335)	(1.025)
% relative to control mean (pre-treat.)	-0.9%	-0.9%	-1.8%	-9.3%	9.3%	-9.4%
Observations	125,864	125,864	125,864	103,384	103,384	103,384
R-squared	0.292	0.292	-	0.343	0.344	-
Weighted by population	Yes	Yes	No	Yes	Yes	No
Control for population density	No	Yes	Yes	No	Yes	Yes
Method	DID	DID	Synthetic DID	DID	DID	Synthetic DID

Notes: Standard errors in parentheses. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The outcome variable is the annual change in disabled beneficiaries per capita. The sample period spans 2016 to 2023, and the model is estimated separately for metropolitan and non-metropolitan ZIP codes. All regressions include ZIP code and year fixed effects, with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. Median household income is also included. Effect sizes are expressed as a percentage of the pre-treatment control group mean of the dependent variable. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 3 displays average treatment effects from the SDID specification estimated separately for metro and non-metro subsamples. The estimates imply that field office closures reduced the number of newly enrolled disabled beneficiaries by about 10 per ZIP code per year in non-metro areas, versus roughly 6 in metro areas. Relative to pre-treatment means, these correspond to declines of 9.4% and 1.8%, respectively, [5] making the proportional effect in non-metro areas roughly five times larger. This pattern is consistent with greater dependence on in-person administrative services in rural locations.

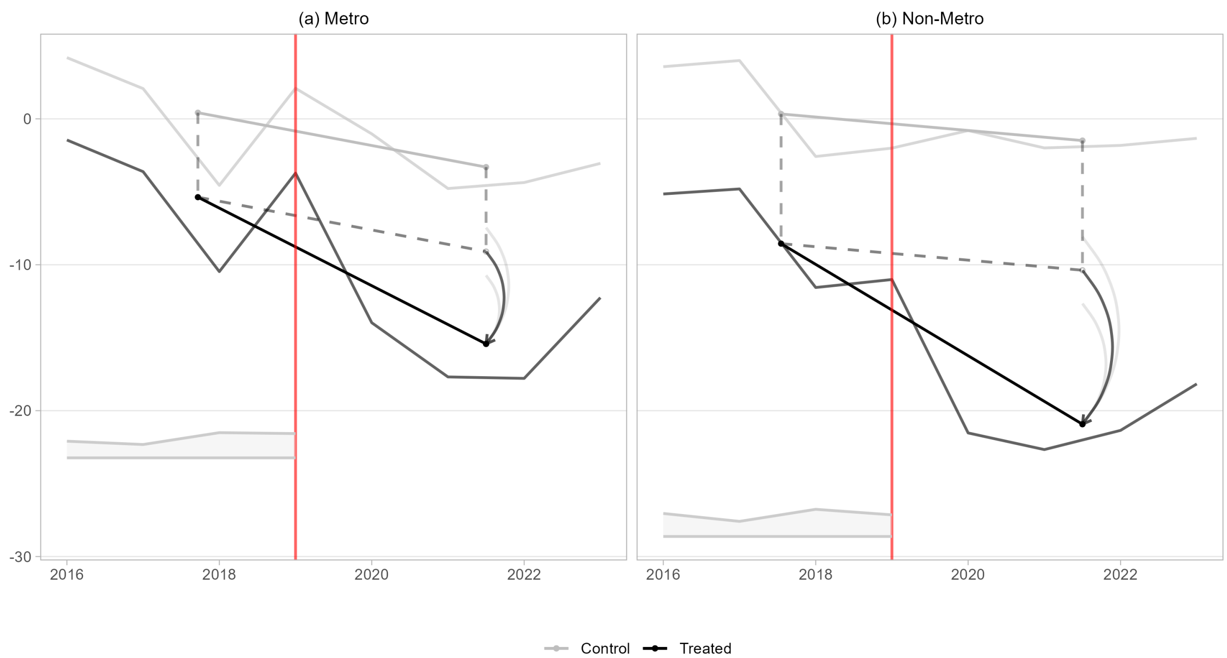
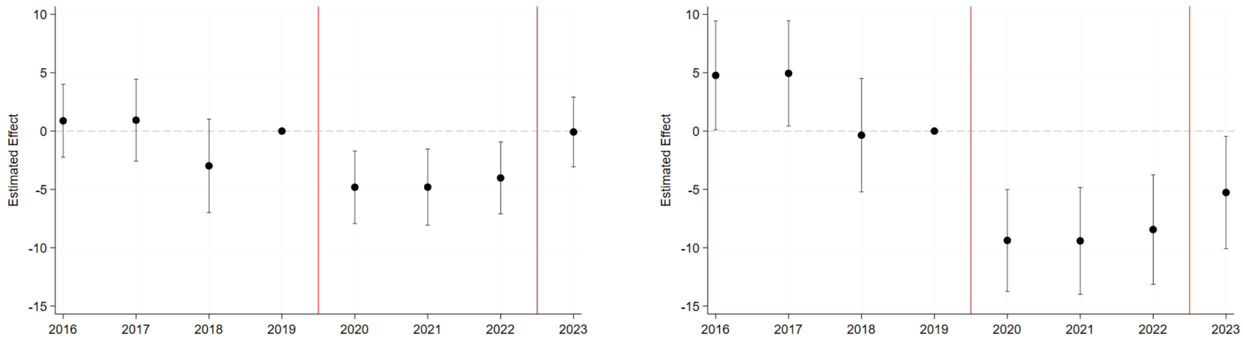


Figure 3: Average Treatment Effects on Disabled Beneficiaries by Metropolitan Status (SDID Estimates).

Notes: This figure presents synthetic difference-in-differences estimates of the impact of SSA field office closures on the annual change in the number of disabled beneficiaries disaggregated by metropolitan and non-metropolitan ZIP codes. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The sample period spans 2016 to 2023. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include population density, the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. The red vertical line denotes the onset of SSA field office closures. The shaded area at the bottom of the figure reflects the sample weights used to construct the synthetic control group. All estimates are statistically significant at the 1 percent level.

To further examine the dynamics of the treatment effect, Figure 4 displays the annual estimates from event-style regressions. In both metro and non-metro ZIP codes, pre-treatment trends are relatively stable. A clear treatment effect emerges, beginning in 2020 and persisting through 2022, with partial recovery evident in 2023 following the reopening of field offices. This pattern reinforces the interpretation that the SSA closures introduced access constraints that were uneven across metro and non-metro areas.

[5] Control-group pre-closure averages were 354.8 disabled beneficiaries in metro areas and 111.9 in non-metro areas.



(a) Metro

(b) Non-Metro

Figure 4: Annual Treatment Effects on Disabled Beneficiaries, by Metropolitan Status.

Notes: This figure presents the annual treatment effects of the impact of SSA field office closures on the annual change in the number of disabled beneficiaries, estimated from an event-style regression and disaggregated by metropolitan status. Data on disabled beneficiaries is from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The sample period spans 2016 to 2023. All regressions are weighted by population and include ZIP code and year fixed effects, with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include population density, the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. The red vertical line between 2019 and 2020 marks the onset of SSA field office closures, while the line between 2022 and 2023 marks their reopening.

6.2 Robustness Checks

6.2.1 Distance to the Nearest SSA Office

To assess the robustness of the ZIP-code-level estimates and address potential contamination from neighboring areas, I re-estimate the main specification models using alternative control groups based on distance from treated ZIP codes. ZIP codes located within five miles of a treated area are excluded to minimize potential spillover effects. The remaining control groups are stratified by increasing distance from the nearest SSA field office: 5-10 miles, 10-20 miles, and more than 20 miles (see section A.2 for more details).

