

Who Is Screened Out?

Application Costs

and the Targeting of Disability Programs

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Abstract

We study the effect of application costs on the number and composition of disability applicants and recipients using the closings of Social Security Administration field offices, which provide assistance with filing disability applications. Using administrative data from the Social Security Administration, we find that field office closings reduce the number of disability allowances by 13 percent in areas surrounding the closed office and by 10 percent in areas surrounding neighboring offices, with effects persistent for at least two years after a closing. The closings disproportionately reduce applications among potential applicants from lower socioeconomic backgrounds and among those with moderately severe conditions. Our estimates suggest that about three-quarters of the reduction in disability applications in areas around closed field offices is attributable to increased congestion at neighboring offices and the remaining amount to increased travel times and costs of information gathering.

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Disability programs in the United States are large and expanding rapidly. Social Security Disability Insurance (SSDI or DI), the insurance program for disabled workers, provided cash benefits and Medicare to nearly 9 million workers in 2014, up from 5 million in 2000. In 2014, Supplemental Security Income (SSI) provided cash welfare and Medicaid eligibility to 7 million low-income, disabled Americans, including 1.4 million children.¹ These programs are intended to provide disability benefits to those—and only those—individuals who have severe disabilities and are in need of assistance. The primary system for targeting disability programs is the disability determination process, in which adjudicators determine whether an individual meets the medical eligibility criteria for these programs. However, even before potential applicants encounter the disability determination system, the cost of applying for disability programs may affect whether they decide to apply and, as a result, whether they receive disability benefits. To apply for disability, individuals must consider whether they are eligible, submit extensive paperwork, and provide access to medical records. The effect of application costs on the targeting of disability programs is ambiguous: application costs could screen out either those most in need or least in need, depending on how potential applicants respond to these costs and whether the disability determination process amplifies or counters differential effects across subgroups. Despite the rapid increase in disability applications and enrollment across the developed world in recent decades, there is virtually no evidence on the effect of application costs on the take-up or targeting of these programs.

In this paper, we provide the first evidence on this question using variation in the timing of closings of Social Security Administration (SSA) field offices, which provide assistance with filing disability applications. Using detailed administrative data on disability applications and applicant characteristics, we estimate the effect of an increase in application costs induced by field office closings on the number and composition of disability applicants and recipients. Using novel programmatic data from SSA, we also study the relative importance of different types of application costs induced by the closings, including travel time to assistance, congestion at neighboring field offices, and information gathering. We employ a difference-in-differences strategy that compares the number and composition of disability applicants and recipients in areas that experience the closing of their nearest field office to areas that do not experience a closing until several years later, before and after the given closing. This empirical strategy requires only that the *timing* of the closings,

¹Annual Statistical Report on the Social Security Disability Insurance Program, 2014; SSI Annual Statistical Report, 2014. SSI provides categorical Medicaid eligibility in most states, except for ten states that use stricter criteria to determine Medicaid eligibility for the disabled; seven other states require SSI recipients to submit a separate Medicaid application to the state. SSI also provides benefits to low-income elderly individuals.

rather than the closings themselves, be as good as random. To establish the validity of this empirical strategy, we demonstrate that treatment and control areas follow similar trends prior to the closing, that macroeconomic conditions do not exhibit trend breaks at the time of the closing, and that observables do not predict the timing of the closings.

We find that field office closings reduce the number of disability applications by 11 percent (12 applications per ZIP per quarter) in ZIPs whose nearest office closes. Closings decrease the number of final allowances by 13 percent (6 allowances per ZIP per quarter) in these ZIPs, meaning that they disproportionately discourage applications from individuals who would have been allowed onto the program if they had applied. These effects are persistent for at least two years after the closing, and they occur for all programs, though the effects are larger for the lower-income SSI population than for the DI population. To address the targeting question, we also study who is screened out by higher application costs. Closings appear to worsen targeting as measured by observable characteristics, with the largest discouragement effects for those with moderately severe conditions, lower education levels, and lower pre-application earnings.

The effects of closings are large, suggesting an implied value of time of \$100 per hour for disability applicants. To understand the magnitude of these effects, we consider the channels through which closings could affect the application decision: congestion at neighboring field offices, travel time to neighboring offices, and other channels, including higher costs of acquiring program information and network effects.² With respect to congestion, walk-in wait time at neighboring offices increases by 21 percent (4.3 minutes) as a result of the closing, and the time it takes the neighboring office to process an application from an affected area increases by 10 percent (3.0 days). Likely as a result of increased congestion, disability allowances fall by 10 percent in ZIPs whose second or third closest field office closes. With respect to travel times, we use calculations from Google Maps to estimate that driving distance, driving time, and public transit time to the nearest open field office all increase by about 40 percent (10 minutes in driving time and 36 minutes in public transit time). We have no direct measures of information, but since field offices no longer perform community outreach, any role of program information is limited to those who visit the office seeking information.

To isolate the effects of congestion at neighboring offices, we compare, in a constant effects model, the effects of the closing in closing ZIPs, which should experience all three channels (congestion, travel times, and information), to the effects on neighboring ZIPs, which should experience only

²Note that the closings do not change who reviews and decides the applicant's case, since these decisions are made at state-level Disability Determination Services offices, rather than at local field offices.

higher congestion costs. To account for the possibility of heterogeneous effects, we use propensity score matching to estimate effects of the closing for neighboring ZIPs that are similar on observables to closing ZIPs. Our estimates suggest that about three-quarters of the reduction in disability applications in closing ZIPs is attributable to increased congestion at neighboring offices and the remaining amount to increased travel times and costs of information gathering.

Although the normative implications of these results depend on societal preferences, we find using current standards for disability receipt that the increase in application costs induced by Social Security field office closings reduces targeting efficiency. We also use our estimates to conduct a cost-benefit analysis of field office closings. On the cost side, we consider the loss in social welfare from lower disability receipt for deserving applicants and the increased time and effort required to apply for disability. On the benefit side, we consider administrative savings from processing fewer applications and shuttering field offices as well as reductions in application costs and earnings decay for individuals who are discouraged from applying. Using conservative assumptions, we estimate a ratio of social costs to social benefits of field office closings of 6 to 1. Moreover, if disability programs are also intended to address economic inequality, then the larger effects for individuals of lower socioeconomic status indicate that field office closings exacerbate the very inequality that disability programs are intended to reduce.

The paper proceeds as follows. Section 1 provides a conceptual framework for how application costs affect targeting efficiency and reviews the literature on “ordeals” involved in accessing benefits or services. In Section 2, we describe the institutional context of Social Security field office closings and describe the administrative and programmatic data from the Social Security Administration. Section 3 outlines the empirical strategy and Section 4 presents estimates of the effect of closings on the number and composition of disability applicants and recipients. In Section 5, we consider the channels through which closings could affect disability applications and decompose the effects into the various channels. Finally, Section 6 provides interpretation of the results and discusses welfare implications, and Section 7 concludes.

1 Framework and Literature

1.A Conceptual framework

Our goal is to estimate the effect of an increase in ordeals on the targeting efficiency of disability programs. We define targeting efficiency as

$$\gamma(\eta) \equiv \frac{Pr(A|D, \eta)}{Pr(A|U, \eta)}$$

where $Pr(A|D, \eta)$ is the probability that someone deserving applies for the disability program given an application cost η , and $Pr(A|U, \eta)$ is the analogous probability for undeserving individuals. Targeting efficiency increases when a larger fraction of deserving individuals apply, or a smaller fraction of undeserving individuals apply.

The object of interest is $\gamma(\eta') - \gamma(\eta)$: how the increase in application costs (from η to η') induced by the field office closing affects targeting efficiency. Suppose that higher-severity individuals are considered more deserving. Field office closings could increase γ if, for example, low-severity individuals are discouraged from applying. On the other hand, closings could decrease γ if applying is now costlier for high-severity types. In the Appendix, we present a model that outlines both of these cases. The critical parameter in determining whether γ increases or decreases is how much more costs increase for high-severity types relative to low-severity types when field offices close.

Unfortunately, there is no direct measure of $\gamma(\eta)$ because neither the econometrician nor the government sees those who do not apply. For this reason, we must relate the object of interest to empirical parameters. We define

$$\Delta_A \equiv \frac{Pr(A|\eta') - Pr(A|\eta)}{Pr(A|\eta)}$$

as the percent change in applications from closings, and Δ_R is defined analogously for recipients. Let p_D (p_U) be the probability of allowing a deserving (undeserving) type. The following theorem states that the difference between Δ_A and Δ_R is informative for the direction of the change in targeting efficiency.

Proposition 1. *If screening technology is good ($p_D > p_U$), then an increase in application costs increases targeting efficiency (i.e., $\gamma(\eta') - \gamma(\eta) > 0$) if and only if the percent decline in recipients is smaller than the percent decline in applicants (i.e., $|\Delta_R| - |\Delta_A| < 0$).*

Proof. See Appendix.

□

Intuitively, if closings reduce applications but not recipients, then those who were discouraged from applying were undeserving as defined by the government’s standards. Note that this theorem assumes that the adjudicator’s preferences for who is deserving or undeserving reflects societal preferences. Since societal preferences may differ from the preferences of the official adjudication process, we also present changes in observable characteristics of applicants and recipients.

1.B Literature and contribution

We study the effect of Social Security field office closings on the number and characteristics of disability applicants and recipients. We address a key question in the public economics literature: do “ordeal mechanisms”—hassles associated with using benefits or services—improve or worsen targeting? Since field offices provide assistance with filing a disability application, their closing increases the ordeal costs of applying for disability programs. Individuals who live near the closed office face increases in several types of costs: 1) longer travel times to get assistance, 2) declines in the amount or quality of assistance, since neighboring offices may experience congestion as they absorb the closed office’s service area, and 3) higher costs of collecting information about disability programs.

In the absence of perfect information about individuals’ skills and abilities, the government can target social safety programs using two mechanisms. The first is tagging, in which the government conditions eligibility on observable characteristics like poor health or low income to target groups who are deserving or most in need ([Akerlof \(1978\)](#)). In the context of disability programs, the government uses disability screening to limit benefits to those with a disability tag.

In this paper, we study the second type of targeting mechanism: self-screening, in which program rules and application requirements affect what types of individuals decide to apply for benefits. Ordeal mechanisms are a specific type of self-screening device, and several papers build the theoretical foundation for the effect of ordeals on selection, including arguments for queuing ([Nichols, Smolensky and Tideman \(1971\)](#)), work requirements or activities with some disutility ([Besley and Coate \(1992\)](#)), and asset tests ([Golosov and Tsyvinski \(2006\)](#)) as screening devices. [Nichols and Zeckhauser \(1982\)](#) posit that ordeals may improve targeting if they impose a higher relative cost on high-ability individuals compared to low-ability individuals. Thus an optimal transfer program that maximizes social welfare may need to sacrifice productive efficiency—time and effort wasted

by applicants on ordeals—to improve targeting efficiency.

Kleven and Kopczuk (2011) develop a theoretical framework that is particularly relevant for the disability context. They consider a targeted program that uses a monitoring technology involving substantial information collection and complexity (e.g., the disability determination process) to determine whether an individual is deserving. A more complex monitoring technology reduces the likelihood of allowing non-disabled individuals (Type II error) or rejecting disabled individuals who apply (“Type Ib” error, in their terminology), but increases the likelihood of discouraging disabled individuals from applying (“Type Ia” error). They find that optimal programs have a high degree of complexity, incomplete take-up, and both Type I and Type II errors.

The question of whether ordeals improve or worsen targeting is ultimately an empirical one, and likely depends on the type of ordeal and the characteristics of the marginal population. [Bertrand, Mullainathan and Shafir \(2004\)](#) hypothesize that administrative hassles associated with program enrollment may in fact deter the individuals that society would like to target to be on these programs. For example, low-ability individuals may face information costs or mental barriers that magnify the effect of application costs on the decision to apply for benefits.

Previous papers have estimated the effect of ordeals (or their reduction) on program take-up, but with less attention to the question of targeting (see [Currie \(2004\)](#) for a review). [Bettinger, Terry Long, Oreopoulos and Sanbonmatsu \(2012\)](#) estimate that Free Application for Federal Student Aid (FAFSA) assistance combined with information on financial aid increases college completion by 8 percentage points, or 29 percent, while information alone has no effect. Automatic enrollment, which changes the default to participation, has been shown to increase participation in retirement savings programs dramatically ([Madrian and Shea \(2001\)](#)). [Rossin-Slater \(2013\)](#) finds that the opening of a Women, Infants, and Children (WIC) program office increases the likelihood that pregnant women in surrounding areas use WIC benefits by 6 percent, with effects driven by urban areas. She hypothesizes that both travel time and program awareness are important channels. [Kopczuk and Pop-Eleches \(2007\)](#) use cross-state variation in the timing of the introduction of electronic filing for the earned income tax credit (EITC) to estimate effects on EITC claiming. They find a significant effect driven primarily by households in the middle of the EITC income range. In a similar spirit, [Ebenstein and Stange \(2010\)](#) study cross-state variation in the timing of phone- and Internet-based unemployment insurance claiming, but find no effect on UI take-up nor any shift in the incomes of claimants.

Recent papers in the developing world address the targeting question more directly. [Alatas,](#)

Banerjee, Hanna, Olken, Purnamasari and Wai-Poi (2016) conduct a field experiment of requiring households in Indonesia to actively apply for a welfare program, rather than the status quo policy of being automatically enrolled in the program. They find that this larger ordeal disproportionately screens out higher-income households and therefore improves targeting on net. However, the ordeal also discourages poor households from applying, with only 60 percent of eligible poor households submitting an application. Cohen, Dupas and Schaner (2015) find in a field experiment in Kenya that increasing the subsidy for antimalarial drugs increases the receipt of drugs but worsens targeting, with one-half of pills going to individuals without malaria.

This paper makes two contributions to the existing literature. First, this is the first paper of which we are aware to estimate empirically the effect of application costs on the targeting, rather than take-up alone, of a large-scale government program in the developed world. Disability programs are of particular interest given their rapid expansion in recent decades and ensuing controversy about who is considered disabled. In contrast to Alatas et al. (2016), who study a small increase in application requirements from a baseline of zero (automatic enrollment), we study the effects of an increase in application requirements from an already high baseline, which could have different effects if application costs are convex. Moreover, we study this increase in which technology should make it easier to manage a complicated application process: applicants can apply online or by phone and find information and assistance online, and they have reliable transportation infrastructure to reach a neighboring office. Despite all this, we find that the increase in application costs reduces the take-up of disability programs substantially and, in contrast to Alatas et al. (2016), worsens targeting efficiency by disproportionately discouraging applicants with low socioeconomic status and relatively severe conditions.

Second, this paper brings together for the first time detailed administrative data on applicants and specific features of individual field offices, allowing us to study both targeting efficiency and the channels through which closings discourage applicants. To address the question of targeting, we use applicant characteristics such as disability type and severity, pre-application earnings, age, education, and language spoken. To study the channels through which closings discourage applications, we collect from SSA program offices several sources of data that have not previously been used for research. These include field office wait times, processing times, and staff counts, and call volumes to the 800 information line, which help us quantify congestion at neighboring offices and information costs. To study travel time, we calculate driving and public transportation times to field offices using Google Maps software.

2 Institutional context and data

2.A Institutional context

The Social Security Administration administers the Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI) programs. SSDI and SSI have the same medical requirements but different non-medical requirements: SSDI requires a work history, while SSI requires low income and assets. Individuals can apply for and receive benefits from both programs concurrently if they meet the requirements of both, with the SSI benefit reduced by the amount of the SSDI benefit.