Table 4 presents the results. Across all three control groups, the estimated treatment effects remain negative and statistically significant, consistent with the primary findings. Importantly, the magnitude of the effect increases with distance from treated ZIP codes. For ZIP codes 5-10 miles away, the estimated reduction is approximately 7 newly approved disabled beneficiaries per year. This effect grows to about 8 beneficiaries in the 10-20 mile group, and exceeds 10 in the group located more than 20 miles away. While there are some differences in magnitude between the DID and SDID estimates, the increasing gradient with distance is evident across both approaches.

Table 4: Effect of SSA Field Office Closures Using Distance-Based Control Groups.

	5 miles < n < 10 miles		10 miles < n < 20 miles		n > 20 miles	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment x Post	-2.207***	-7.307***	-5.202***	-8.374***	-10.942***	-10.082***
	(0.852)	(0.795)	(0.840)	(0.709)	(0.865)	(0.738)
% relative to control mean (pre-treat.)	-0.6%	-1.9%	-2.4%	-3.9%	-9.8%	-9%
Observations	48,000	48,000	76,376	76,376	99,312	99,312
R-squared	0.400	-	0.414	-	0.456	-
Weighted by population	Yes	No	Yes	No	Yes	No
Control for population density	Yes	Yes	Yes	Yes	Yes	Yes
Method	DID	Synthetic DID	DID	Synthetic DID	DID	Synthetic DID

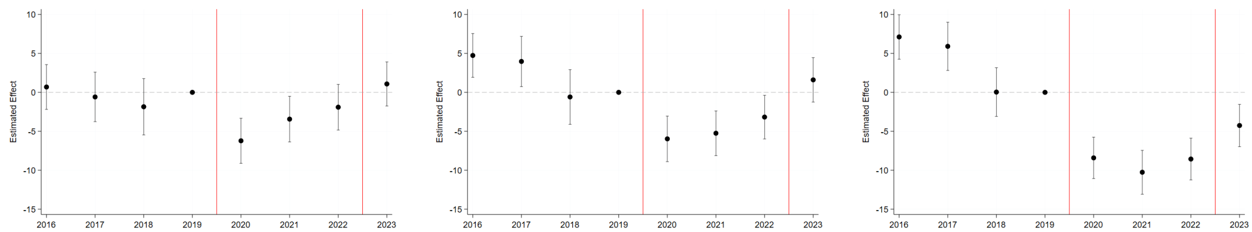
Notes: Standard errors in parentheses. Data on disabled beneficiaries are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The outcome variable is the annual change in disabled beneficiaries. The sample period spans 2016 to 2023. The treatment group consists of ZIP codes that hosted SSA field offices before the pandemic. Control groups are defined by their distance from treated ZIP codes: (a) 5-10 miles, (b) 10-20 miles, and (c) more than 20 miles away. ZIP codes within 5 miles of a treated area are excluded to avoid spillover effects. All regressions include ZIP code and year fixed effects, with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. Median household income is also included. Effect sizes are expressed as a percentage of the pre-treatment control group mean of the dependent variable. *** p<0.01, ** p<0.05, * p<0.1.

The larger treatment effects observed in more distant control groups support the interpretation that ZIP codes closer to field offices may share unobserved similarities with treated areas, including reliance on the same regional service infrastructure. In contrast, ZIP codes farther from treated areas are less likely to have had regular access to SSA offices before the pandemic, making them a cleaner counterfactual for identifying causal effects.

Figure 5 presents annual treatment effect estimates using control groups defined by increasing distance from treated ZIP codes. Panel 5a uses nearby ZIP codes located 5 to 10 miles away. The decline in disabled beneficiaries is modest and partially reversed by 2022, likely reflecting shared access to services or demographic similarities with treated areas. Panel 5b, using ZIP codes 10 to 20 miles away, shows a more substantial and persistent reduction, consistent with greater pre-pandemic separation in access to in-person services. Panel 5c compares treated ZIP codes to those located more than 20 miles away and reveals the sharpest and most sustained declines, indicating a cleaner counterfactual and stronger identification of the treatment effect, consistent with the DID models from Table 4.

The increasing magnitude of effects with greater geographic distance reinforces the interpretation that SSA field office closures significantly disrupted access to disability benefits. The SDID estimates further ensure that pre-treatment trends are adequately balanced, lending additional credibility to the causal interpretation (Figure 6). These results also confirm that the observed declines are not artifacts of control group contamination or differential pre-trends but rather reflect real disruptions in benefit access, particularly in areas that previously relied on nearby in-person administrative services.

Overall, while the estimates are somewhat sensitive to the choice of control group, the direction and statistical significance of the effects remain robust. The distance-based analysis strengthens the conclusion that the loss of physical access to SSA services during the pandemic meaningfully suppressed disability program participation, especially in ZIP codes dependent on field offices for service delivery.



(a) 5 miles < n < 10 miles (b) 10 miles < n < 20 miles (c) n > 20 miles

Figure 5: Annual Treatment Effects on Disabled Beneficiaries Using Distance-Based Control Groups.

Notes: This figure presents the annual treatment effects of the impact of SSA field office closures on the annual change in the number of disabled beneficiaries, estimated from an event-style regression using different distance-based control groups. The treatment group consists of ZIP codes that hosted SSA field offices before the pandemic. Control groups are defined by their distance from treated ZIP codes: (a) 510 miles, (b) 1020 miles, and (c) more than 20 miles away. ZIP codes within 5 miles of a treated area are excluded to avoid spillover effects. Data on disabled beneficiaries is from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The sample period spans 2016 to 2023. All regressions are weighted by population and include ZIP code and year fixed effects, with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include population density, the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. The red vertical line between 2019 and 2020 marks the onset of SSA field office closures, while the line between 2022 and 2023 marks their reopening.

Figure 6: Average Treatment Effects on Disabled Beneficiaries Using Distance-Based Control Groups (SDID Estimates).

Notes: This figure presents synthetic difference-in-differences estimates of the impact of SSA field office closures on the annual change in the number of disabled beneficiaries using alternative distance-based control groups. The treatment group consists of ZIP codes that hosted SSA field offices before the pandemic. Control groups are defined by their distance from treated ZIP codes: (a) 510 miles, (b) 1020 miles, and (c) more than 20 miles away. ZIP codes within 5 miles of a treated area are excluded to avoid spillover effects. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The sample period spans 2016 to 2023. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include population density, the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. The red vertical line denotes the onset of SSA field office closures. The shaded area at the bottom of the figure reflects the sample weights used to construct the synthetic control group. All estimates are statistically significant at the 1 percent level.

6.2.2 State Level Policies

To address the potential confounding influence of time-varying, state-specific factors, such as differences in state-level COVID-19 policies, economic recovery efforts, or administrative responses, Table A4 in the Appendix presents results that include state-by-year fixed effects for the full sample, as well as for metropolitan and non-metropolitan subsamples. Across all specifications, the estimated treatment effects remain negative, statistically significant, and consistent in magnitude with the baseline results. This confirms that the observed declines in disability program participation are not driven by concurrent state-level policy changes or unobserved shocks at the state-year level. The persistence of the treatment effect, even after accounting for granular policy variation, further supports the robustness of the empirical evidence that SSA field office closures directly suppressed new benefit enrollment.