Potential applicants can apply for SSDI and SSI by filing a claim in person at a Social Security field office, filing a claim over the phone with a claimants' representative at a Social Security field office, or—for SSDI applicants only—by filing the claim online. Regardless of how the application is filed, the application is generally processed by the field office that serves the ZIP code in which the applicant resides. The applications in our data are identified by the claimant's ZIP code of residence. In processing the claim, the field office verifies that applicants meet the non-medical requirements (work history for SSDI and income and assets for SSI) and often collects information that the disability examiner needs to make a medical decision, such as medical records and (for children) school records. The field office then transfers the application to the state disability determination services (DDS) office, where a disability examiner decides whether the applicant meets medical requirements. Applicants can appeal the initial examiner's decision, first to the DDS office itself (in all but 10 states), then to an administrative law judge (ALJ), then to the Appeals Council, and finally, for a very small fraction of cases, to federal court.

The first Social Security field office opened in Austin, Texas, in October 1936. Today there are approximately 1,230 Social Security field offices in the United States. Field offices serve many functions, including taking applications for new or replacement Social Security cards, providing benefit verifications, assisting with disability and retirement claims, and processing disability claims before transferring them to the state DDS office. According to SSA testimony, 30 percent of visits to field offices are for Social Security cards and 10 percent of visits are for filing disability and retirement claims. However, disability claims take up a disproportionate amount of staff time, with two-thirds of SSA's administrative budget going to disability claims.³ According to SSA testimony,

³Testimony of Jo Anne B. Barnhart, Commissioner of the Social Security Administration, to the U.S. House of Representatives, March 4, 2003. SSA's administrative budget reflects both field office and state DDS costs. Social Security field office functions include issuing new or replacement Social Security cards, assisting with retirement and disability claims, providing verification of benefits, processing claims, assisting state offices with continuing disability reviews, and conducting SSI non-medical redeterminations.

“disability claims...are particularly time intensive as employees help claimants complete detailed forms about medications, treatment, medical testing, work history, and daily activities.”⁴

Since Social Security field offices provide assistance with applications, the closing of field offices is expected to (weakly) increase the cost of applying. Potential applicants must travel farther for in-person assistance, may experience congestion at neighboring offices, and may find it more costly to gather program information. We use recent Social Security field office closings to study the effect of application costs on selection into disability programs. Although there were very few closings prior to 2000, there have been 125 closings since that year, with approximately half of those closings occurring since 2009 (see Figure 1). The obvious concern with this empirical strategy is that SSA may be closing offices in areas where disability applications are already falling or where the composition of disability applicants is already changing.⁵ To address this issue, we use areas that experience a closing in the future as controls for areas that experience a closing today. The identifying assumption is that the exact timing of the closing is uncorrelated with changes in the number and type of disability applicants. We demonstrate below that there are no pre-trends in the outcome variables, that macroeconomic variables such as population and unemployment rate do not exhibit a break at the time of the closing, and that no observable characteristics of the office or location predict the timing of closings.

2.B Data

We use confidential administrative and programmatic data from the Social Security Administration. We collected data on Social Security field offices from several SSA program offices. From the Office of Analysis, Development, and Support (OADS) and the Office of Earnings, Enumeration, and Administrative Systems (OEEAS), we have data identifying all field offices ever in operation, including field office number, street address, and closing date if it closed (no opening date). From the Office of Public Service and Operations Support (OPSOS), we have data on walk-in wait times at Social Security field offices going back to Fiscal Year (FY) 2005. These wait times are not specific to disability applicants; they reflect the average time that any individual entering a field office waits

⁴Testimony of Nancy Berryhill, Deputy Commissioner for Operations, SSA, to Special Committee on Aging, United States Senate, June 18, 2014.

⁵According to a Congressional report, the 64 closings that have occurred since 2009 have been in response to “technological, demographic, and budgetary” changes at the federal level. We show empirically in the next section that areas that experience closings look similar on demographic characteristics to areas that do not experience a closing. However, we find evidence of spillovers to “neighboring” ZIPs, which means that “unaffected” ZIPs may also be affected by the closings and therefore may not be an appropriate control group for areas that experience a closing. In Section 4.D, as a robustness check, we use unaffected ZIPs as the control group and find estimates similar to our main estimates.

until being served by a field office worker, and we use them as a measure of field office congestion. We also have data on the number of staff members at each field office going back to FY 1997 from OPSOS, and on Social Security card issuances by field office going back to FY 2005 from OEEAS. Finally, from SSA’s Office of Customer Service, we have the volume of calls to SSA’s 800 phone number by area code by month from January 2014 to April 2016.

We use data on applicants (and recipients) from a number of sources. We start with 831 application data for all cases with a disability examiner decision between 1990 and 2015. The 831 files include several applicant characteristics, including age, body system code (i.e., general disability category), medical diary reason (a measure of severity), and education (for adults only). The 831 files also provide the date on which the application was filed, the date on which the field office transferred the file to a state DDS office, whether the case was allowed at the disability examiner level, and applicant ZIP code up to 2010. For additional applicant characteristics and applicant ZIP codes after 2010, we use data from the Structured Data Repository (SDR), which starts in 2005. Applicant characteristics in the SDR include whether the applicant files online, whether the applicant has legal representation, whether the applicant has a representative payee, whether the applicant has an email address, and whether the applicant speaks English. We use the Disability Research File (DRF) and the Master Earnings File for pre-application earnings of applicants. Finally, we use the Master Beneficiary Record and Supplemental Security Record to observe the final determination for each case at the end of the adjudication process.

We collapse the Social Security data by the ZIP of the applicant’s address and link it to publicly available ZIP Code Tabulation Area data from the Census Bureau. We have a total of 33,649 ZIPs; Figure 2 shows their boundaries. For each ZIP code, we use the GIS software to find its centroid and apply the Haversine formula to calculate the great-circle distance—the shortest distance over the earth’s surface—between ZIP code centroid and each field office in the United States. In addition to this “as-the-crow-flies” distance, we also compute driving distance, driving time, and public transportation time using Google Maps APIs. Combining the distance and time measures with the information on field office closings provided by the SSA, we assign each ZIP to its nearest, second nearest, and third nearest field offices for each quarter from 1990 to 2015. We classify ZIPs into three categories: ZIPs whose nearest office was closed (“closing” ZIPs), ZIPs whose nearest office is the second or the third nearest field office of a closing ZIP prior to the closing event (“neighboring” ZIPs), and all remaining ZIPs (“unaffected” ZIPs).⁶ Figure 2 shows the locations of all Social Security field

⁶Note that assignments and ZIP code classifications differ by the employed distance and time measure.

offices since 2000 and demonstrates the classification of closing, neighboring, and unaffected ZIPs. Appendix Figure A.1 shows a zoomed-in version of this map for the state of New York.

We collect ZIP code level demographic information from the 2000 Census.⁷ Since information at the ZIP level is limited and is not available between Census years, we also collect county level information and link ZIP codes to counties with the largest shared areas. At the county level, we have quarterly data on employment, unemployment, labor force and payrolls from the Bureau of Labor Statistics; semiannual data on broadband access from the Federal Communications Commissions; annual data on personal income from the Bureau of Economic Analysis; annual data on population estimates and business patterns from the Census; and annual data on SSDI/SSI recipients from publicly available SSA publications. Finally, to analyze call volumes to SSA’s 800 number, we also link ZIP codes to their respective area codes as of May 2016 using ZIP Express software.

3 Empirical strategy

We estimate the effects of field office closings by comparing the number and characteristics of disability applicants and recipients in areas that experience a closing at a given time relative to areas that experience a closing in the future. The motivation for this empirical strategy is that areas that experience closings at some time are likely more similar to each other than they are to areas that never experience a closing. Table 1 presents the characteristics of ZIP codes that have an average of at least three disability applications per quarter in the year 2000, across closing, neighboring and unaffected ZIPs, as defined in Section 2.B. The ZIP means across the three groups are similar; the most apparent differences are that closing and neighboring ZIPs have larger populations and more disability applications in the year 2000 than unaffected ZIPs. Given the large number of ZIPs, however, the differences across them are precisely estimated and t-tests find significant differences across the groups for nearly all characteristics. Appendix Table A.1 presents the same summary statistics for all ZIPs in the United States.

Given potential differences in observable and unobservable characteristics between closing and unaffected ZIPs, we restrict our sample only to closing ZIPs. For any given closing, we take ZIPs that experience the current closing as treated ZIPs, and ZIPs that experience a closing in the future as control ZIPs. Specifically, we construct our sample as follows. First, we create separate datasets for each of the 125 closings. In each dataset, ZIPs that experience the current closing are labelled as

⁷For 2010, information about marital status, income, and educational attainment comes from the 2007-2011 American Community Survey.

treated ZIPs, while ZIPs that experience a closing more than two years in the future are labelled as control ZIPs. Event quarters are specified relative to the quarter of the closing. Second, to eliminate ZIPs with tiny populations, we drop ZIPs (both treatment and control) with an average of fewer than three disability applications per quarter in the year before the closing. Third, we append all 125 datasets into one dataset.

Figure 3 shows raw plots of the number of disability applications in control and treatment ZIP codes relative to the quarter of the closing. The drop in applications in treatment ZIPs is apparent, while control ZIPs follow a smooth upward trend in applications. Appendix Table A.2 compares pre-closing characteristics of treatment and control ZIPs and shows that they are similar on demographics, walk-in wait times, and number of disability applications, though t-tests yield statistically significant differences between the groups due to the large number of ZIP codes.

To estimate the effects of the closings in regression form, we estimate the following equation on the sample:

$$Y_{isct} = \alpha_i + \gamma_{st} + \Sigma_{\tau} D_{ct}^{\tau} + \Sigma_{\tau} \delta_{\tau} (Treated_{ic} \times D_{ct}^{\tau}) + \epsilon_{isct} \quad (1)$$

where Y_{isct} is an “outcome” (i.e., number or characteristics of disability applicants or recipients) for ZIP i in state s for closing c in quarter t . The α_i are ZIP fixed effects, and γ_{st} are calendar quarter by state fixed effects. The variable $Treated_{ic}$ is an indicator equal to 1 if ZIP i is a treated ZIP (i.e., closing ZIP) for closing c and the D_{ct}^{τ} are indicators equal to 1 if quarter t is τ quarters after (or before, if negative) the quarter of the closing and 0 otherwise. We weight ZIPs by the number of pre-closing applications, and we cluster standard errors at the closing level. The coefficients of interest are the δ_{τ} ; they represent the difference between treated and control ZIPs in outcome Y , τ quarters after the closing. The graphs presented in the following sections plot the δ_{τ} estimates in event time.

For table estimates, we estimate a pre-post version of equation (1):

$$Y_{isct} = \alpha_i + \gamma_{st} + \Sigma_{\tau} D_{ct}^{\tau} + \beta (Treated_{ic} \times Post_{ct}) + \kappa (Treated_{ic} \times Zero_{ct}) + \epsilon_{isct} \quad (2)$$

where $Post_{ct}$ is an indicator equal to 1 if quarter t is after the closing and $Zero_{ct}$ is an indicator equal to 1 if quarter t is the quarter of the closing. We dummy out the quarter of the closing because the closing could occur at the beginning or the end of the quarter, and therefore it is unclear whether to group the quarter of the closing with the “pre” or “post” period. We report estimates of β in our

tables.

This form of difference-in-differences uses variation in the timing of closings, rather than variation in the occurrence of closings (Guryan (2004); Fadlon and Nielsen (2015)).⁸ We use ZIPs that experience a field office closing more than two years in the future as controls for field offices that experience a closing today. The identifying assumption of the difference-in-differences model is that, in the absence of the closing, the number and characteristics of disability applicants and recipients would have evolved similarly in areas that experience a closing today relative to areas that experience a closing in the future. Rather than the closings themselves being random events, the empirical strategy of using future closing ZIPs as controls requires only that the timing of the closings be as good as random. In the figures presented below, we demonstrate that the treated and control ZIPs exhibit parallel trends in the quarters before the closing in both number of applications and characteristics of disability applicants. In robustness checks in Section 4.D, we find similar estimates of the treatment effect using an event study design, but the event study design has pre-trends.

4 Estimates of the effect of closings on applicants and recipients

4.A Effect of closings on number of applicants and recipients

Figure 4 shows the effect of field office closings on the log number of disability applications in closing ZIPs, based on estimates from equation (1), where applications are assigned to quarter based on the date the application was filed. Notice that the treated and control ZIPs exhibit parallel trends in disability applications prior to event quarter 0. Disability applications fall by 11 percent (12 applications per ZIP per quarter) as a result of a field office closing in closing ZIPs. It takes two quarters after the closing for disability applications to reach a stable 11 percent decline, likely because some applicants who visited the field office before the closing submit their applications after the closing. The effect is persistent even two years after the closing. Although we cannot test for intertemporal substitution because we cannot identify individuals who do not apply, the persistence of the effects suggests that applicants discouraged by the closing do not apply for at least another two years. Table 2 provides estimates of β from equation (2).

The decline in applications has different implications depending on whether it leads to a decline

⁸For example, Fadlon and Nielsen (2015) use this strategy to study the effect of worker deaths on spousal labor supply. Based on the insight that households that experience a death are more similar to each other than they are to households that never experience a death, the authors use households that experience a death in the future as controls for households that experience a death today.

in final allowances. We examine whether field office closings discourage applications by those who would have been allowed onto the program, or only those who would have been denied anyway. Figure 4 shows that the number of disability recipients declines by 13 percent (6 allowances per quarter per ZIP) in closing ZIPs, compared to the 11 percent decline in applications (see Table 3). The applicant and recipient estimates are statistically different (Appendix Table A.4). The results imply that closings disproportionately discourage applications by those who would have been allowed by SSA adjudicators if they had applied.⁹

4.B Effect of closings on targeting

Who is screened out by higher application costs? We measure effects on composition in two ways: 1) by estimating the effect of the closings on applicants and recipients separately for each subgroup (first set of columns in of Tables 2 and 3), and 2) by estimating the effect of the closings on the proportion of applicants and recipients with a given characteristic (e.g., proportion with mental condition) or on the average value of the characteristic (e.g., average age), similar to the approach taken by Gruber, Levine, and Staiger (1999) and Einav, Finkelstein, and Cullen (2010) (second set of columns of Tables 2 and 3). While the proportion/average estimates summarize overall effects on a characteristic, the estimates by subgroup provide a fuller picture of the effects of the closings. Appendix Table A.4 presents results of tests for statistically differences across subgroups. This analysis rests on the assumption, discussed in detail in Section 4.D, that the closings do not affect how applicants are classified.

We find that composition changes are similar at the applicant and recipient levels, so we focus mainly on the applicant level in the exposition, since it provides a direct measure of applicant behavior. We start with measures of health. Whether field office closings disproportionately discourage higher severity or lower severity potential applicants is ex ante ambiguous: higher severity potential applicants may face higher costs of reaching a neighboring office or applying through other means because of their health, while less severely disabled applicants may no longer find it worth applying given the increase in application costs. We categorize applicants into four severity categories: those

⁹We estimate the effect of the closings in different time periods to see if closings have larger effects in some time periods than in others. Given that we have only 125 closings since 2000, we have limited power and so split the sample into an equal number of “early” and “late” closings, with 2011 as the dividing year. We find that early and late closings are comparable in their effects on disability applications, but late closings—all of which occur in the Great Recession—have a much larger effect on initial and final allowances (see Appendix Table A.5). These results suggest that the *composition* of discouraged applications is different between the two time periods: most of the applicants discouraged in the earlier period would not have been allowed onto the disability program had they applied, whereas many of the discouraged applicants in the late period would have been allowed had they applied.

who are never allowed (“low” severity); those who are denied at the initial level but allowed on appeal (“medium” severity); those allowed at the initial level and labelled “medical improvement expected” or “medical improvement possible” (“high” severity); and those allowed at the initial level and labelled “medical improvement not expected” (“very high” severity).¹⁰ As shown in Figure 5, the decline in applications is non-monotonic in severity, with smaller effects for low severity (8 percent) and very-high severity (5 percent) applicants, but large effects for medium severity (27 percent) and high severity (16 percent) applicants. The differences across severity subgroups are statistically significant.

Another observable measure of health is disability type. We categorize applicants into three disability types based on the body system code on their record: mental conditions, which have accounted for a substantial increase in disability enrollment for both adults and children; musculoskeletal conditions (such as back pain), which have also risen substantially for adults in recent decades; and other physical conditions.¹¹ As shown in Figure 5, the decline in applications is nearly twice as large for mental conditions (12 percent) and physical conditions (12 percent) compared to musculoskeletal (7 percent) conditions, and this difference is statistically significant.

Turning to socioeconomic status, we estimate the effects of the closings by education, pre-application earnings, and whether the applicant speaks English. We observe these characteristics for adults only and therefore estimate effects on these characteristics excluding SSI children. The effects of the closing are monotonically decreasing in education level: from Figure 5 and Table 2, applications decline by 13 percent for high school dropouts, by 9 percent for high school graduates, and by 4 percent for college graduates, though these differences are not significant. The effects of the closings are also monotonically decreasing in pre-application earnings, which we measure as annual earnings in the five years prior to the year of application. Applications decline by 14 percent in the lowest earnings category (\$0-\$5,000) but do not change for the highest earnings category (above \$25,000). The result of these differential effects is that average annual pre-application earnings increase by a statistically significant \$590, or 3.7 percent, after a closing. Interestingly, the estimates

¹⁰SSA’s standard for “medical improvement not expected” is as follows: “Medical impairment is extremely severe, as determined on the basis of existing medical technology and/or our experience in administering disability programs. These impairments do not improve over time, and more likely are progressive either by themselves or by reason of related complications. The likelihood of medical improvement so as to permit the individual to engage in substantial gainful activity is extremely remote” (SSA Program Operations Manual System DI 13005.022, <https://secure.ssa.gov/poms.nsf/lnx/0413005022>). We do not use the severity designation at the final allowance level as a measure of severity because the applicant’s health status may change between the initial and final decisions and the closing itself could affect time to final decision.

¹¹The “other physical” category includes the following body system codes: special senses and speech, respiratory, cardiovascular, digestive, genitourinary, hematological, skin, endocrine, congenital, neurological, cancer, immune system, growth impairment, and special/other.

in Figure 5 show a spike in applications by higher-earning applicants in the quarter of and just before the closing. We interpret this spike as anticipatory behavior: higher-earning applicants, who may also be more informed, rush to submit their applications before the office closes. The subsequent decline in applications for this group could be intertemporal substitution. In contrast, applications from lower-earning applicants remain depressed at the end of the two-year period. Finally, we find that field office closings disproportionately discourage English speakers from applying (8 percent decline) relative to non-English speakers (0.2 percent increase). We find little heterogeneity by age for adults.

All disability programs experience substantial declines in the number of applicants, but the point estimates for the adult SSI (15 percent) and child SSI (15 percent) programs are twice as large as those for the adult SSDI (7 percent) program (Appendix Table A.11). The smaller decline in SSDI applications is consistent with the availability of an online application for SSDI and the higher socioeconomic status of the SSDI population, which might afford easier access to alternatives to the closed field office.¹²

We find that the adjudication process generally maintains, rather than counters, the differential effects across subgroups relative to the application level. Figure A.3 depicts effects by subgroup at the allowance level. Changes in age, education, and earnings after the closing are similar in percentage terms for disability recipients and disability applicants. (Because severity is defined according to the allowance decision, the severity results are mechanically the same at the applicant and recipient margins.)

4.C Effects on applicants and recipients in neighboring ZIPs

We also examine the effects of the closing on neighboring ZIPs, which are ZIPs whose nearest office is the second or third closest office of a closing ZIP prior to the closing event. Neighboring field offices may experience an increase in congestion due to an expanded service area after the closing, which could discourage applications in neighboring ZIPs. To estimate effects on neighboring ZIPs, we construct the sample in a similar way as the main analysis, except that for each closing the treatment group is neighboring ZIPs for that closing and the control group is neighboring ZIPs in future closings. We estimate equations analogous to (1) and (2), replacing the $Treated_{ic}$ dummy with a $TreatedNbr_{ic}$ dummy:

¹²We also estimate the effects of field office closings on Social Security card issuances and find null effects, as shown in Appendix Figure A.2.

$$Y_{isct} = \alpha_i + \gamma_{st} + \Sigma_{\tau} D_{ct}^{\tau} + \Sigma_{\tau} \delta_{\tau}^N (TreatedNbr_{ic} \times D_{ct}^{\tau}) + \epsilon_{isct} \quad (3)$$

$$Y_{isct} = \alpha_i + \gamma_{st} + \Sigma_{\tau} D_{ct}^{\tau} + \beta^N (TreatedNbr_{ic} \times Post_{ct}) + \kappa^N (TreatedNbr_{ic} \times Zero_{ct}) + \epsilon_{isct} \quad (4)$$

where the N superscripts on the coefficients indicate that the estimates are for neighboring ZIPs.

We find large and persistent decreases in applications and final allowances for neighboring ZIPs. The number of applications falls by 5.4 percent and the number of final allowances falls by 9.7 percent (Table 4). As shown in Appendix Figure A.4, the control and treatment groups exhibit parallel trends prior to the closing, but applications and allowances fall for the treatment group after the closing and remain depressed even two years after the closing.

4.D Robustness

The identifying assumption of the difference-in-differences design is that control and treatment ZIPs would experience parallel trends in outcomes in the absence of the field office closing. As seen in Figures 4 and 5, control and treatment ZIPs exhibit parallel trends in the number and composition of applicants prior to the closing. However, it is still possible that the closing itself is prompted by a change in macroeconomic conditions in the treatment ZIPs, and those changes in economic conditions could lead to changes in the number and composition of residents in those ZIP codes. For example, the Social Security Administration may decide to close offices in areas that experience an adverse economic shock or a declining population. In this case, we would mistakenly attribute the change in the number and composition of disability applicants and recipients to the closing, when the closing is merely a symptom of (or coincidental with) changes in macroeconomic conditions.

To probe this threat to validity, we estimate differential trends in macroeconomic conditions between control and treatment ZIPs. Specifically, we put macroeconomic variables on the left-hand side of equation (1) and plot estimates of the δ_{τ} coefficients in Appendix Figure A.5. We find smooth trends through the closing date in population, labor force, unemployment rate, and personal income. Graphs show a positive trend in population, which suggests that the decline in applications is not explained by outmigration from the areas surrounding the closed office. The other graphs show positive trends in economic conditions: increasing labor force and personal income, and declining unemployment rates. However, there is no trend break in any of the macroeconomic variables; the

trends are gradual and are not consistent with the abrupt drop in disability applications and receipt in treated ZIPs. These figures suggest that the changes in the number and composition of applicants and recipients are not caused by macroeconomic shocks.

To further probe the robustness of our results to macroeconomic shocks, we augment equations (1) and (2) to include controls for the local unemployment rate and population, with results shown in Appendix Figure A.6. The point estimates including these controls are declines of 10 percent for applications and 14 percent for recipients, compared to 11 percent and 13 percent without the controls.¹³ We also estimate the effects of the closing using different minimum lengths of time between treatment closings and control closings; the estimates using windows of 4, 6, 10, and 12 quarters are nearly indistinguishable from our original estimates using an 8-quarter window (see Appendix Figure A.7).

To probe whether offices were closed strategically based on anticipated future applications, we investigate what observable factors predict the timing of closings.¹⁴ For each year between 2000 and 2012, we limit the sample to offices that are open in that year but will close in the future and estimate the following equation:

$$\begin{aligned} CloseYr_i = & \alpha + \beta_1 Pop2000_i + \beta_2 Density_i + \beta_3 Apps_i \\ & + \beta_4 FOProcess_i + \beta_5 NumOffice_i + \beta_6 Wait_i + \epsilon_i \end{aligned} \quad (5)$$

where $CloseYr_i$ is the year in which office i closed; $Pop2000_i$ is the population of the service area of office i in the year 2000; $Density_i$ is the population density of the service area of office i in the year 2000; $Apps_i$ is the number of disability applications submitted in office i 's service area in the year before the closing; $FOProcess_i$ is the application processing time for office i in the year before the closing; $NumOffice_i$ is the number of offices within 20 miles of office i before the closing; and $Wait_i$ is walk-in wait time for office i in the year before the closing (available only for 2006 and later). The results are shown in Appendix Table A.3. There is no single factor that consistently predicts closings across time. In 2000, the number of applications in the previous year increases the likelihood of a later closing, but this is not true for future years. Population density increases the

¹³ Another potential threat is that control ZIPs (those that experience their own closing at least two years later) could be neighboring ZIPs of the closing for which they serve as a control. Since, as we show, neighboring ZIPs also experience effects from the closing, using neighboring ZIPs as controls would lead us to underestimate the effect of the closing on surrounding areas. Empirically, we find that just 0.3 percent of control ZIPs are neighbors and the estimates do not change when we exclude neighbors from the sample.

¹⁴ According to Congressional testimony, SSA has not considered local economic or other conditions in deciding what offices to close.

likelihood of a later closing in 2010 but decreases it in 2012; number of proximate offices decreases the likelihood of a later closing in 2010 but increases it in 2012.

We also probe the robustness of our results to different measures of distance, since distance determines whether ZIPs are classified as closing, neighboring, or unaffected. Our main results use straight-line distance and define closings ZIPs as ZIPs whose nearest office closes. We estimate the effects of the closing using two other strategies: 1) using driving time as the measure of distance to classify ZIPs, and 2) defining closing ZIPs as ZIPs within a certain radius (as measured by straight-line distance) of the field office. The estimates using the alternative measures are given in Appendix Table A.6 and are within 15 percent of the main estimates for applications and within 6 percent of the main estimates for allowances.

As another robustness check, we estimate the effects of the closings using event study specifications instead of the differences-in-differences approach. We use the following estimating equation:

$$Y_{isct} = \alpha_i + \gamma_{st} + \sum_{\tau} \delta_{\tau} D_{ct}^{\tau} + \epsilon_{isct} \quad (6)$$

where D_{ct}^{τ} is now a vector of separate indicator variables for each of the quarters before and after a closing. We estimate one version that includes unaffected ZIPs as controls to help identify state-by-time fixed effects, and another version that includes only closing ZIPs. For control (unaffected) ZIPs, all D_{ct}^{τ} are set to zero. For treatment (closing) ZIPs, the D_{ct}^{τ} are equal to one when the quarter is τ quarters after (or before, if negative) the closing. Figure 6 shows both versions of the event study. The version using unaffected ZIPs as controls (left side) shows an upward pre-trend in the number of applications, meaning that SSA closed offices in areas where the number of applications was increasing faster than in other areas. However, the fall in applications in treatment ZIPs after the closing is still apparent, and the estimates are approximately the same magnitude (around 10 percent) as in our preferred empirical strategy. The version using only closing ZIPs (right side) has a less pronounced pre-trend and a drop of similar magnitude in applications.

Finally, the interpretation of our estimates of the effect of closings on the composition of applicants and recipients depends on whether the closings affect the classification of applicants. If the closings affect the likelihood that an applicant is classified as high severity, for example, then the change in severity composition reflects not differential responsiveness of severity types to the closing, but also a change in the likelihood of being classified as a given severity type. For severity, severity classification decisions are made at the state DDS office, which does not change after

the local field office closes. Within DDS offices, cases are assigned to disability examiners in an effectively random way and not based on geography.¹⁵ Examiners are responsible for verifying that the medical records in the case are complete, and if incomplete must request full medical records. Our back-of-the-envelope calculations indicate that the decline in applications from a field office closing is on average less than 2 percent of the DDS caseload, which makes it unlikely that the field office closing has an effect on disability examiner decision-making or severity classification.¹⁶ For disability type, the examiner also decides this classification (e.g., mental or musculoskeletal) based on what is stated in the application and on the applicant’s medical records. If field offices lead applicants to provide more information or list more conditions, the field office closing may affect the examiner’s classification of disability type. For socioeconomic status, we measure pre-application earnings using administrative data, so there can be no change in the pre-application earnings classification after the closing. Education level and age are self-reported on the application, but we have no reason to believe that field offices affect how applicants report them.¹⁷

5 Channels for closing effects

Our estimates give the effect of field office closings on the number and composition of disability applicants and recipients. A key question in interpreting these results is through what channels the closings affect disability applications. We use detailed Social Security data on field office features and GIS data to measure the effects of the closing on various channels: congestion at neighboring field offices, which could reduce the quantity or quality of assistance received; travel time to get assistance; and other potential mechanisms, including the costs of acquiring program information and information spillovers.

Congestion at neighboring offices: Congestion at the neighboring office can take many forms, including longer waiting times to get assistance or a decline in the amount or quality of assistance received. Using estimating equation (3), we estimate the effects of the closings on two measures of congestion in Figure 7: walk-in wait time (in minutes) at neighboring offices and the number of days it takes the neighboring office to process an application before sending it to the state DDS office.¹⁸ Note that these measures are merely proxies for overall congestion, which can

¹⁵See, e.g., Maestas, Mullen and Strand (2013) for a description of the assignment system.

¹⁶If anything, we would expect field offices to increase the likelihood that an applicants are classified as high severity by encouraging applicants to list all conditions on the application. Instead, applicants in closing ZIPs are more likely to be classified as high severity after a field office closes.

¹⁷This observation is based on our visits to field offices and discussions with current and former field office staff.

¹⁸We also estimate effects on the number of field office staff per capita in the service area of the ZIP’s nearest

take many forms, including less time for assistance and lower quality of assistance. Using estimating equation (4), we find that closings lead to a significant increase in walk-in wait time of 21 percent (4.3 minutes) for neighboring ZIPs (Table 4 and Appendix Figure A.8). Processing time increases by a significant 10 percent (3.0 days), although there is an upward pre-trend in processing time starting four quarters before the closing.¹⁹ We expect congestion to affect not only potential applicants who visit a field office in person, but also the much larger number of applicants who seek field office assistance by phone.

Travel times: We expect travel times to affect only potential applicants who visit an office in person. We use calculations from Google Maps to estimate increases in driving distance, driving time, and public transportation time, using estimating equation (2). We find that the closings result in an increase of about 40 percent in all types of travel cost measures (10 minutes in driving time, 12 miles in driving distance, and 36 minutes in public transit time). Unlike the congestion measures, which include behavioral responses, our estimates for changes in travel time and distance are purely mechanical; we do not use actual trips of potential applicants to estimate them. However, the mechanical estimates provide a proxy for the increase in travel costs and we use them in the interpretation of our results.

We examine heterogeneity in the effect of the closing by the proximity of the ZIP to the closest (closed) office and the second closest (neighboring) office, since distance to the neighboring office varies by geographic area (see Figure 2). One might expect the effects of the closing to be decreasing in distance to the closest office, since closer ZIPs use the office more. We find that this pattern holds in the point estimates, though there is no substantial heterogeneity (Appendix Table A.7). The effects of the closing are non-monotonic in distance to the neighboring office, though as expected they are largest when the neighboring office is very far.²⁰

field office. We find that the number of staff per capita actually increases (by 30 percent) after a closing, which is consistent with SSA’s policy of reassigning staff from the closed office to nearby offices. However, staff count is only one input into field office congestion; closings may affect staff productivity as reassigned staff learn new procedures or develop new relationships with schools and health care providers. In addition, depending on their location, offices often face much higher demand for DI services than SSI services, or vice versa, and may therefore employ field office staff who specialize in one of the programs. When staff who specialize in one program transfer to an office with high demand for the other program, it may take time for the transferred staff to learn the details of the other program. We use walk-in wait time and field office processing time to measure congestion because they are direct measures rather than inputs.