6.3 Mechanism Analysis: Access to Internet

One plausible mechanism driving disability program participation is differential access to digital connectivity following the closure of SSA field offices. During the pandemic, in-person services were abruptly suspended, and applicants were expected to navigate SSA procedures through online portals or telephone-based alternatives. This transition may have disproportionately affected areas with limited internet connectivity or broadband infrastructure, creating new barriers to benefit access.

Table 5: Effect of SSA Field Office Closures on Disabled Beneficiaries, by Internet Access Level.

	Full Sample			High Internet Access			Low Internet Access		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel (a)									
Treatment × Post	-3.880***	-2.746***	-6.199***						
	(0.824)	(0.862)	(0.917)						
Panel (b)									
Treatment × Post	-3.881***	-2.716***	-6.202***	-1.951*	-1.694	-5.453***	-8.457***	-4.451***	-7.624***
	(0.824)	(0.860)	(0.917)	(1.004)	(1.137)	(1.103)	(1.270)	(1.208)	(1.502)
Internet Access	0.009	-0.137**	0.038						
	(0.063)	(0.069)	(0.032)						
% relative to control mean (pre-treat.)	-1.6%	-0.7%	-2.7%			-1.7%	-4.8%	-1.2%	-5.2%
Observations	202,902	118,045	163,172	101,454	59,074	80,719	101,444	58,530	81,399
R-squared	0.317	0.305	0.406	0.499	0.471	0.530	0.520	0.516	0.452
Internet Access	ACS 5	ACS 1	FCC	ACS 5	ACS 1	FCC	ACS 5	ACS 1	FCC

Notes: Standard errors in parentheses. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The outcome variable is the annual change in disabled beneficiaries. The sample period spans 2016 to 2023. All regressions include ZIP code and year fixed effects, weighted by population, and with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include the percentage of the population below the poverty line, unemployment rate, and educational attainment. Internet access is measured using three county-level indicators: ACS 5-Year Estimates (ACS 5), ACS 1-Year Estimates (ACS 1), and FCC broadband provider data. High internet access indicates above-median values; low internet access indicates below-median values. Effect sizes are expressed as a percentage of the pre-treatment control group mean of the dependent variable. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5 explores the role of internet access in shaping the effects of SSA field office closures on disability program participation. The estimates in columns (1) through (3) confirm that the treatment effect remains negative and statistically significant across all full-sample models that incorporate different measures of internet connectivity (ACS 5-Year internet subscriptions, ACS 1-Year subscriptions, and FCC broadband provider coverage). When the sample is split by high and low internet access, a consistent pattern emerges: ZIP codes with below-median connectivity experience substantially larger and statistically significant declines in new disabled beneficiaries.

Figure 7 presents the SDID estimates for ZIP codes with low internet access across the three measures. In panel (a), the point estimate is -11.734; in panel (b), it is -7.506; and in panel (c), it is -10.636. All are statistically significant at the 1 percent level (see Table A5 for full statistics with standard errors). The magnitudes of the effects are slightly larger when estimated using DID without population weights, but the direction of the results remains the same. For instance, under the ACS 5-Year specification, which is relatively a more representative sample given broader data availability, the effect in low-access ZIP codes corresponds to a 4.8% decline using the DID estimates and a 6.65% decline using the SDID estimates. Both are more than twice the magnitude of the baseline estimate of -2.3%.[6]

Figure 7: Average Treatment Effects on Disabled Beneficiaries in Low Internet Access (SDID Estimates).

Notes: This figure presents synthetic difference-in-differences estimates of the impact of SSA field office closures on the annual change in the number of disabled beneficiaries for ZIP codes with below-median internet access. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The outcome variable is the annual change in disabled beneficiaries. The sample period spans 2016 to 2023. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include population density, the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The share of residents with a postgraduate degree is omitted and serves as the reference category. Internet access is measured using three county-level indicators: ACS 5-Year Estimates (ACS 5) for the percentage of households with an internet subscription, ACS 1-Year Estimates (ACS 1) for the same variable based on annual data, and FCC data representing the percentage of broadband providers. These measures are assigned to ZIP codes based on the county in which each ZIP code is located. ZIP codes are classified as having low internet access if they fall below the median of each respective metric. The red vertical line marks the onset of SSA field office closures. The shaded area at the bottom of the figure reflects the sample weights used to construct the synthetic control group. All estimates are statistically significant at the 1 percent level.

This divergence reinforces that remote service capacity was not equally available across locations. High-access ZIP codes, likely more digitally equipped, showed smaller or

[6]The control group pre-treatment average for the low internet access based on the ACS 5-year estimates sample was 176.4 disabled beneficiaries.

insignificant effects, suggesting greater resilience in transitioning to online platforms. In contrast, areas with limited broadband infrastructure faced a compounded disadvantage, losing physical access to SSA services without having sufficient digital alternatives. These communities were less able to navigate benefit applications remotely, amplifying the administrative barriers introduced by office closures.

The results highlight how gaps in digital infrastructure can exacerbate exclusion from federal social safety net programs. When in-person access is removed, internet connectivity becomes a vital substitute channel. Without it, service disruptions are more likely to translate into real declines in benefit uptake. As such, universal shifts toward remote service delivery, while administratively efficient, risk widening geographic disparities and disproportionately affecting digitally disconnected communities.

Overall, these findings highlight the important role of digital infrastructure in ensuring equitable access to public services and provide evidence that technological capacity must be accounted for when designing inclusive administrative systems.

7 Discussion

Field office closures increased the effective cost of entering the social safety net, with the burden falling most on rural communities and on places with limited broadband access. In these locations, in-person help is difficult to replace through phone and internet channels. Travel distances are longer, digital access is limited, and completing complex forms without staff assistance is more difficult. The pattern is consistent with an access mechanism: reductions in approved beneficiaries are largest where substitutes for in-person assistance are scarce, which points to a widening divide in access to disability insurance rather than a temporary change in how people apply.

There are several other forces that likely shaped SSDI applications and approvals during the period of office closures. These include broader macroeconomic conditions, shifts in labor market opportunities, and changes in both the application behavior of potential beneficiaries (demand for services) and the administrative processing of claims (supply of services). Each of these channels interacted with the closure of field offices in different ways. The discussion that follows examines how these mechanisms were at play.

Macroeconomic conditions and access moved together during this period. Maestas et al. (2015) show that SSDI applications rise when unemployment increases. During COVID-19, however, SSDI applications fell rather than rose, which runs counter to this usual cyclical pattern. This is consistent with access constraints and remote service frictions that reduced successful applications and approvals. Deshpande and Li (2019) show that field office closures reduce both applications and recipients, reinforcing the role of physical access, findings that align closely with the results here. What remains unclear is what drove the decline in applications during the economic recession.

The CARES Act and later laws raised weekly Unemployment Insurance payments, extended UI duration, broadened UI eligibility, and the Paycheck Protection Program helped firms keep workers on payroll. These policies could have led potential SSDI applicants to delay applications or remain attached to work, including by moving into remote jobs. Each of these channels reduces applications and, by extension, approvals, even without any change in physical access.

Employment opportunities for disabled workers rebounded faster in 2021 to 2022 in places with more teleworkable and non-frontline jobs (Ne'eman and Maestas, 2023b). Better job options could reduce applications; however, this cannot be directly observed in the data. Broadband remains the key mediating factor. Without reliable broadband, both remote work and online applications are limited. Phone filing is a partial fallback, but longer waits, higher abandonment rates, and document handling requirements make it an imperfect substitute for in-person help (U.S. Government Accountability Office, 2022).