¹⁹Field office staff suggest that this pre-trend could be explained by workload shifting to the neighboring office in preparation for the closing, but we have no definitive evidence on this. Another concern is that the increase in application processing time may be a result of a change in the composition of applicants, rather than an increase in congestion. To test this hypothesis, we estimate the effect of the closing on the amount of time it takes the DDS examiner to decide the case and find that examiner decision time *declines* slightly, by 4 percent. This leads us to conclude that the increase in field office processing time is likely a result of congestion.

²⁰The effects of the closing are monotonically decreasing in ZIP population density. These patterns with respect to

Other mechanisms: Another potential mechanism for the effect of closings on applications is the cost of acquiring program information. We do not have direct measures of information acquisition costs. According to SSA officials, field offices stopped doing community outreach about SSA programs in the early 2000s due to budget cuts, so the role of field offices in providing program information is limited to individuals who visit the field office. Evidence of the effect of information on the take-up of government benefits is mixed. [Bhargava and Manoli \(2015\)](#) find that informing households about EITC eligibility increases take-up substantially, while [Bettinger et al. \(2012\)](#) find that information alone does not increase FAFSA completion rates, though information may still be a necessary condition for take-up.

Closings may also affect applications through network effects; for example, closings may discourage one person from applying and that person may affect the application decisions of others through network effects. [Bertrand, Luttmer and Mullainathan \(2000\)](#) and [Dahl, Kostol and Mogstad \(2014\)](#) find evidence for the importance of networks in the decision to apply for government benefits. If this mechanism were important in the field office context, we might expect to see the effect of field office closings increasing over time. Instead, from [Figure 4](#), we see that the number of applications declines in the first few quarters and then remains at a lower level for the rest of the two-year window.

5.A Decomposition of channels

Ideally, we would decompose the total decline in applications into the parts attributable to each of these channels: congestion at neighboring offices, travel time, and information and network mechanisms. We are limited by having one instrument and multiple endogenous variables. However, we attempt to isolate the effects of congestion at neighboring offices by comparing the effect of the closing on neighboring ZIPs to the effect on closing ZIPs. The assumption behind this decomposition is that neighboring ZIPs experience only, to first order, the effects of congestion at the neighboring office, while closing ZIPs experience effects through all three channels.

We use the following decomposition:

$$\hat{\beta}^{App,Closing} = \hat{\beta}^N + \tilde{\beta}^R$$

where $\hat{\beta}^{App,Closing}$ is the effect of the closing on log applications in closing ZIPs, estimated from own office distance, neighboring office distance, and population density generally hold even after controlling for the other two characteristics.

equation (2); and $\hat{\beta}^N \equiv \hat{\beta}^{App,Nbr} \frac{\hat{\beta}^{Cong,Closing}}{\hat{\beta}^{Cong,Nbr}}$ is the effect of the closing on log applications in neighboring ZIPs, normalized by the ratio of the percent increase in congestion (i.e., as measured by walk-in wait time or application processing time) in closing ZIPs to the percent increase in congestion in neighboring ZIPs.²¹ The terms $\hat{\beta}^{App,Nbr}$ and $\hat{\beta}^{Cong,Nbr}$ are estimates of the effect of the closing on applications and congestion, respectively, in neighboring ZIPs (estimating from equation (4)), and $\hat{\beta}^{Cong,Closing}$ is the estimate of the effect of the closing on congestion for closing ZIPs, again from equation (2). Under the assumptions outlined below, we take $\hat{\beta}^N$ to be the effect of the closing operating through field office congestion and $\tilde{\beta}^R$ (“residual”) to be the effect of the closing operating through all remaining channels—travel time, information, and network effects.

This decomposition requires two major assumptions. The first is that neighboring ZIPs have the same response to an increase in congestion costs as the closing ZIPs. This assumption could be satisfied either in a “constant effects” framework—meaning that all individuals respond the same way to an increase in congestion costs—or if individuals in closing ZIPs and neighboring ZIPs have observably and unobservably similar populations. The second assumption is that the effect of channels is additive with no interactions across channels—e.g., that experiencing both travel costs and congestion costs does not dampen or amplify the effects of the congestion costs.

To address the first assumption of similar populations, we estimate the effects of the closing on applications in neighboring ZIPs using only neighboring ZIPs that are observably similar to closing ZIPs. We first estimate a propensity score based on 2000 Census ZIP characteristics as well as the number and composition of applicants in 2000 and then estimate effects on neighboring ZIPs who have a propensity score above the median. Based on this decomposition exercise, we estimate that 82 percent of the decline in applications is attributable to an increase in congestion costs using walk-in wait time as the measure of congestion (59 percent using application processing time as the measure of congestion). The remaining 20-40 percent of the decline in applications is therefore attributable to a combination of travel time, information, and network effects.²²

Using these back-of-the-envelope estimates, we calculate the elasticity of disability applications with respect to each type of cost. Using the wait time measure for congestion, a 10 percent increase in field office congestion decreases disability applications by 2.8 percent, while a 10 percent increase

²¹We standardize by the ratio of congestion cost increases because closing ZIPs experience larger increases in congestion than neighboring ZIPs. Multiplying by the ratio of congestion costs gives a standardized measure of the effect of one-unit increase in congestion on applications.

²²The propensity score reweighting does not change the results substantially. Without reweighting, the estimate of the effect of closings on applications in neighboring ZIPs (reported above) is 0.054. With reweighting, it is 0.061. The decomposition results are 73 percent from congestion costs without reweighting for walk-in wait time (52 percent for processing time), and 83 percent (59 percent) with reweighting.

in travel time decreases disability applications by (at most, since this figure also includes information costs) 0.5 percent.²³ One explanation for the importance of field office congestion relative to travel cost is that most interactions with the field office regarding disability applications occur by phone (e.g., for follow-up), rather than in person. Travel times affect only those visiting the field office in person, while field office congestion affects both phone and in-person interactions.²⁴

5.B Use of potential field office substitutes

Resources that provide information and assistance with disability applications may mitigate the effects of field office closings. We study the effects of the closings on the use of three potential field office substitutes: the online application, SSA’s 800 phone line, and third-party representation. As shown in Table 2, the number of applicants who file in person or by phone declines by 15 percent, while the number of applicants who file online *increases* by 7 percent. This differential effect could reflect either higher discouragement among those with less access to or familiarity with technology, or it could reflect applicants turning to the online application as a substitute for filing at a field office. We also estimate these effects by education subgroup in Appendix Table A.9: the number of college graduates applying online increases by 10.3 percent, while the increase is an insignificant 5.7 percent for high school graduates and 0.4 percent for high school dropouts. If we interpret the estimates in terms of applicant behavior, they suggest that more-educated applicants substitute to the online application, while less-educated applicants do not.

Another potential field office substitute is SSA’s 800 number, which handles inquiries regarding disability applications and other Social Security matters (e.g., retirement claims and Social Security card issuances). We find evidence, shown in Appendix Figure A.9, that the closings stem a downward trend in call volumes to the 800 number.²⁵ The closing increases the likelihood of having

²³To get 2.8 percent, we calculate $0.11 \cdot 0.82 / (4.314 / 13.6) \cdot 0.1 = 0.028$. Similarly, to get 0.5 percent, we calculate $0.11 \cdot 0.18 / (9.974 / 23.5) \cdot 0.1 = 0.005$.

²⁴In the Appendix, we outline an IV strategy for decomposing the different channels using distance to the neighboring office as an instrument for travel costs and wait time at the neighboring office as an instrument for congestion costs. Given the limited number of closings, however, the results are imprecise and we cannot make definitive statements.

²⁵We have call volumes by area code by month from January 2014 to April 2016 from SSA’s Office of Telephone Services. We estimate an event-study-style regression using the 15 field office closings that occur in 2014:

$$Y_{it} = \alpha_i + \sum_{\tau} \beta_{\tau} D_{it}^{\tau} + \mu_t + \epsilon_{it} \quad (7)$$

where Y_{it} is call volume from area code i in month t ; α_i are area code fixed effects; and μ_t are calendar month fixed effects. The vector D_{it}^{τ} includes indicator variables for each of the months before and after a closing. The sample includes all area codes in the United States, but the D_{it}^{τ} are set equal to zero for unaffected area codes; the unaffected area codes help to identify the μ_t . Unfortunately, the pre-period is limited because all but one of the 15 closings occurs in March of 2014, just two months after the data begin. Although the pre-period is limited, we find evidence that closings stem a downward trend in call volumes to the 800 number.

representation, but the change is not significant, likely because only 5 percent of applicants are represented at the initial level at baseline.

6 Interpreting the effects of field office closings

We find in the previous section that field office closings reduce disability applications by 7 percent for SSDI and 15 percent for SSI, and reduce disability receipt by 12 percent for SSDI and 15 percent for SSI. These are large effects, implying a value of time of approximately \$100 per hour for both SSI and DI applicants.²⁶ How do the effects of field office closings compare to the effects of ordeals in other contexts? [Bettinger et al. \(2012\)](#) estimate a 29 percent increase in college completion from providing assistance with the FAFSA, while [Madrian and Shea \(2001\)](#) estimate a 130 percent increase in 401(k) enrollment from automatically enrolling individuals. Quasi-experimental estimates of ordeal reductions are smaller: [Rossin-Slater \(2013\)](#) finds that openings of WIC offices increase take-up by 6 percent in surrounding areas, [Kopczuk and Pop-Eleches \(2007\)](#) estimate a 12 percent increase in EITC claiming from electronic filing, and [Ebenstein and Stange \(2010\)](#) find no effect of Internet-based UI claiming on take-up.

We also compare the effects of the closings to other determinants of disability application and receipt, such as economic conditions, program rules, and health shocks. These comparisons suggest that the closing of a field office has effects *at least* as large as a 10 percent change in earnings or a 10 percent change in replacement rates, but much smaller than a severe health shock. Of course, the normative implications of disability reductions from closings versus earnings gains or health shocks are likely different.²⁷

Field office closings present a tradeoff between Type I and Type II error: they discourage applications among the less deserving, but also discourage applications among the more deserving

²⁶Suppose, conservatively, those who do not apply because of the closing lose two years of DI benefits, which average \$1,300 per month. With an overall 2/3 probability of allowance, the expected benefit of applying is \$20,800. From our estimates, closings reduce the probability of applying by 7 percent for the DI program. If the field office closing increases the amount of time required to apply by 15 hours, then the value of time that rationalizes the decision not to apply is $(0.07 * \$20,800) / 15 = \97 . By similar logic, and using the 14 percent decline and \$700/month in benefits, the value of time for SSI recipients is \$105.

²⁷[Black, Daniel and Sanders \(2002\)](#) study the effects of the coal boom and bust on disability payments. They estimate that a 10 percent increase in earnings reduces DI payments by 3 to 4 percent and SSI payments by 4 to 7 percent. [Duggan and Imberman \(2009\)](#) decompose DI program growth from 1984 to 2003 into various determinants, including program changes and economic conditions. Their estimates suggest that a 10 percent increase in replacement rates would increase DI enrollment by 7 percent. With respect to the effect of health shocks, the [Meyer and Mok \(2013\)](#) estimates suggest that having a chronic severe condition increases the likelihood of disability receipt by 88 percent relative to a chronic non-severe condition.

(increasing “Type Ia” error, in the language of Kleven and Kopczuk 2011).²⁸ Applying the model from Section 1.A, we find that field office closings reduce targeting efficiency when targeting efficiency is defined in terms of adjudicator preferences of who is deserving and undeserving. Specifically, we estimate statistically different declines of 11 percent for applications and 13 percent for recipients, which yields $\Delta_R - \Delta_A = -0.13 - (-0.11) = -0.02 < 0$. It follows, using the theorem, that $\gamma(\eta') - \gamma(\eta) < 0$, which signifies a decline in targeting efficiency.

If societal preferences differ from adjudicator preferences, then changes in observable characteristics of applicants and recipients are relevant for assessing targeting efficiency. For every 10 low-severity potential applicants who are discouraged from applying due to a closing, 6 medium-severity applicants, 5 high-severity applicants, and 1 very high severity applicant are also discouraged. Society may also have preferences over socioeconomic status if disability programs are viewed as social insurance against disadvantages other than disability, such as low education levels or low earnings. We find that for every 10 college graduates discouraged from applying, 150 high school dropouts and 230 high school graduates are discouraged (see full log and level estimates in Appendix Tables A.13 and A.14).²⁹

Finally, we present a cost-benefit analysis of field office closings considering both targeting efficiency and productive efficiency. The most important assumption we make in the cost-benefit analysis is that applicants who are ultimately allowed by SSA—at any level of adjudication—are deserving of disability benefits, while those with a final denial decision are not. More precisely, we assume that allowed applicants have a higher willingness to pay for disability benefits than the average taxpayer, while rejected applicants have the same willingness to pay for disability benefits as the average taxpayer. Under this assumption, the costs of closings include the loss in social welfare from lower receipt rates of deserving applicants in areas around the closed office and neighboring offices, increased time and effort required to apply for all applicants, and increased time and effort for other visitors to Social Security field offices. The benefits of closings include the administrative

²⁸By Type I error, we mean less deserving (e.g., lower severity) applicants applying for and receiving disability benefits. By Type II error, we mean more deserving (e.g., higher-severity) applicants not applying for and receiving disability benefits.

²⁹Of course, characteristics of applicants are not necessarily independent; for example, a highly educated potential applicant (considered less deserving on the basis of socioeconomic status) may be more likely to be severely disabled. Indeed, the correlation between college education and high severity is a positive 0.05. For this reason, we also estimate in Table 5 the effect of field office closings on characteristics jointly—i.e., effects on applications in each of the nine education-by-severity cells. We find results that are consistent with the separate education and severity estimates: the effects are largest for potential applicants with lower education levels and low- to medium-severity conditions. College graduates do not experience large declines in any severity category, and similarly, high severity potential applicants experience small declines regardless of education category. We also estimate effects by education-by-disability type cells and again find results that are consistent with the separate education and disability type estimates.

savings from processing fewer applications and shuttering the field office, the reduction in application costs for those who are discouraged from applying, and the reduction in earnings decay from waiting for the disability decision for applicants who would have been rejected.

Table 6 presents our annual cost-benefit analysis estimates, with detailed calculations presented in the Appendix. Starting with costs, we first estimate the loss in social welfare from lower receipt rates in closing and neighboring ZIPs. For each program, we calculate from our estimates the number of discouraged applicants per closing who would have been allowed. We then assume that the average discouraged applicant who would have been allowed values disability benefits (including the value of Medicaid or Medicare) 50% more than the average taxpayer. We also assume—very conservatively—that discouraged applicants who would have been allowed lose two years of disability benefits (i.e., they would eventually apply and be approved in two years). Given these assumptions, we estimate losses of \$3.1 million from closing ZIPs and \$14.1 million from neighboring ZIPs, since there are many more neighboring ZIPs than closing ZIPs. To estimate the cost of increasing applicant time and effort, we calculate the value of lost time from increased travel and wait times and the lost earnings from increase in processing times based on estimates from [Autor, Maestas, Mullen and Strand \(2015\)](#); the total losses are around \$1.3 million. We estimate losses of around \$1.7 million to other visitors of the field office based on the number of visitors per office per year from SSA statistics. Total costs are around \$20.2 million per year. Our conservative assumptions likely make this an underestimate.

Turning to benefits, we estimate the administrative savings from processing fewer applications by dividing the total annual administrative budget spent on disability programs by the number of applications processed by field offices in a year, and then multiplying this ratio by the reduction in applications; these amount to \$2.2 million per year. Next, we take administrative savings from the closing itself to be \$0.4 million based on SSA testimony. Finally, we estimate savings of \$1.0 million for discouraged applicants who no longer incur application costs. Total benefits are around \$3.6 million per year.

Putting these figures together, we find that the social costs of the average field office closing outweigh the social benefits by a ratio of 6 to 1, mostly because of the large loss in social welfare from discouraging applicants who would have been allowed had they applied. Of course, this analysis has a number of limitations, including that it does not consider other characteristics besides potential applicant severity and does not capture all costs imposed on applicants due to field office closings.

In the calculation above, we assume the average discouraged applicant who would have been

allowed values the disability benefit 50 percent more than the average taxpayer. An alternative approach to weighing the costs and benefits of closings is to calculate how much more the average accepted applicant must value disability benefits relative to the average taxpayer for the closings to have no net effect on welfare. We find that if the average discouraged applicant (who would have been allowed) values disability benefits at least 1.6 percent more than the average taxpayer, then the closings are welfare-reducing.

7 Conclusion

The effect of application costs on the targeting of social safety net programs is theoretically ambiguous: application costs could improve targeting if they discourage high-ability people with a high opportunity cost of time from applying, or they could worsen targeting if they disproportionately discourage low-ability people from applying. In this paper, we provide the first evidence on this question in the context of disability programs, which are some of the largest social programs in the developed world and have expanded rapidly in recent decades. We find that the closings of Social Security field offices, which provide assistance with disability applications, reduce disability applications by 11 percent and final disability allowances by 13 percent in neighborhoods whose nearest office closes, and have smaller but sizable effects in neighborhoods whose second or third closest office closes. The effects are persistent, with applications showing no sign of recovering even eight quarters after the closings. We also use detailed administrative data on applicant characteristics to determine *who* is screened out by higher application costs. Closings disproportionately discourage applicants with lower education and pre-application earnings levels and applicants with moderately severe conditions.

What are the policy implications of these results? First, the services provided by field offices are highly valuable to disability applicants and indeed are instrumental for 11 percent of applicants in the decision to apply, the majority of whom would be allowed if they had applied. This raises the question of why private industry does not attempt to meet the demand for assistance with disability applications. Possible reasons include credit constraints faced by disability applicants or government regulations that limit the compensation of disability representatives.³⁰ Second, we find that field office closings affect certain populations more than others. Field office closings appear particularly consequential for potential applicants with low levels of education, with highly educated

³⁰Paid representatives must register with SSA and they are limiting to collecting 25 percent of past due benefits owed to the disability applicant. See Code of Federal Regulations §404.1720 and §404.1730.

applicants more likely to substitute to the online application or seek assistance elsewhere. Future decisions about field office placement could consider the distributional consequences of closings.

In terms of normative implications, [Nichols and Zeckhauser \(1982\)](#) hypothesize that ordeals may increase overall social welfare by sacrificing a small amount of productive efficiency (i.e., more applicant time and effort required to apply) for a large increase in targeting efficiency. We find instead that the increase in ordeals induced by Social Security field office closings reduces both productive efficiency and targeting efficiency, as measured by current standards for disability receipt. Moreover, if disability programs are also intended to address economic inequality, then the results by socioeconomic status indicate that field office closings exacerbate the very inequality that disability programs are intended to mitigate.

Given the magnitude of the effects, an outstanding question for future research is why closings have such strong discouragement effects. Our results suggest an implied value of time of approximately \$100 per hour, even for SSI applicants, who by definition have very low income and asset levels. Our examination of potential channels points to congestion at neighboring offices as a more important contributor to the decline in applications than travel times or information costs. Understanding why individuals with a seemingly low opportunity cost of time are so discouraged by congestion effects is an interesting question for future work to address.

References

- Akerlof, George A.**, “The Economics of "Tagging" as Applied to the Optimal Income Tax, Welfare Programs, and Manpower Planning,” *American Economic Review*, 1978, 68 (1), 8–19.
- Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A Olken, Ririn Purnamasari, and Matthew Wai-Poi**, “Self-Targeting: Evidence from a Field Experiment in Indonesia,” *Journal of Political Economy*, 2016, 124 (2), 371–427.
- Autor, David H., Nicole Maestas, Kathleen Mullen, and Alexander Strand**, “Does Delay Cause Decay? The Effect of Administrative Decision Time on the Labor Force Participation and Earnings of Disability Applicants,” 2015.
- Bertrand, Marianne, Erzo F.P. Luttmer, and Sendhil Mullainathan**, “Network Effects and Welfare Cultures,” *Quarterly Journal of Economics*, 2000, 115 (3), 1019–1055.
- , **Sendhil Mullainathan, and Eldar Shafir**, “A Behavioral-Economics View of Poverty,” *American Economic Review: Papers & Proceedings*, 2004, 94 (2), 419–423.
- Besley, Timothy and Stephen Coate**, “Workfare versus Welfare: Incentive Arguments for Work Requirements in Poverty-Alleviation Programs,” *American Economic Review*, 1992, 82 (1), 249–261.
- Bettinger, E. P., B. Terry Long, P. Oreopoulos, and L. Sanbonmatsu**, “The Role of Application Assistance and Information in College Decisions: Results from the H&R Block FAFSA Experiment,” *The Quarterly Journal of Economics*, 2012, pp. 1205–1242.
- Bhargava, Saurabh and Dayanand Manoli**, “Psychological Frictions and the Incomplete Take-Up of Social Benefits: Evidence from an IRS Field Experiment,” *American Economic Review*, 2015, 105 (11), 3489–3529.
- Black, Dan, Kermit Daniel, and Seth Sanders**, “The Impact of Economic Conditions on Participation in Disability Programs: Evidence from the Coal Boom and Bust,” *American Economic Review*, 2002, 92 (1), 27–50.
- Cohen, Jessica, Pascaline Dupas, and Simone Schaner**, “Price Subsidies, Diagnostic Tests, and Targeting of Malaria Treatment: Evidence from a Randomized Controlled Trial,” *American Economic Review*, 2015, 105 (2), 609–645.

- Currie, Janet**, “The Take Up of Social Benefits,” 2004.
- Dahl, Gordon B, Andreas Kostol, and Magne Mogstad**, “Family Welfare Cultures,” *Quarterly Journal of Economics*, 2014, 129 (4), 1711–1752.
- Duggan, Mark and Scott A Imberman**, “Why Are the Disability Rolls Skyrocketing? The Contribution of Population Characteristics, Economic Conditions, and Program Generosity,” in “Health at Older Ages: The Causes and Consequences of Declining Disability among the Elderly” number January 2009, pp. 337–379.
- Ebenstein, Avraham and Kevin Stange**, “Does Inconvenience Explain Low Take-Up? Evidence from Unemployment Insurance,” *Journal of Policy Analysis and Management*, 2010, 29 (1), 111–136.
- Fadlon, Itzik and Torben Heien Nielsen**, “Household Responses to Severe Health Shocks and the Design of Social Insurance,” 2015.
- Finkelstein, Amy, Nathaniel Hendren, and Erzo F.P. Luttmer**, “The Value of Medicaid: Welfare Analysis of Public Health Insurance Expansions,” 2015.
- Golosov, Mikhail and Aleh Tsyvinski**, “Designing Optimal Disability Insurance: A Case for Asset Testing,” *Journal of Political Economy*, 2006, 114 (2), 257–279.
- Guryan, Jonathan**, “Desegregation and Black Dropout Rates,” *American Economic Review*, 2004, 94 (4), 919–943.
- Kopczuk, Wojciech and Cristian Pop-Eleches**, “Electronic Filing, Tax Preparers and Participation in the Earned Income Tax Credit,” *Journal of Public Economics*, 2007, 91 (7-8), 1351–1367.
- Madrian, Brigitte C. and Dennis F. Shea**, “The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior,” *Quarterly Journal of Economics*, 2001, CXVI (4), 1149–1187.
- Maestas, Nicole, Kathleen J Mullen, and Alexander Strand**, “Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects,” *American Economic Review*, 2013, 103 (5), 1797–1829.
- Meyer, Bruce D. and Wallace K.C. Mok**, “Disability, Earnings, Income, and Consumption,” 2013.

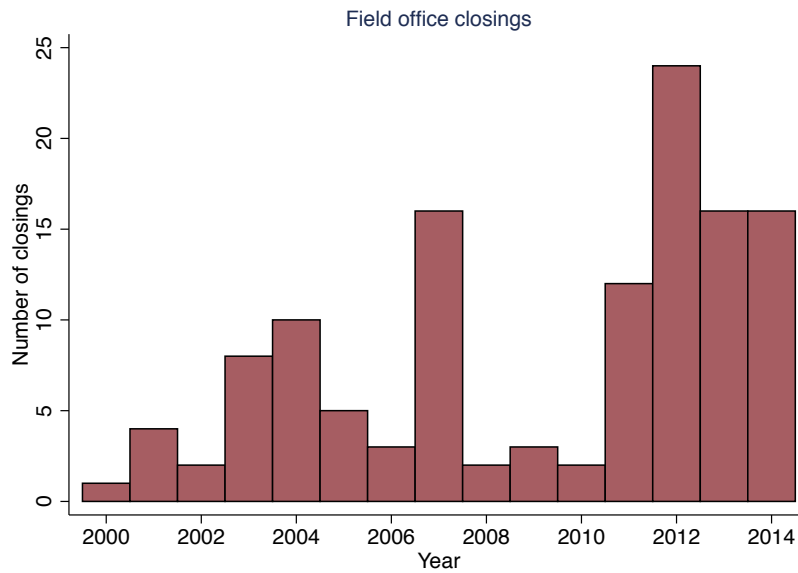
Nichols, Albert L. and Richard J. Zeckhauser, “Targeting Transfers through Restrictions on Recipients,” *American Economic Review*, 1982, 72 (2), 372–377.

Nichols, D., E Smolensky, and T N Tideman, “Discrimination by Waiting Time in Merit Goods,” *American Economic Review*, 1971, 61 (3), 312–323.

Rossin-Slater, Maya, “WIC in Your Neighborhood: New Evidence on the Impacts of Geographic Access to Clinics,” *Journal of Public Economics*, 2013, 102 (March), 51–69.

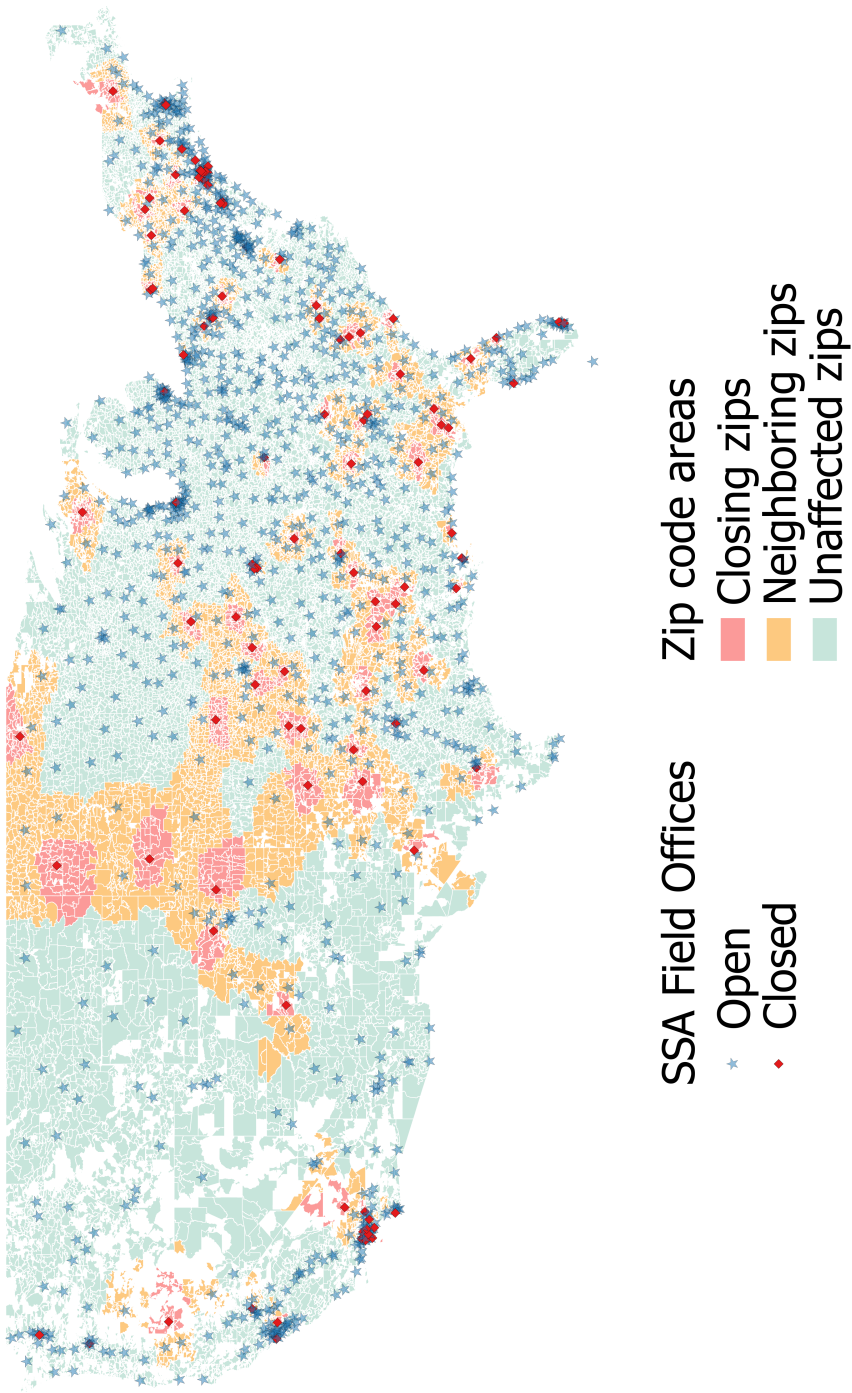
Main Figures and Tables

Figure 1: Timing of Field Office Closings



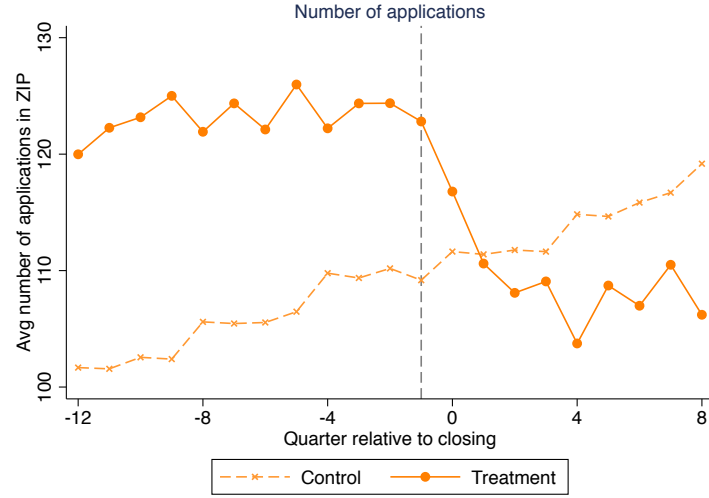
Source: Authors' calculations based on Social Security Administration data.

Figure 2: Map of Field Office Closings and ZIP Classification in United States



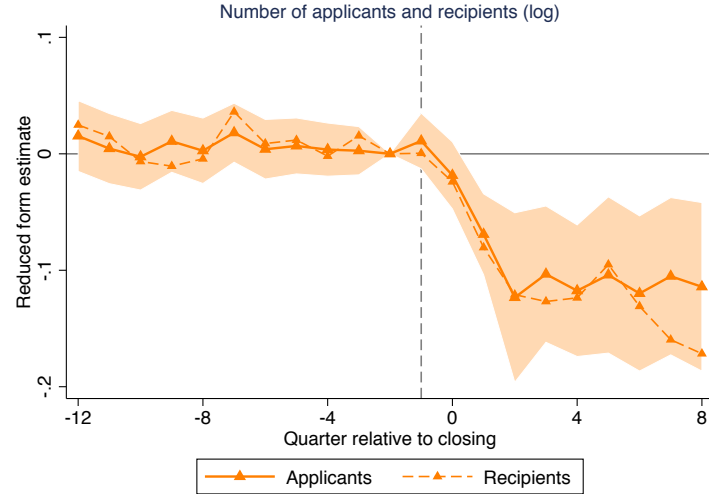
Source: Social Security Administration and Census Bureau.