These points suggest that the observed effect of losing in-person access is likely underestimated. The true effect may be larger if labor market conditions and remote work had not influenced applications and if these factors had been the same across locations. The inclusion of unemployment rates as controls and state-by-year fixed effects addresses these factors to some extent, but the extensions of Unemployment Insurance, which were both large and prolonged, and the stimulus payments could still have played a role.

Despite these theoretical predictions, the relatively larger effects found in low-internet and non-metro ZIP code locations, cannot plausibly be explained by telework opportunities. Instead, with limited access to remote work and online services, the observed decline in disabled beneficiaries is more likely to reflect real access costs. This reinforces the internet access mechanism and highlights the particularly high impact of office closures in rural areas.

The OASDI data do not allow me to observe applications directly at the local level, which presents a limitation and can obscure other mechanisms at play. The decision to apply for benefits and the delivery of services from SSA offices are both operating when looking at the change in disabled beneficiaries, the outcome variable. Applications and approvals can move differently when staffing or backlogs slow down decisions. In the short run, slower processing of claims lowers approvals even if application intent is unchanged, which could overestimate the size of the observed effect. Over a longer horizon, as pending cases are decided, this mechanical effect can fade, and the initial decline can move toward zero. This may have occurred alongside the reopening of offices in April 2022, when staff returned to local offices and program participation began returning to pre-closure levels.

Service delivery shifted away from in-person assistance and increasingly leaned toward phone and internet channels following the office closures induced by the pandemic (U.S. Government Accountability Office, 2022). Before the closures, applications could be submitted by phone as well as online, but the online portal was further developed afterward. Calls to field offices and the national 800 number rose, average wait times increased, and call abandonment rates were higher than before the pandemic. These changes raised the time and hassle costs for phone users and reduced completion for people with low digital literacy or unstable connectivity.

Field offices also handle retirement and survivors' services. Changes in these workloads can affect the same phone lines and staff that disability insurance applicants use. If retirement traffic crowded out disability intake capacity, access constraints for SSDI claimants would intensify, making the decline appear larger.

The specific application channel used is not observed at the ZIP code level, which could matter in areas with low internet connectivity, where phone calls might serve as a substitute and prevent people from being completely cut off from services during the closure period. If the focus were solely on application behavior and channels, this could influence the estimates. However, since newly approved beneficiaries reflect all application channels, differences in how people chose to apply should not heavily affect the estimated effects. In all cases, in-person access was cut off, which supports the identification strategy to draw causal effects. Taken together, these considerations suggest that the estimates capture the overall effect, net of both demand-side application behavior and supply-side service delivery constraints.

However, from another perspective, if areas with low internet connectivity could substitute for phone calls for applications, this could weaken the interpretation of the internet mechanism as fundamental for program participation. Although phone calls could be used for applications, digital adoption also accelerated during the pandemic (U.S. Government Accountability Office, 2022). Online transactions increased, and internet applications rose, lowering the marginal cost of applying for connected households. However, substitution was incomplete. Online pathways and language access were limited for some groups, including claimants who needed Spanish interfaces, which potentially increased application costs and restricted digital substitution. In places where such groups are more prevalent, the decline would be larger.

Lastly, it remains unclear how disabling conditions from long COVID, which was approved as a qualifying disability condition in July 2021, affected outcomes during the closures. This could potentially increase applications for disability benefits, particularly in 2022 and 2023 when offices were reopening. The extent of this effect would also depend on the geographic distribution of long COVID cases, as regional variation in incidence could drive heterogeneous application responses. Disentangling these relationships is only possible once data on disability application conditions and severity status become available.

Future work should leverage administrative data from the SSA to disentangle applications from approvals, assess whether the choice of channel matters, and evaluate the extent to which phone calls truly substituted for internet-based applications. Linking office-level phone performance and appointment rules to local exposure, as well as exploiting cross-state variation in UI parameters, could further illuminate program substitution. Heterogeneity by age and language, together with broadband-linked measures of digital access, would allow researchers to quantify substitution to remote channels and identify barriers beyond internet connectivity and literacy. Additional attention could also be given to retirement benefits. Finally, integrating health data to proxy the geographic prevalence of long COVID would help isolate channel access effects from changes in underlying need.

8 Conclusion

This paper examines the causal effects of administrative disruptions on disability program participation by leveraging the nationwide closure of over 1,200 SSA field offices during the COVID-19 pandemic. Using a rich panel of ZIP-code-level data on disabled beneficiaries, combined with quasi-experimental causal inference methods, the analysis isolates the effect of losing in-person access to SSA services on benefit enrollment.

The results consistently show that ZIP codes that lost access to a local SSA field office experienced statistically significant declines in the number of newly enrolled disabled beneficiaries, relative to areas that did not have an office. These effects persisted through the closure period and only began to reverse following the return of in-person services in 2022-2023. The magnitude of the decline, while modest in absolute terms, is meaningful when aggregated across the full set of affected ZIP codes and reflects a real constraint on access to federal safety net programs.

Importantly, the analysis reveals that these access disruptions were not experienced uniformly. The effects were larger in non-metropolitan areas and in ZIP codes with limited internet access, locations where residents are more likely to rely on in-person services and less equipped to transition to remote service channels. This heterogeneity underscores the distributional consequences of administrative policy design: when agencies move toward remote delivery without accounting for digital infrastructure gaps or transportation barriers, they risk disproportionately excluding the very populations most in need of support.

These findings contribute to a growing literature on the role of administrative burdens in shaping program take-up. While much prior work emphasizes the benefits of expanding online services or simplifying application procedures, this study highlights the risks associated with removing physical access points. In doing so, it shifts the conversation from how governments can increase efficiency to how they can preserve accessibility, especially in contexts where structural inequities limit digital engagement.

From a policy perspective, the results suggest that maintaining a geographically equitable presence of administrative offices remains a critical component of effective program delivery. As agencies modernize and digitize their operations, complementary investments in broadband access and digital literacy are necessary to ensure that these changes do not unintentionally widen gaps in service provision. Moreover, policy evaluations should incorporate measures of administrative accessibility as a core element of distributional impact assessments.

Ultimately, this study demonstrates that administrative infrastructure is not a neutral delivery channel but a key determinant of who benefits from public programs. Understanding where and how access constraints emerge is essential for designing inclusive and responsive safety net systems.

References

Arbogast, Iris, Anna Chorniy, and Janet Currie (2022), "Administrative burdens and child medicaid enrollments." Working Paper 30580, National Bureau of Economic Research.

Arkhangelsky, Dmitry, Susan Athey, David A. Hirshberg, Guido W. Imbens, and Stefan Wager (2021), "Synthetic difference-in-differences." *American Economic Review*, 111, 40884118, URL `https://www.aeaweb.org/articles?id=10.1257/aer.20190159`.

Autor, David, Andreas Kostøl, Magne Mogstad, and Bradley Setzler (2019), "Disability benefits, consumption insurance, and household labor supply." *American Economic Review*, 109, 2613–2654.

Bratsberg, Bernt, Elisabeth Fevang, and Knut Røed (2013), "Job loss and disability insurance." *Labour Economics*, 24, 137–150.