Figure 3: Raw Plots of Number of Applications in Control and Treatment ZIPs



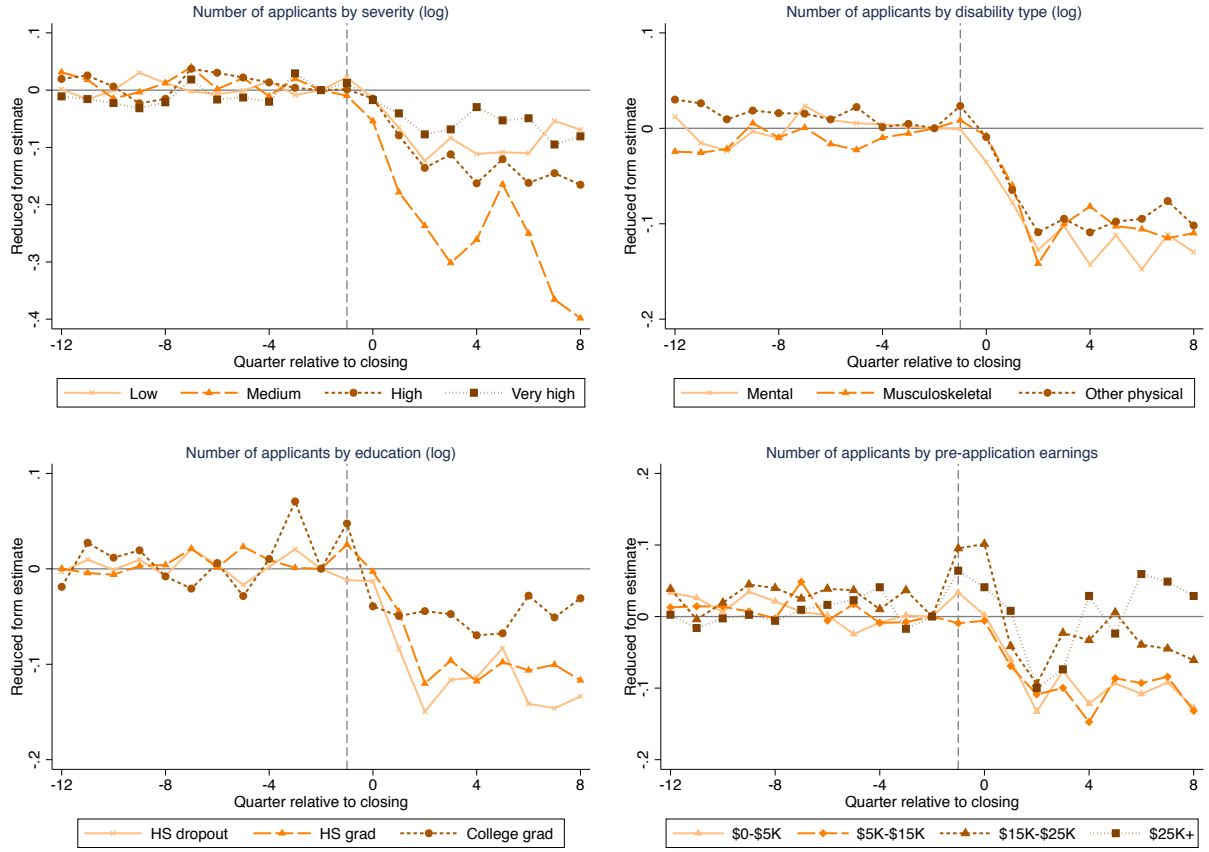
Notes: Figure plots raw (non-regression-adjusted) counts of applications in control and treatment ZIPs relative to the quarter of the closing. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Treatment ZIPs are ZIPs whose nearest office closes for a given closing, while control ZIPs are ZIPs whose nearest office closes in a future closing.

Figure 4: Effect of Closings on Number of Disability Applications and Allowances



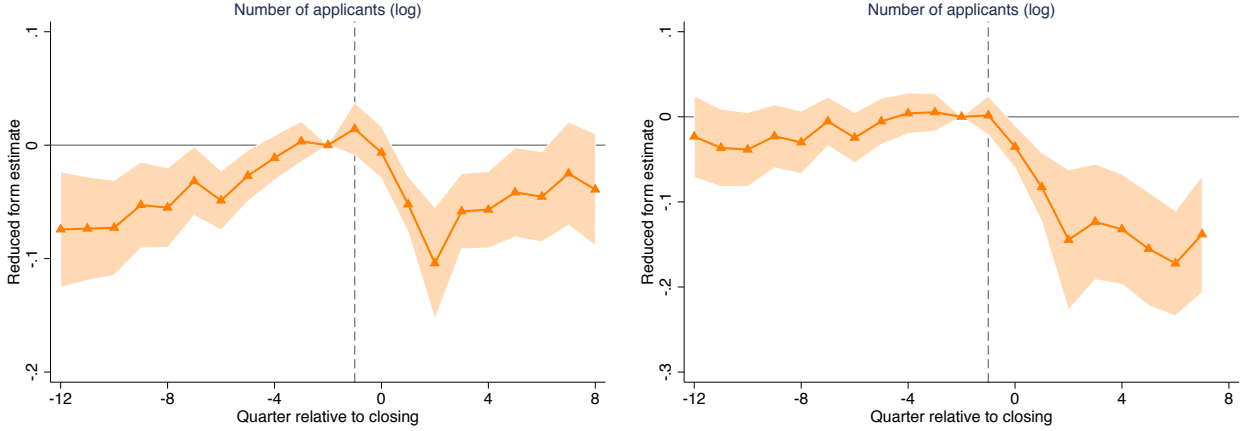
Notes: Figure plots estimates of δ_τ coefficients from equation (1), where the dependent variable is the log number of disability applications (solid series) or the log number of disability recipients (dashed series). Shaded region is 95 percent confidence interval for disability applications (solid series). Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Figure 5: Effect of Closings on Number of Disability Applications, by Subgroup



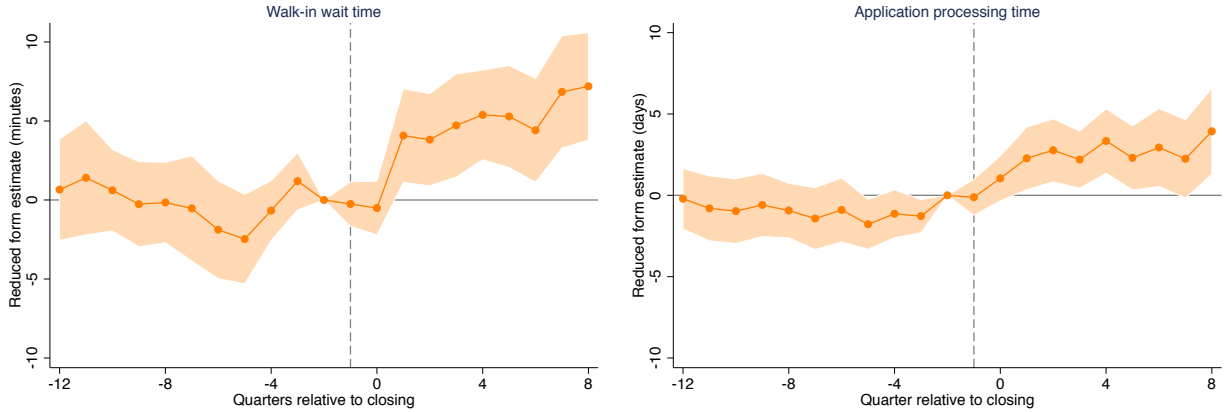
Notes: Figure plots estimates of δ_T coefficients from equation (1), where the dependent variable is the log number of disability applications by subgroup. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Figure 6: Robustness: Event Study Specifications, with and without Unaffected ZIPs



Notes: Figures plot estimates of δ_τ coefficients from equation (6), where the dependent variable is the log number of disability applications. The left graph includes unaffected ZIPs as controls, while the right graph includes only closing ZIPs. For both, the sample contains only ZIPs with an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Figure 7: Effect of Closings on Measures of Field Office Congestion



Notes: Figure plots estimates of β_τ coefficients from equation (1), where the dependent variable is average walk-in wait time in minutes at nearest field office (left) or the average number of days it takes the field office to process a disability application (right). Shaded region is 95 percent confidence interval. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Table 1: Summary Statistics of Closing, Neighboring, and Unaffected ZIP Codes in Sample

	Closing ZIPs		Neighboring ZIPs		Unaffected ZIPs		T-test p-values		
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Closed vs. neighbor	Closed vs. unaffected	Neighbor vs. unaffected
ZIP characteristics (2000)									
Population	15,276	16,378	14,582	15,511	13,073	13,913	0.224	0.000	0.000
Poverty rate	14%	9%	14%	9%	13%	9%	0.968	0.189	0.019
Median income	\$41,608	\$18,164	\$40,456	\$16,664	\$40,405	\$15,453	0.064	0.015	0.596
Male	49%	3%	49%	3%	49%	3%	0.253	0.000	0.000
Female	51%	3%	51%	3%	51%	3%	0.253	0.000	0.000
White	77%	23%	78%	23%	82%	21%	0.225	0.000	0.000
Black	14%	21%	12%	20%	9%	17%	0.028	0.000	0.000
Hispanic	8%	14%	8%	13%	8%	15%	0.686	0.926	0.375
Other race	1%	12%	2%	12%	0%	13%	0.091	0.017	0.000
Age 0-19	27%	6%	28%	5%	28%	5%	0.000	0.000	0.000
Age 20-44	35%	7%	35%	6%	35%	6%	0.325	0.002	0.001
Age 45-64	23%	4%	23%	4%	23%	4%	0.317	0.361	0.000
Age 65+	14%	5%	14%	5%	13%	6%	0.040	0.000	0.002
HS dropout	21%	11%	22%	11%	22%	12%	0.685	0.000	0.001
HS graduate	31%	10%	32%	10%	33%	10%	0.054	0.001	0.000
Some college	25%	6%	26%	7%	26%	7%	0.002	0.000	0.465
College graduate	22%	16%	20%	14%	18%	13%	0.004	0.000	0.000
Never married	26%	9%	25%	9%	24%	8%	0.103	0.000	0.000
Currently married	55%	10%	56%	10%	57%	9%	0.080	0.000	0.000
Previously married	19%	5%	19%	5%	19%	5%	0.492	0.000	0.000
Walk-in wait time (2005)	8.47	7.47	10.65	9.78	9.69	8.60	0.000	0.000	0.000
Num. disability apps (2000)	125	170	128	170	112	149	0.553	0.006	0.000
N	1,090		4,571		14,350				

Notes: Table presents summary statistics for ZIP codes with an average of at least three disability applications per quarter in the year 2000. Closing ZIPs are ZIPs whose nearest office closes. Neighboring ZIPs are ZIPs whose nearest office is a neighbor of a closing office (the second or third closest office to a ZIP whose closest office closes). Unaffected ZIPs are ZIPs that are neither closing nor neighboring ZIPs. "ZIP characteristics" are calculated from the 2000 Census, "Walk-in wait time" from Social Security Administration data (where 2005 is the earliest available year), and "Number of disability applications" from Social Security Administration data.

Table 2: Estimates of the Effect of Closings on Disability Applications

	Count (log)		Proportion/average		
	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.	Mean
All	-0.110***	(0.0300)			
Severity					
Low	-0.0842***	(0.0322)	0.0146**	(0.00601)	0.425
Medium	-0.269***	(0.0518)	-0.0146***	(0.00349)	0.184
High	-0.161***	(0.0393)	-0.00882**	(0.00419)	0.209
Very high	-0.0477	(0.0302)	0.00872***	(0.00243)	0.183
Disability type					
Mental	-0.116***	(0.0351)	-0.00337	(0.00434)	0.289
Musculoskeletal	-0.0656**	(0.0318)	0.00828***	(0.00272)	0.276
Other physical	-0.116***	(0.0309)	-0.00491	(0.00452)	0.435
Education (years)			0.0591**	(0.0266)	11.8
HS dropout	-0.130***	(0.0316)			
HS graduate	-0.0882***	(0.0264)			
College graduate	-0.0398	(0.0311)			
Pre-application earnings (\$)			575.0**	(264.2)	\$15,400
\$0-\$5,000	-0.136***	(0.0473)			
\$5,000-\$15,000	-0.119**	(0.0570)			
\$15,000-\$25,000	-0.0448	(0.0757)			
\$25,000+	0.0111	(0.0743)			
Language					
Speaks English	-0.0787	(0.0623)	-0.0157***	(0.00575)	0.623
Does not speak English	0.00187	(0.0663)			
Age (years)			0.231	(0.149)	40.7
18-34	-0.118***	(0.0350)			
35-49	-0.116***	(0.0318)			
50+	-0.0886***	(0.0266)			
Applicant behavior					
Files online	0.0710	(0.0565)	0.0268***	(0.00858)	0.074
Files in person or by phone	-0.150***	(0.0338)			
Provides email address	0.0750	(0.0608)	0.0190*	(0.00984)	0.111
No email address	-0.130***	(0.0341)			
Has representation	0.0515	(0.0692)	0.00444	(0.00525)	0.054
No representation	-0.115***	(0.0313)			

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The first set of columns presents estimates of the effect of field office closings on log applications by subgroup, specifically estimates of β from equation (2). The second set of columns gives results by proportion for indicator variables (severity, disability type, applicant behavior, language) and by average for continuous variables (education, earnings, age). If some subgroups are small, the change in proportion may be small even when there is substantial heterogeneity in the effects across subgroups. Earnings and education estimates include only adult applicants. The last column is the mean of the control group over the post-closing period. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table 3: Estimates of the Effect of Closings on Disability Allowances

	Count (log)		Proportion/average		
	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.	Mean
All	-0.134***	(0.0312)			
Severity					
Low	N/A		N/A		
Medium	-0.244***	(0.0478)	-0.0256***	(0.00570)	0.329
High	-0.149***	(0.0371)	-0.00649	(0.00538)	0.359
Very high	-0.0412	(0.0286)	0.0321***	(0.00600)	0.312
Disability type					
Mental	-0.152***	(0.0341)	-0.00904**	(0.00393)	0.289
Musculoskeletal	-0.109***	(0.0358)	0.00122	(0.00352)	0.252
Other physical	-0.110***	(0.0311)	0.00783*	(0.00458)	0.459
Education (years)			0.0265	(0.0316)	11.9
HS dropout	-0.123***	(0.0338)			
HS graduate	-0.124***	(0.0298)			
College graduate	-0.0509	(0.0318)			
Pre-application earnings (\$)			799.4**	(314.2)	\$18,717
\$0-\$5,000	-0.152***	(0.0488)			
\$5,000-\$15,000	-0.134**	(0.0630)			
\$15,000-\$25,000	-0.0590	(0.0670)			
\$25,000+	-0.0116	(0.0703)			
Age (years)			0.236	(0.178)	43.0
18-34	-0.133***	(0.0358)			
35-49	-0.185***	(0.0397)			
50+	-0.108***	(0.0290)			

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The first set of columns presents estimates of the effect of field office closings on log final allowances by subgroup, specifically estimates of β from equation (2). The second set of columns gives results by proportion for indicator variables (severity, disability type) and by average for continuous variables (education, earnings, age). Earnings and education estimates include only adult allowances. The last column is the mean of the control group over the post-closing period. "Low" severity not applicable at the allowance level because low severity is defined as being denied from disability. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table 4: Estimates of the Effect of Closings on Types of Application Costs

	Closing ZIP			Neighboring ZIP		
	Pt. Est.	Std. Err.	Mean	Pt. Est.	Std. Err.	Mean
Applications (log)	-0.110***	(0.0300)	39.6	-0.0539***	(0.0176)	42.5
Recipients (log)	-0.134***	(0.0312)	21.7	-0.0967***	(0.0188)	22.6
Congestion measures						
FO processing time	3.032***	(1.095)	28.8	2.804***	(0.731)	28.4
Walk-in wait times	4.314***	(1.416)	13.6	3.472***	(1.126)	16.3
Travel cost measures						
Driving time	9.974***	(1.636)	23.5			
Driving distance	11.97***	(1.337)	24.3			
Transit time	35.76***	(6.427)	89.4			

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates of the effect of field office closings on log applications, log allowances, and measures of application costs for closed and neighboring ZIPs, specifically estimates of β from equations (2) and (4), respectively. A closing ZIP is a ZIP whose nearest office closes. A neighboring ZIP is a ZIP whose nearest office is the second or third closest office of a closing ZIP. Walk-in wait time is the average time (in minutes) that a visitor to a field office waits to be seen. Processing time is the number of days it takes a field office to send an application to a state disability determination services office. Driving time, driving distance, and public transit time to the nearest field office are calculated using Google maps with the trip originating from the ZIP centroid. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table 5: Estimates of the Effect of Closings on Log Applications, by Education and Health Subgroup

	Severity			Disability type		
	Low/medium	High	Very high	Mental	Musc.	Oth. Phys.
Log applications						
HS dropout	-0.139*** (0.0324)	-0.124*** (0.0427)	-0.00485 (0.0314)	-0.136*** (0.0374)	-0.0791** (0.0333)	-0.122*** (0.0323)
HS graduate	-0.0831*** (0.0281)	-0.123*** (0.0397)	-0.0459 (0.0289)	-0.0810** (0.0342)	-0.0512* (0.0306)	-0.0980*** (0.0286)
College graduate	-0.0104 (0.0275)	-0.0245 (0.0166)	0.0127 (0.0206)	-0.0118 (0.0199)	-0.00721 (0.0237)	-0.000691 (0.0307)
Correlation						
HS dropout	0.012	-0.004	-0.011	0.018	-0.008	-0.008
HS graduate	0.014	-0.005	-0.013	-0.020	-0.005	0.023
College graduate	-0.056	0.020	0.053	0.005	0.027	-0.033

Notes: *** p<0.01, ** p<0.05, * p<0.1. The top panel of the table presents estimates of the effect of field office closings on log applications by education and health subgroup, specifically estimates of β from equation (2). The bottom panel presents estimates of the correlation between education characteristics and health characteristics. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table 6: Costs and Benefits of Field Office Closings

Costs of closing (thousands)	
Lower receipt in closing ZIPs	\$3,100
Lower receipt in neighboring ZIPs	\$14,100
Higher applicant time and earnings decay	\$1,300
Increased time for other office visitors	\$1,700
Total	\$20,200
Benefits of closing (thousands)	
Administrative savings from processing fewer applications	\$2,200
Administrative savings from closing field office	\$400
Application cost savings from discouraged applicants	\$1,000
Total	\$3,600
Ratio of costs to benefits	6

Notes: Table presents estimates of costs and benefits of field office closings, in thousands of dollars. See Appendix for detailed explanation of calculations.

Appendix (For Online Publication)

Conceptual Framework

Proof of Proposition

Proposition: If screening technology is good ($p_D > p_U$), then targeting efficiency increases (i.e., $\gamma(\eta') - \gamma(\eta) > 0$) if and only if the percent change in recipients exceeds the percent change in applicants (i.e., $\Delta_R - \Delta_A > 0$).

Proof. Let π be the fraction deserving and $1 - \pi$ the fraction of undeserving. Then

$$\begin{aligned}\Delta_R - \Delta_A &= \frac{Pr(R|\eta') - Pr(R|\eta)}{Pr(R|\eta)} - \frac{Pr(A|\eta') - Pr(A|\eta)}{Pr(A|\eta)} \\ &= \frac{Pr(R|\eta')}{Pr(R|\eta)} - \frac{Pr(A|\eta')}{Pr(A|\eta)} \\ &= \frac{Pr(A|U, \eta')}{Pr(A|U, \eta)} \frac{\pi(1 - \pi)(p_D - p_U)}{(\pi\gamma(\eta)p_D + (1 - \pi)p_U)(\pi\gamma(\eta) + (1 - \pi))} [\gamma(\eta') - \gamma(\eta)]\end{aligned}$$

Therefore if $p_D - p_U > 0$, then $\gamma(\eta') - \gamma(\eta) > 0$ if and only if $\Delta_R - \Delta_A > 0$.

□

Theoretically Ambiguous Effect of Closings on Targeting Efficiency

We provide a conceptual framework demonstrating that a change in the cost of applying has an ambiguous effect on targeting efficiency (γ). In particular, the effect on targeting depends on the differential effect of a cost increase on the application behavior of more- vs. less-deserving (e.g., high- vs. low-severity) individuals. The ambiguous theoretical effect means that empirical evidence is needed to determine the effect of application costs on targeting.

Let $z(h, \eta)$ denote the cost of filing an application, where η represents the cost of visiting a field office (e.g., travel and time costs) and $h \in [0, 1]$ indicates the severity of the individual's condition. We assume that $z_h(h, \eta) > 0$, meaning that individuals in worse health have more difficulty filing an application; $z_\eta(h, \eta) > 0$ so that increased travel or time cost to get to a field office increases the cost of filing an application; $z_{hh}(h, \eta) \geq 0$, meaning that the cost of filing is convex in severity; and $z_{h\eta}(h, \eta) \geq 0$, meaning that increases in travel and time costs are weakly more costly to high-severity individuals than low-severity individuals.

Let $g(h)$ denote the benefit of filing an application. We assume that $g(h)$ is a twice differentiable function with $g'(h) > 0$ and $g''(h) < 0$, meaning that the benefit of applying is increasing in severity

but at a decreasing rate. The concavity of the g function reflects that lower life expectancy (or lower quality of life) among high-severity individuals might lead to higher discount rates.

Suppose at baseline that there is some h_1^* such that individuals with severity $h \leq h_1^*$ do not apply for benefits while individuals with severity $h > h_1^*$ apply for benefits, as shown in Appendix Figure A.10. At h_1^* , $g'(h_1^*) > z_h(h_1^*, \eta)$. Suppose that SSA closes a field office, increasing travel and time costs to $\eta' > \eta$ and the total application cost to $z(h, \eta')$. We assume the increase in η is modest enough that some individuals still apply for disability after the closing. Consider the following two cases:

Case 1. $z(1, \eta') < g(1)$

Proposition 2. *If $z(1, \eta') < g(1)$, then there exists $h_1^{*'} > h_1^*$ such that only individuals with $h > h_1^{*'}$ apply for disability benefits.*

Proof. Since $g(0) < z(0, \eta) < z(0, \eta') < z(1, \eta') < g(1)$, $g(h)$ intersects $z(h, \eta')$ only once in the support of $[0, 1]$. Denote this single intersection as $h_1^{*'}$. At this point, $g(h_1^{*'}) = z(h_1^{*'}, \eta')$ and $g'(h_1^{*'}) > z_h(h_1^{*'}, \eta')$, meaning that only individuals with $h > h_1^{*'}$ apply for disability benefits. To show that $h_1^{*' > h_1^*$, suppose that this is not the case. Then $g(h_1^*) > z(h_1^*, \eta') > z(h_1^*, \eta)$ where the first inequality holds because those with $h > h_1^{*'}$ apply for benefits. But this is a contradiction since $g(h_1^*) = z(h_1^*, \eta)$. □

Case 2. $z(1, \eta') > g(1)$

Proposition 3. *If $z(1, \eta') > g(1)$, then there exists $h_1^{*' > h_1^*$ and $h_2^{*' < 1$ such that only individuals with $h_1^{*' < h < h_2^{*'}$ apply for disability benefits.*

Proof. We assume above that a positive number of individuals apply for disability benefits after the increase in η . For this to be true when $z(1, \eta') > g(1)$, $g(h)$ must intersect $z(h, \eta')$ twice in the support of $[0, 1]$. Denote the two intersection points as $h_1^{*'}$ and $h_2^{*'}$, where $h_2^{*' > h_1^{*'}$. In this case only individuals with $h_1^{*' < h < h_2^{*'}$ apply for benefits. We showed in the proof to Proposition 1 that $h_1^{*' > h_1^*$. Now we need to show that $h_2^{*' < 1$. Suppose not; then $g(1) \geq z(1, \eta')$, which is a contradiction since $g(1) < z(1, \eta')$. □

In Case 1, depicted in the left-hand-side graph of Appendix Figure A.10, the closing of the field office unambiguously improves the targeting of the disability program by increasing the severity

threshold above which the benefit of applying exceeds the cost. In Case 2, if individuals are uniformly distributed in $h \in [0, 1]$ and we measure targeting in terms of the absolute number of high- or low-severity individuals screened in or out, then the targeting of the program improves if $1 - h_2^{*'} < h_1^{*'} - h_1^*$ and worsens if $1 - h_2^{*'} > h_1^{*'} - h_1^*$ (right-hand-side graph of Appendix Figure A.10). Specifically, the cross-partial derivative $z_{h\eta}(h, \eta)$ determines the relative positions of $h_1^{*'}$ and $h_2^{*'}$. Since the theoretical effect of the closing is ambiguous in this case, empirical evidence is needed to determine whether the closing improves or worsens targeting.

IV strategy to decompose channels

We use variation in ZIP proximity to and wait time at a its second closest office (the closest office after the closing) to decompose the total decline in applications into the parts attributable to each of the congestion and travel cost channels. For the purposes of this exercise, we assume that the information channel has no effect.³¹ The structural equation of interest is the following:

$$Y_{isct} = \alpha_i + \gamma_{st} + \beta \text{Congestion}_{ict} + \kappa \text{Distance}_{ict} + \epsilon_{isct} \quad (8)$$

where Congestion_{ict} is a measure of congestion (e.g., walk-in wait time) at the office that is closest to ZIP i in quarter t , and Distance_{ict} is the driving distance between ZIP i and its closest office in quarter t . Congestion and distance could be endogenous to the number of disability applications; for example, a rural ZIP may have longer distances than an urban ZIP and also more disability applications because of a less healthy population. For this reason, we use instruments that limit the variation in each endogenous variable to that induced by 1) the closing and 2) differences in new wait time or distance at the now-closest office relative to the previously-closest office. Specifically, as an instrument for congestion, we interact the Treated_{ic} and Post_t variables with the difference between pre-closing wait time at the now-closest office and pre-closing wait time at the previously-closest office. Similarly, as an instrument for distance, we interact the Treated_{ic} and Post_t variables with the difference between the driving distance to the the now-closest office and the driving distance to the previously-closest office.³² The first stage equations are as follows:

³¹We recognize that more than one cost may deter someone from applying for disability. For example, someone may decide not to wait for assistance at a field office because of congestion, and that visit may have provided the individual with information about the program. Under the assumptions of this exercise, we would attribute all of the deterrence effect to congestion.

³²We use the *difference* in wait times as the instrument instead of just pre-closing wait time at the now-closest office because walk-in wait times are spatially correlated: a high wait time at the now-closest office predicts a high wait time at the previously-closest office, and therefore does a poor job predicting the increase in wait time that the ZIP

$$Congestion_{isct} = \alpha_i + \gamma_{st} + \beta_1(Treated_{ic} \times Post_t \times CongestionDiff_{ic}) + \nu_{isct} \quad (9)$$

$$Distance_{isct} = \alpha_i + \gamma_{st} + \kappa_1(Treated_{ic} \times Post_t \times DistanceDiff_{ic}) + \xi_{isct} \quad (10)$$

where $CongestionDiff_{isc}$ is the difference between the walk-in wait time at the now-closest office and the walk-in wait time at the previously-closest office in the four quarters before the closing, and $DistanceDiff_{ic}$ is the difference between the driving distance from ZIP i to the now-closest office and the driving distance from ZIP i to the previously-closest office. The first stage, reduced form, and IV estimates are given in Table A.10. As expected, the first stage effects are strong: a one-minute difference in pre-closing wait times between the closest and second-closest office predicts a 0.5-minute higher wait-time after the closing, and a one-kilometer difference in driving distance predicts a nearly one-kilometer increase in driving distance after the closing, both significant at the 1% level. Unfortunately, the reduced form and IV estimates are imprecise and we cannot make definitive statements from them.

Cost-Benefit Calculations

Here we outline the calculations in Table 6 in detail.

Lower receipt in closing ZIPs: We calculate losses from lower receipt separately for SSDI adults, SSI adults, and SSI children. From Table A.12, the decline in SSDI receipt in closing ZIPs is 11.9 percent. The mean number of DI allowances per quarter per ZIP is 12.8, and there are an average of 17 affected ZIPs per closing. This amounts to an annual decline of 104 SSDI recipients as a result of the average closing. The average DI benefit is around \$1,300 per month. We also consider the value of Medicare: from the CPS, we estimate that approximately 20 percent of DI beneficiaries in the Medicare waiting period do not have health insurance, and we use the Finkelstein, Hendren and Luttmer (2015) estimate of the value of Medicaid (\$1600/year) as a conservative estimate for the value of Medicare for those without health insurance coverage. In addition, we assume—again, conservatively—that the discouraged applicant loses 2 years of benefits, meaning that the discouraged applicant eventually applies and receives disability benefits. We assume that the average SSDI recipient values the SSDI benefit and health insurance coverage 50 percent more than the average taxpayer, so we multiply the total benefit by 0.5. The social value of SSDI benefits

experiences after the closing. The first stage using pre-closing wait time at the now-closest office is an insignificant 0.142, as opposed to a highly significant 0.489 using the difference in wait times. For the same reason, using the difference between distance to the now-closest office and distance to the previously-closest office produces a first stage of 0.993, while using distance to the now-closest office produces a first stage of 0.576 (though still highly significant).

(including insurance coverage) foregone is therefore \$1.7 million.

We use an analogous analysis to calculate losses from the decline in SSI receipt. For SSI adults, the decline in receipt is 15.4 percent from Table A.12; there are 10.1 SSI adult recipients per quarter per ZIP and 17 affected ZIPs per closing, resulting in 106 fewer SSI adult recipients. The monthly SSI benefit is approximately \$700; from the CPS, we estimate that 50 percent of SSI adult recipients would not have health insurance without SSI. The calculation for SSI children is similar: a decline in receipt of 12.8 percent, an average of 6.5 SSI children per quarter per ZIP, 17 affected ZIPs per closing. This results in 56 fewer SSI child recipients. We assume that all SSI children would have health insurance without SSI. Under the same assumptions used for the SSDI calculations, the social value of SSI benefits foregone is \$1.4 million.

Lower receipt in neighboring ZIPs: We calculate losses from lower SSDI and SSI receipt in neighboring ZIPs in the same way that we calculate losses in closing ZIPs. The decline in neighboring ZIPs is 9.7 percent for SSDI (average of 13.2 recipients per quarter per ZIP), 10.1 percent for SSI adults (average of 10.4 recipients per quarter per ZIP), and 10.1 percent for SSI children (average of 6.6 recipients per quarter per ZIP). There are an average of 99 neighboring ZIPs per closing, resulting in declines of 506 SSDI recipients, 416 SSI adult recipients, and 264 SSI child recipients per closing per year. This translates into losses of \$8.1 million for SSDI and \$6.0 million for SSI. The neighboring ZIP losses are substantially larger than the closing ZIP losses because there are many more neighboring ZIPs than closing ZIPs.