Burns, Marguerite and Laura Dague (2017), "The effect of expanding medicaid eligibility on supplemental security income program participation." *Journal of Public Economics*, 149, 20–34.

Deshpande, Manasi (2016a), "Does welfare inhibit success? the long-term effects of removing low-income youth from the disability rolls." *American Economic Review*, 106, 3300–3330.

Deshpande, Manasi (2016b), "The effect of disability payments on household earnings and income: Evidence from the ssi children's program." *Review of Economics and Statistics*, 98, 638–654.

Deshpande, Manasi and Yue Li (2019), "Who is screened out? application costs and the targeting of disability programs." *American Economic Journal: Economic Policy*, 11, 213–248.

Deshpande, Manasi and Michael Mueller-Smith (2022), "Does welfare prevent crime? the criminal justice outcomes of youth removed from ssi." *The Quarterly Journal of Economics*, 137, 2263–2307.

Foote, Andrew, Michel Grosz, and Stephanie Rennane (2019), "The effect of lower transaction costs on social security disability insurance application rates and participation." *Journal of Policy Analysis and Management*, 38, 99–123.

French, Eric and Jae Song (2014), "The effect of disability insurance receipt on labor supply." *American Economic Journal: Economic Policy*, 6, 291–337.

Giannella, Eric, Tatiana Homonoff, Gwen Rino, and Jason Somerville (2024), "Administrative burden and procedural denials: Experimental evidence from snap." *American Economic Journal: Economic Policy*, 16, 316–340.

Gray, Colin (2019), "Leaving benefits on the table: Evidence from snap." *Journal of Public Economics*, 179, 104054.

Grubesic, Tony H. (2012), "The u.s. national broadband map: Data limitations and implications." *Telecommunications Policy*, 36, 113–126, URL `https://www.sciencedirect.com/science/article/pii/S0308596111002266`.

Haeder, Simon F. and Donald Moynihan (2023), "Race and racial perceptions shape burden tolerance for medicaid and supplemental nutritional assistance program." *Health Affairs*, 42, 1334–1343.

Heinrich, Carolyn J., Sayil Camacho, Sarah Clark Henderson, Mónica Hernández, and Ela Joshi (2022), "Consequences of administrative burden for social safety nets that support the healthy development of children." *Journal of Policy Analysis and Management*, 41, 11–44.

Herd, Pamela and Rebecca A. Johnson (2024), "Rationing rights: Administrative burden in medicaid long term care programs." *Journal of Health Politics, Policy, and Law*.

Herd, Pamela and Donald Moynihan (2023), "Administrative burdens in the social safety net." *Journal of Economic Perspectives*, 37, 189–212, URL `https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.20231394`.

Homonoff, Tatiana and Jason Somerville (2021), "Program recertification costs: Evidence from snap." *American Economic Journal: Economic Policy*, 13, 271–298.

Hoynes, Hilary, Diane Whitmore Schanzenbach, and Douglas Almond (2016), "Long-run impacts of childhood access to the safety net." *American Economic Review*, 106, 903–934.

Maestas, Nicole, Kathleen J Mullen, and Alexander Strand (2015), "Disability insurance and the great recession." *American Economic Review*, 105, 177–182.

McKinney, Emma Louise and Leslie Swartz (2021), "Employment integration barriers: Experiences of people with disabilities." *The International Journal of Human Resource Management*, 32, 2298–2320.

Meyer, Bruce D and Wallace KC Mok (2019), "Disability, earnings, income and consumption." *Journal of Public Economics*, 171, 51–69.

Ne'eman, Ari and Nicole Maestas (2023a), "How does medicaid expansion impact income support program participation and employment for different types of people with disabilities?" Working Paper 31816, National Bureau of Economic Research, URL `http://www.nber.org/papers/w31816`.

Ne'eman, Ari and Nicole Maestas (2023b), "How has covid-19 impacted disability employment?" *Disability and Health Journal*, 16, 101429.

Powell, David and Seth Seabury (2018), "Medical care spending and labor market outcomes: Evidence from workers compensation reforms." *American Economic Review*, 108, 2995–3027.

Social Security Administration, Office of the Inspector General (2023), "The covid-19 pandemics effect on disability determination services processing of disability claims." Technical Report A-01-20-50963, Social Security Administration, Office of Audit, Washington, DC, URL https://oig.ssa.gov/reports/2023/a-01-20-50963/. Audit Report.

U.S. Government Accountability Office (2022), "Social security administration: Remote service delivery increased during covid-19, but more could be done to assist vulnerable populations." URL https://www.gao.gov/assets/gao-23-104650.pdf.

Appendix

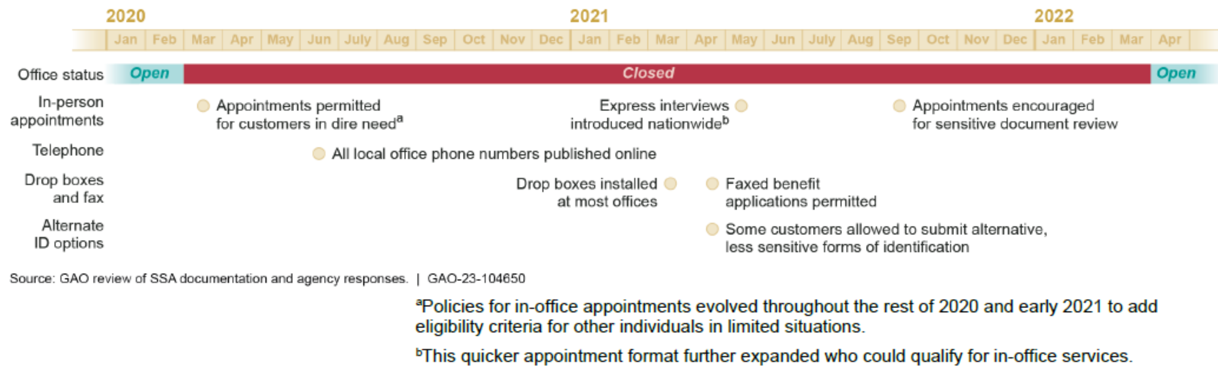


Figure A1: Timeline of Social Security Administration (SSA) Field Office Service Delivery Changes during the COVID-19 Pandemic, January 2020-April 2022.

Source: U.S. Government Accountability Office (2022).

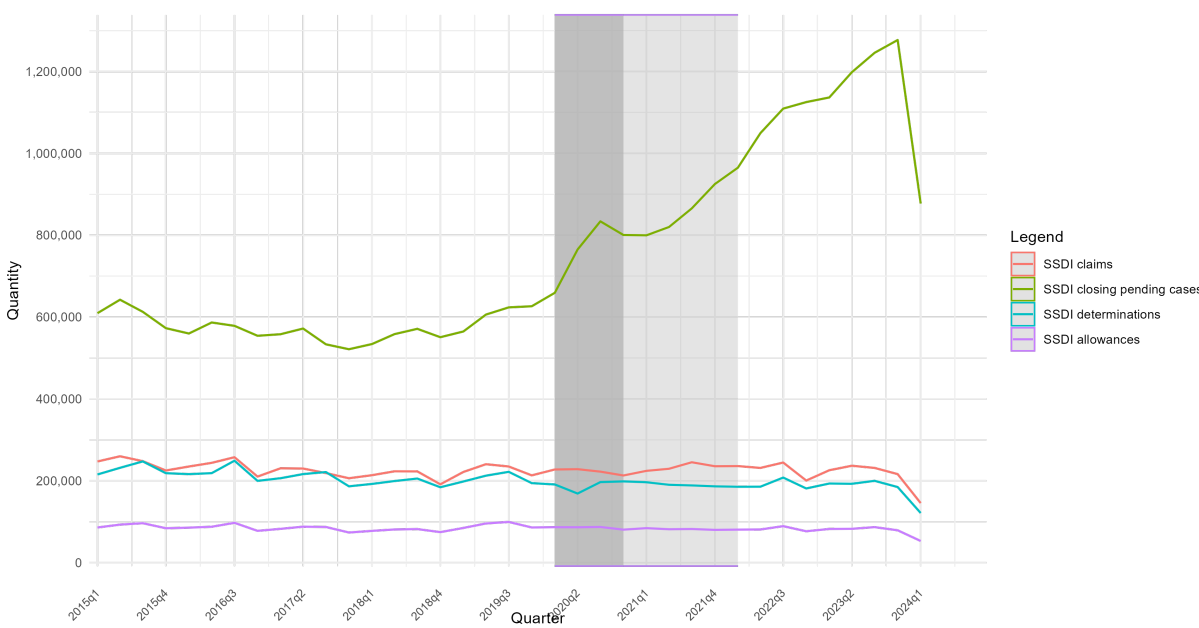


Figure A2: SSDI Claims from January 2015 to January 2024.

Notes: The data come from the SSA State Agency Monthly Workload Data, covering the period from the first quarter of 2015 to the first quarter of 2024. This figure presents trends in applications, pending cases, determinations, and allowances for SSDI claims, providing a descriptive overview of these outcomes over time. The dark gray shaded area marks March 2020 to December 2020, and the lighter gray area indicates the full period during which all SSA field offices were closed (March 2020 to March 2022).

Table A1: Summary Statistics for SSDI Claims, Reconsiderations, and CDRs.

	Full Sample Mean (SD)	SSA Offices Open Mean (SD)	SSA Offices Closed Mean (SD)	p-value
Claims				
Applications	1,492	1,491	1,494	0.955
	(1,543)	(1,524)	(1,607)	
Closing Pending	4,988	4,840	5,492	0.000
	(5,770)	(5,837)	(5,505)	
Determinations	1,320	1,347	1,228	0.007
	(1,393)	(1,408)	(1,338)	
Allowances	552.8	556.5	540.0	0.352
	(557.0)	(557.6)	(554.8)	
Reconsiderations				
Applications	372.9	364.3	402.4	0.006
	(436.7)	(429.3)	(459.7)	
Closing Pending	1,210	1,153	1,404	0.000
	(1,609)	(1,641)	(1,479)	
Determinations	331.4	329.9	336.7	0.597
	(407.4)	(409.8)	(399.3)	
Allowances	52.36	51.97	53.67	0.395
	(62.85)	(62.80)	(63.05)	
Continuing Disability Reviews (CDRs)				
Applications	394.8	428.6	280.0	0.000
	(449.7)	(471.6)	(341.9)	
Closing Pending	1,306	1,328	1,231	0.022
	(1,323)	(1,349)	(1,227)	
Determinations	354.7	391.6	229.3	0.000
	(403.9)	(427.8)	(274.6)	
Allowances	300.4	331.4	195.0	0.000
	(335.2)	(354.5)	(229.8)	
Observations	5,610	4,335	1,275	

Notes: The full sample is derived from the SSA State Agency Monthly Workload data spanning January 2015 to January 2024. Claims refer to initial applications for SSDI. Reconsiderations are filed when an initial claim is denied, while Continuing Disability Reviews (CDRs) are periodic reviews conducted for existing beneficiaries to reassess eligibility. Within each category, outcomes include applications, pending cases, determinations, and allowances. Applications represent the total number of claims, reconsiderations, and CDR submissions received each month. Pending cases capture unresolved applications, determinations reflect all processed cases with a decision (favorable, partially favorable, or unfavorable), and allowances specifically measure favorable outcomes. SSA Offices Open refers to months when local SSA field offices were operating normally. SSA Offices Closed corresponds to the period from March 2020 to March 2022, when in-person access was suspended. Means are shown with standard deviations in parentheses. p-values are from t-tests of differences between open and closed periods.

Table A2: Effect of SSA Field Office Closures on SSDI Claims, Reconsiderations, and CDRs, state-level analysis.

	Applications	Pending Cases	Determinations	Allowances
Panel A. Claims				
SSA Closure	2.77	652.20***	−119.09***	−16.51**
	(35.10)	(146.42)	(21.39)	(6.54)
R-squared	0.00	0.01	0.02	0.00
Panel B. Reconsiderations				
SSA Closure	38.05	250.65**	6.86	1.71
	(24.10)	(94.76)	(23.52)	(3.97)
R-squared	0.007	0.011	0.000	0.000
Panel C. Continuing Disability Reviews (CDRs)				
SSA Closure	−148.58***	−96.76**	−162.25***	−136.39***
	(20.79)	(41.81)	(21.70)	(17.35)
R-squared	0.056	0.005	0.092	0.089
Observations	5,610	5,610	5,610	5,610

Notes: Standard errors in parentheses. All regressions include state and year fixed effects, with standard errors clustered at the state level. The sample covers the period from January 2015 to January 2024, using state-level data. SSAClosure_{st} is a binary indicator equal to one during the SSA field office closure period (March 2020 to April 2022). Data are sourced from the SSA State Agency Monthly Workload dataset. Claims refer to initial applications for SSDI. Reconsiderations are filed when an initial claim is denied, while Continuing Disability Reviews (CDRs) are periodic reviews conducted for existing beneficiaries to reassess eligibility. Within each category, outcomes include applications, pending cases, determinations, and allowances. Applications represent the total number of claims, reconsiderations, and CDR submissions received each month. Pending cases capture unresolved applications, determinations reflect all processed cases with a decision (favorable, partially favorable, or unfavorable), and allowances specifically measure favorable outcomes. *** p<0.01, ** p<0.05, * p<0.1.

A Additional Robustness Checks and Mechanism

A.1 Heterogeneity by Metro and Non-Metro Areas

To examine whether the impact of SSA field office closures varied by regional context, I estimate all core specifications separately for metropolitan and non-metropolitan ZIP codes. All regressions include the same set of covariates, fixed effects, and are weighted by population. This heterogeneity analysis is motivated by differences in service infrastructure, digital access, and population characteristics across urban and rural areas.

The underlying hypothesis is that non-metropolitan areas may have been more severely affected by the closure of local SSA offices. These areas often face more limited broadband access, lower levels of digital literacy, and fewer administrative alternatives. Residents in rural communities are also less likely to have flexible transportation options and more likely to depend on in-person services for navigating benefit enrollment processes. In contrast, residents of metropolitan areas tend to have better internet infrastructure, higher educational attainment, and greater familiarity with digital platforms. As a result, they may have been better equipped to adapt to the temporary shift toward remote service delivery during the pandemic.

This analysis enables an empirical test of whether reliance on physical access points created disproportionate barriers to benefit participation in less urbanized settings. If residents in non-metropolitan areas lacked viable digital alternatives, then the impact of SSA office closures would be expected to be larger in those ZIP codes. Identifying such heterogeneous effects is particularly relevant from a policy perspective, as it highlights whether the transition to remote access introduces uneven burdens across geographic regions with varying infrastructure and support systems.

A.2 Distance-Based Sensitivity Analysis

To test the robustness of the identification strategy and further assess the validity of the control group, I implement a distance-based sensitivity analysis. The goal of this approach is to address potential violations of the Stable Unit Treatment Value Assumption (SUTVA), particularly the possibility that ZIP codes geographically close to treated areas may have been indirectly affected by SSA field office closures. Proximity-based spillovers could contaminate the control group and bias the estimated treatment effects downward. To mitigate this concern, I redefine the control group based on geographic distance to the nearest treated ZIP code.

To visually inspect how treatment proximity relates to changes in disabled beneficiaries, I construct a binned scatterplot of the annual change in disabled beneficiaries against distance to the nearest treated ZIP code. The plot, shown in Figure A3, smooths the data by grouping ZIP codes into equal-width distance bins and plotting the average change in disabled beneficiaries within each bin. The figure reveals a steep negative gradient in the number of new disabled beneficiaries at short distances, which gradually flattens beyond approximately 20 miles. This pattern suggests that ZIP codes near treated areas were more negatively affected.

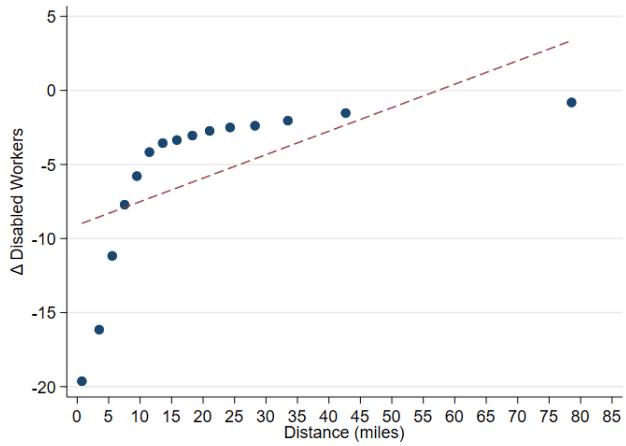


Figure A3: Relationship Between Distance to Treated ZIP Code and Change in Disabled Beneficiaries.

Notes: This figure presents a binscatter plot showing the relationship between the annual change in the number of disabled beneficiaries and the distance (in miles) to the nearest treated ZIP code.

Motivated by this observed pattern, I re-estimate the main specifications using three alternative control groups defined by increasing distance from treated ZIP codes. All treated ZIP codes are retained in the sample. However, to avoid potential spillover contamination, ZIP codes located within five miles of a treated ZIP code are excluded entirely from the sample. I then classify the remaining control ZIP codes into three mutually exclusive distance bands: (i) ZIP codes located between 5 and 10 miles from a treated ZIP code, (ii) those between 10 and 20 miles, and (iii) those more than 20 miles away.

This stratified framework allows me to test whether estimated treatment effects are sensitive to the geographic proximity of control units and whether greater distance yields stronger contrasts by minimizing reliance on neighboring SSA field offices. If the hypothesis is correct, that residents primarily use SSA offices located nearby, then more distant control groups should provide cleaner comparisons and yield larger estimated effects of office closures.

A.3 State Level Policies

To account for substantial heterogeneity in state-level responses to the COVID-19 pandemic, I include state-by-year fixed effects in the main ZIP-code-level regression models. This specification controls for time-varying, state-specific shocks and serves as a robustness check to assess whether the estimated effects are sensitive to unobserved policy variation across states and time. State governments implemented a wide range of emergency policies during the pandemic, including differential lockdown measures, extensions to unemployment insurance, public health orders, and administrative adjustments.

These interventions varied not only across states but also over time, potentially confounding the estimated impact of SSA office closures if not properly accounted for. Including state-by-year fixed effects allows me to net out these evolving policy environments and isolate the causal effect of reduced physical access to SSA services. This approach strengthens the internal validity of the estimates by addressing omitted variable bias arising from correlated shocks at the state level.

A.4 Mechanism

One plausible mechanism driving disability program participation is differential access to digital connectivity following the closure of SSA field offices. During the pandemic, in-person services were abruptly suspended, and applicants were expected to navigate SSA procedures through online portals or telephone-based alternatives. This transition may have disproportionately affected areas with limited internet connectivity or broadband infrastructure, creating new barriers to benefit access.

To test this mechanism, I estimate heterogeneous treatment effects based on local levels of internet access. For each internet access variable, I re-estimate the main specification models with the inclusion of internet access as an additional control, and I also estimate the models separately for subsamples defined by high and low levels of connectivity. In addition to continuous measures of internet access, I construct binary indicators for high versus low access based on whether a ZIP code falls above or below the median for each internet metric in 2019 (the baseline year). I then stratify the sample into high-access and low-access ZIP codes and re-estimate the treatment effects separately. This approach allows me to test whether the impact of SSA office closures was concentrated in low-connectivity areas, where residents had fewer alternatives to in-person service delivery.

The hypothesis is that ZIP codes with lower internet access may have faced greater barriers to applying for and receiving disability benefits following the closure of SSA field offices. In these areas, the absence of reliable broadband infrastructure may have limited individuals' ability to substitute for remote or digital channels for accessing services. If this mechanism is at play, one would expect to observe larger declines in program participation in ZIP codes with below-average internet access, compared to areas with stronger digital adoption.

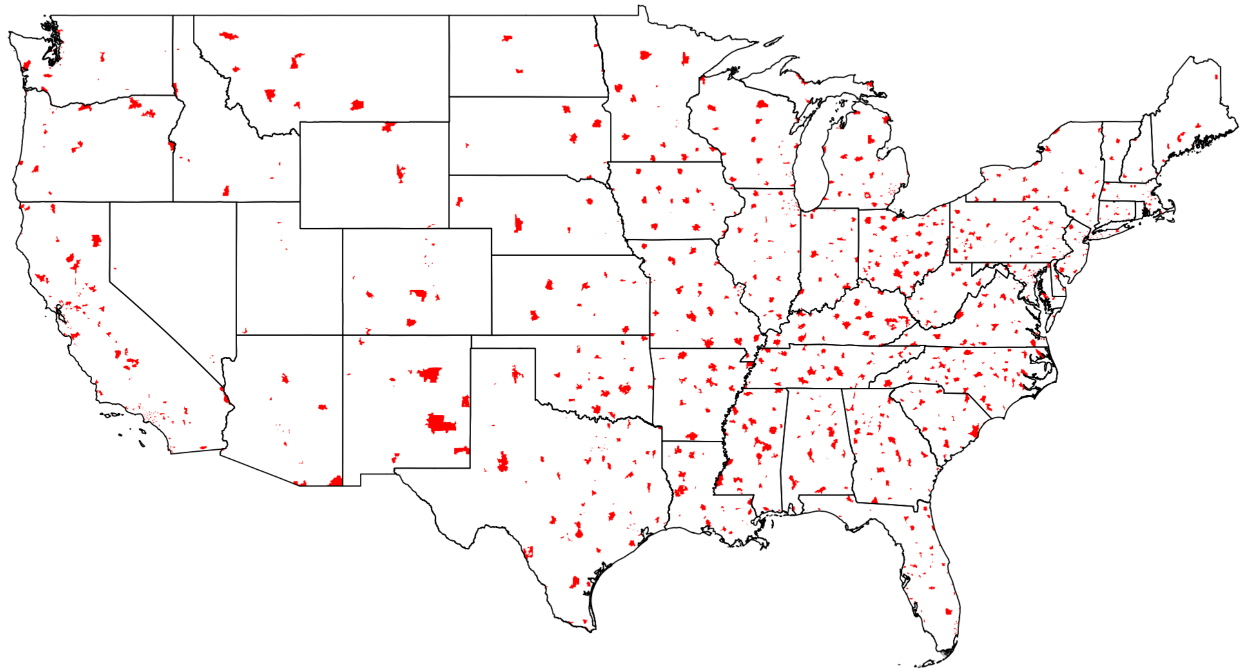


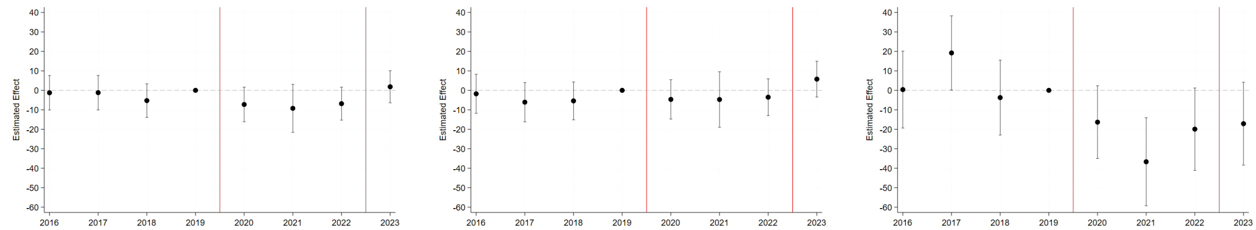
Figure A4: Social Security Administration (SSA) Field Offices Locations in the Contiguous U.S.

Notes: The map was constructed by the author using the SSAs publicly available list of current field office addresses, which were matched to ZIP codes and assigned as treated areas (in red). The shapefile was obtained from the U.S. Census Bureau. Red areas on the map indicate ZIP codes where SSA field offices are located. Black lines delineate state boundaries in the contiguous United States. The map provides a visual representation of the distribution of SSA field offices relative to state geography.

Table A3: Effect of SSA Field Office Closures on Disabled Beneficiaries Per Capita.

	Full Sample				Metro		Non-metro	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post	-19.883**	-3.457	-3.979	-3.457	0.824	1.525	-21.333***	-26.455***
	(8.968)	(2.578)	(2.583)	(2.578)	(2.911)	(2.903)	(5.669)	(6.157)
Observations	231,888	231,888	231,888	231,888	125,864	125,864	103,384	103,384
R-squared	0.073	0.113	0.112	0.113	0.139	0.141	0.088	0.100
Weighted by population	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Control for population density	No	Yes	No	Yes	No	Yes	No	Yes
Method	DID	DID	DID	DID	DID	DID	DID	DID

Notes: Standard errors in parentheses. Data are from the Social Security Administrations ZIPcodelevel counts of OldAge, Survivors, and Disability Insurance (OASDI) beneficiaries. The outcome variable is the annual change in disabled beneficiaries per capita. The sample period spans 2016 to 2023. All regressions include ZIP code and year fixed effects, with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include the percentage of the population below the poverty line, unemployment rate, and educational attainment (shares with a high school diploma, some college, an associate degree, or a college degree; postgraduate share omitted as the reference). Median household income is also included. *** p<0.01, ** p<0.05, * p<0.1.



(a) Full Sample (b) Metro (c) Non-Metro

Figure A5: Annual Treatment Effects on Disabled Beneficiaries Per Capita.

Notes: This figure presents the annual treatment effects of the impact of SSA field office closures on the annual change in the number of disabled beneficiaries per capita, estimated from an event-style regression. Each panel shows results for a different subsample: (a) full sample, (b) metropolitan ZIP codes, and (c) non-metropolitan ZIP codes. Data on disabled beneficiaries is from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The outcome variable is the annual change in disabled beneficiaries per capita. All regressions are weighted by population and include ZIP code and year fixed effects, with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include population density, the percentage of the population below the poverty line, unemployment rate, and educational attainment, measured as the share of residents with a high school diploma, some college, an associate degree, or a college degree. The percentage of residents with a postgraduate degree is omitted and serves as the reference category. The red vertical line between 2019 and 2020 marks the onset of SSA field office closures, while the line between 2022 and 2023 marks their reopening.

Table A4: Effect of SSA Field Office Closures on Disabled Beneficiaries, with State-by-Year Fixed Effects.

	Full Sample				Metro		Non-metro	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Without State-by-Year Fixed Effects								
Treatment × Post	-9.577***	-4.291***	-4.315***	-4.291***	-3.166***	-3.132***	-10.421***	-10.449***
	(0.616)	(0.775)	(0.777)	(0.775)	(0.906)	(0.903)	(1.337)	(1.335)
% relative to control mean (pre-treat.)	-3.9%	-1.8%	-1.8%	-1.8%	-0.9%	-0.9%	-9.3%	-9.3%
Panel B: With State-by-Year Fixed Effects								
Treatment × Post	-9.155***	-4.613***	-4.638***	-4.613***	-3.375***	-3.339***	-10.432***	-10.453***
	(0.608)	(0.759)	(0.760)	(0.759)	(0.894)	(0.892)	(1.264)	(1.263)
% relative to control mean (pre-treat.)	-3.8%	-1.9%	-1.9%	-1.9%	-1.0%	-0.9%	-9.3%	-9.3%
Observations	231,886	231,886	231,886	231,886	125,862	125,862	103,384	103,384
R-squared	0.435	0.477	0.477	0.477	0.480	0.480	0.441	0.441
Weighted by population	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Control for population density	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Standard errors in parentheses. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The outcome variable is the annual change in disabled beneficiaries. The sample period spans 2016 to 2023. All regressions include ZIP code and year fixed effects, with standard errors clustered at the ZIP code level. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include the percentage of the population below the poverty line, unemployment rate, and educational attainment (share with a high school diploma, some college, an associate degree, or a college degree; postgraduate share omitted as the reference). Median household income is also included. Effect sizes are expressed as a percentage of the pre-treatment control group mean of the dependent variable. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: Effect of SSA Field Office Closures on Disabled Beneficiaries in Areas with Low Internet Access: DID vs. SDID Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment x Post	-12.503***	-11.734***	-9.149***	-7.506***	-11.573***	-10.636***
	(0.878)	(1.041)	(1.073)	(1.187)	(1.063)	(1.115)
Observations	101,444	101,444	58,530	58,530	81,399	81,399
Method	DID	SDID	DID	SDID	DID	SDID
Low Internet Access	ACS 5	ACS 5	ACS 1	ACS 1	FCC	FCC

Notes: Standard errors in parentheses. Data are from the Social Security Administrations ZIP-code-level counts of Old-Age, Survivors, and Disability Insurance (OASDI) beneficiaries. The outcome variable is the annual change in disabled beneficiaries. The sample period spans 2016 to 2023. All regressions include ZIP code and year fixed effects. Difference-in-differences regressions are not weighted by population. Control variables from the American Community Survey (ACS), measured at the ZIP code level, include the percentage of the population below the poverty line, unemployment rate, and educational attainment. Internet access is measured using three county-level indicators: ACS 5-Year Estimates (ACS 5), ACS 1-Year Estimates (ACS 1), and FCC broadband provider data. High internet access indicates above-median values; low internet access indicates below-median values. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.