Higher applicant time and earnings decay: We consider time costs from increased office congestion and longer travel time as well as earnings decay from longer processing times. We assume a two-hour increase in application time from congestion and use the estimate from Table 4 of a 0.2 hour increase in travel time. There are 17 affected ZIP on average per closing, with 39.6 applicants per ZIP per quarter. We assume a \$20/hour value of time and that one-half of applicants are actually affected by these costs (i.e., some applicants never interact with the field office). This gives 1,348 affected applicants per closing, with a total cost of \$54,000 for congestion costs and \$5,000 for travel costs for closed ZIPs. For neighboring ZIPs, we consider only congestion costs and estimate them at \$337,000 using the same method.

To calculate earnings decay from longer processing time, we use the increase in processing time resulting from the closing from Table 4: 3.0 days for closing ZIPs and 2.8 days for neighboring ZIPs. Autor et al. (2015) estimate that a 2.4 month increase in processing time reduces annual employment by one percentage point. From this estimate, a one-day increase in processing translates

into a 0.0139 percentage point reduction in employment, which amounts to \$2.78 annually assuming average annual earnings of \$20,000. We assume that this earnings decay lasts for a period of 10 years, so the average earnings decay is \$28 per additional day of processing time. We multiply this decay by the increase in processing days, and then multiply this amount by the number of applicants per ZIP, the number of affected ZIPs, and a 60 percent applicant rejection rate (since the earnings decay only applies to rejected applicants). These assumptions yield earnings decay costs of \$137,000 for closed ZIPs and \$792,000 for neighboring ZIPs.

Increased time for other office visitors: Most field office visits are unrelated to the disability programs. From SSA’s “Yearly Data for Field Office Visitors,” field offices together get approximately 160,000 visitors daily. We divide this number by the number of field offices (1,230) and calculate the annual number of visitors per office to be 34,000. From our data, we calculate that there are on average five affected offices per closing (the closed office plus four neighbors on average). We assume that services take 30 minutes longer to access and that the value of time is \$20/hour. This yields a cost to field office visitors of \$1.7 million annually.

Administrative savings from processing fewer applications: We start with the SSA’s annual administrative budget of \$12 billion,³³ two-thirds of which is used to administer the disability programs.³⁴ We calculate from our data that field offices process approximately 4.4 million disability applications per year. This yields an estimated cost of \$1,800 in processing costs per application. The reduction in applications is 11.0 percent for closing ZIPs (with 17 ZIPs on average per closing and 40 applicants per ZIP per quarter) and 5.4 percent for neighboring ZIPs (with 99 ZIPs on average per closing and 43 applicants per ZIP per quarter). We multiply the \$1,800 in processing costs per application by the application decrease of 1,204 to get an estimated \$2.2 million in administrative savings per closing.

Administrative savings from closing field office: According to a recent Congressional report, recent field office closings have saved \$4 million over 10 years in lease costs.³⁵ We therefore estimate an annual savings of \$400,000 per closing.

Application cost savings from discouraged applicants: Since we include foregone benefits of discouraged applicants in the costs of field office closings, we include application cost savings to discouraged applicants as a benefit of field office closings. As in “administrative savings from

³³See Social Security Administration FY 2017 Budget Overview.

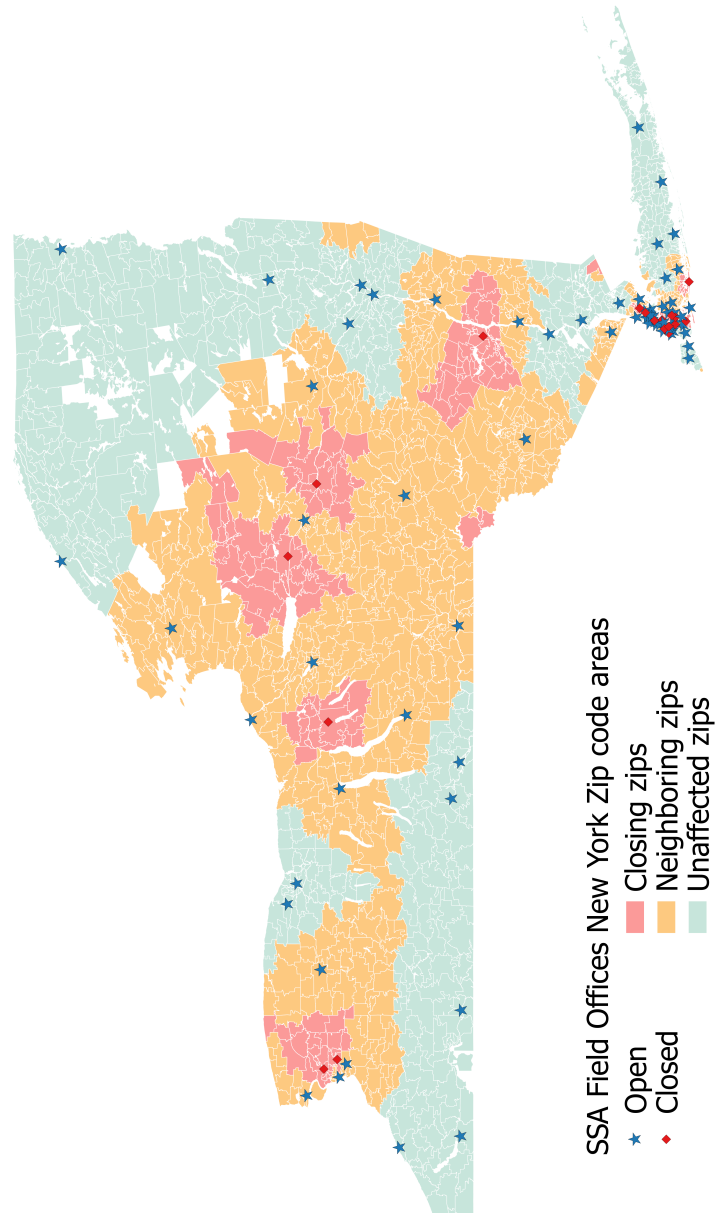
³⁴“SSA’s Administrative Costs by Funding Source—INFORMATION,” Letter from Robert M. Rothenberg to Margaret Malone, Wayne Sulfridge, and David Warner, December 8, 1999.

³⁵“Reduction in Face-to-Face Services at the Social Security Administration,” United States Senate Special Committee on Aging, Summary of Committee Staff Investigation, No Date, page 15.

processing fewer applications,” there are 1,204 fewer applicants between closing and neighboring ZIPs. We assume that applications take on average 40 hours to complete and the applicant value of time is \$20 per hour. This amounts to \$1.0 million in applicant cost savings.

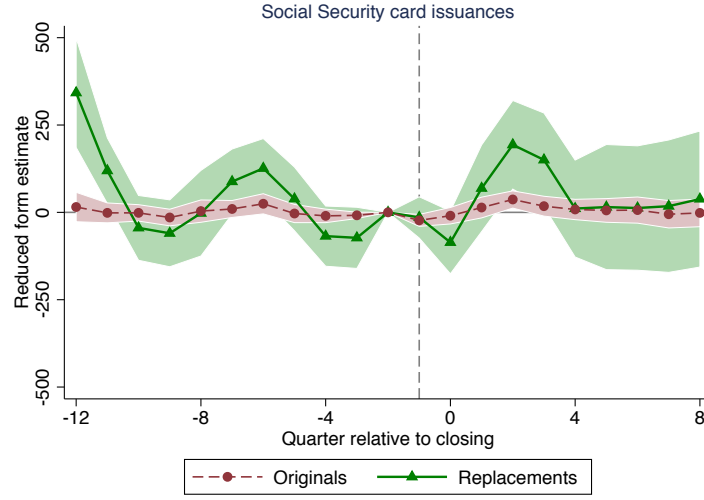
Appendix Figures and Tables

Figure A.1: Map of Field Office Closings and ZIP Classification in New York



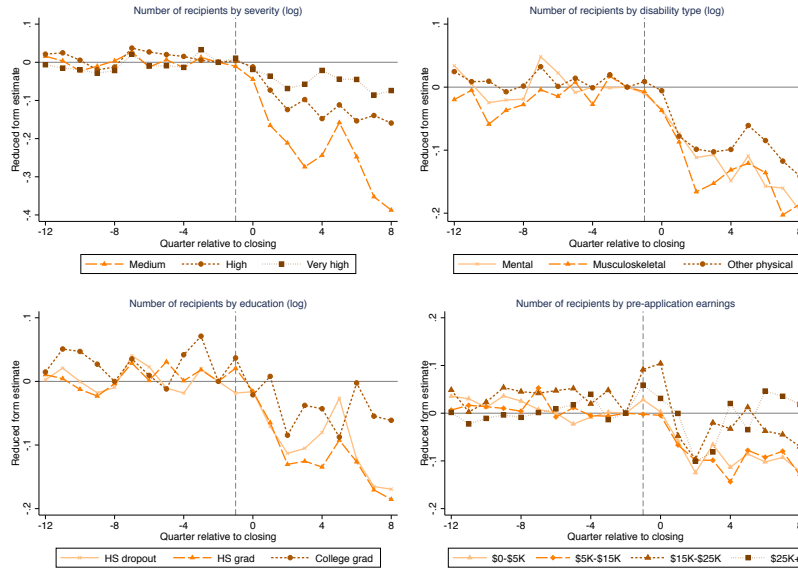
Source: Social Security Administration and Census Bureau.

Figure A.2: Effect of Closings on Social Security Card Issuances



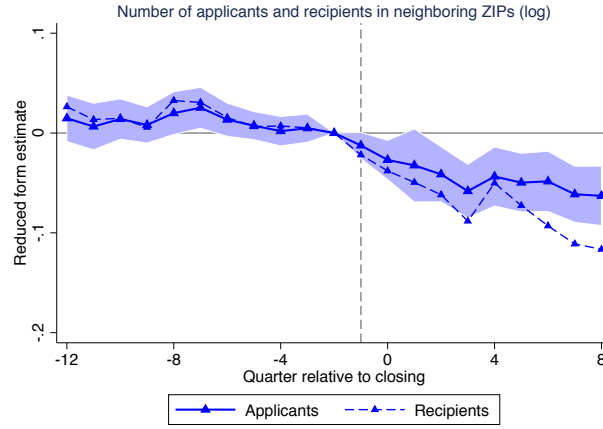
Notes: Figure plots estimates of δ_τ coefficients from equation (1), where the dependent variable is Social Security card issuances (either original or replacement) in a given ZIP and quarter. Shaded regions are 95 percent confidence intervals.

Figure A.3: Effect of Closings on Number of Disability Allowances, by Subgroup



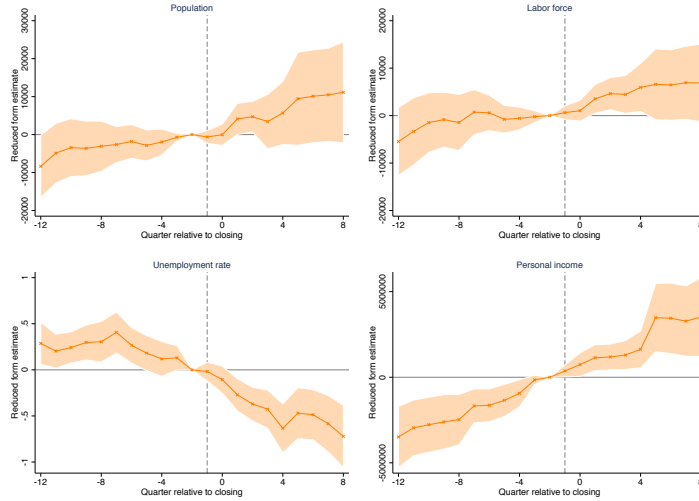
Notes: Figure plots estimates of δ_τ coefficients from equation (1), where the dependent variable is the log number of disability allowances by subgroup. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Figure A.4: Effect of Closings on Number of Disability Applications and Allowances for Neighboring ZIPs



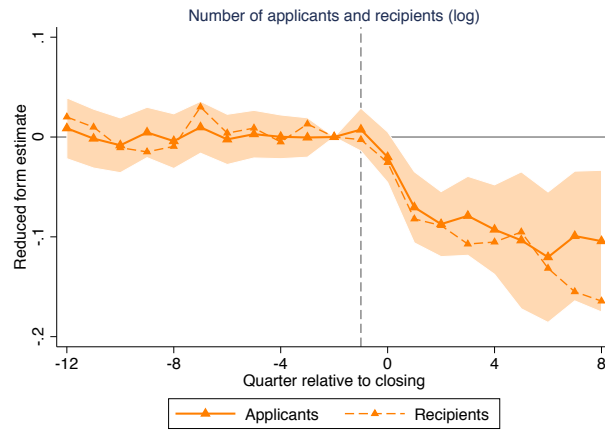
Notes: Figure plots estimates of δ_τ coefficients from equation (3). The dependent variable is the log number of disability applications (solid series) or the log number of disability recipients (dashed series). Shaded region is 95 percent confidence interval for disability applications (solid series). Sample is ZIP codes whose nearest office is a neighbor of an office that closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. "Neighboring" ZIPs are ZIPs whose nearest office is the second or third closest office of a closing ZIP prior to the closing event. Regressions are weighted by application volume in the year before the closing.

Figure A.5: Differential Trends in Macroeconomic Conditions Between Control and Treatment ZIPs



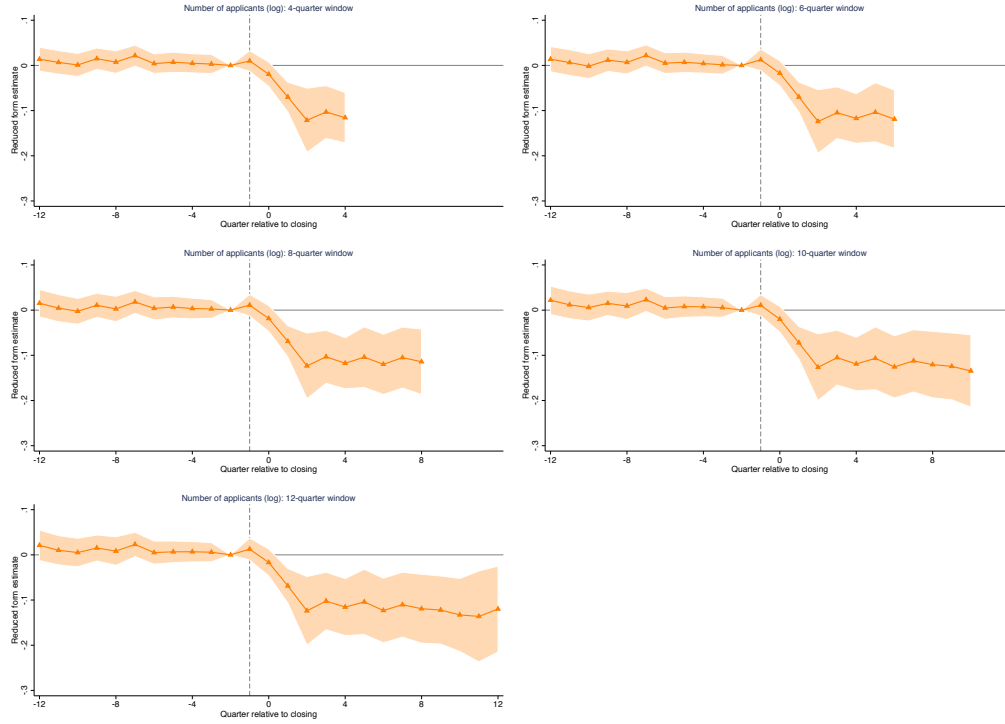
Notes: Figure plots estimates of δ_τ coefficients from equation (1), where the dependent variable is the macroeconomic measure indicated. Shaded region is 95 percent confidence interval. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Figure A.6: Effect of Closings on Applications and Allowances, Controlling for Local Economic Conditions



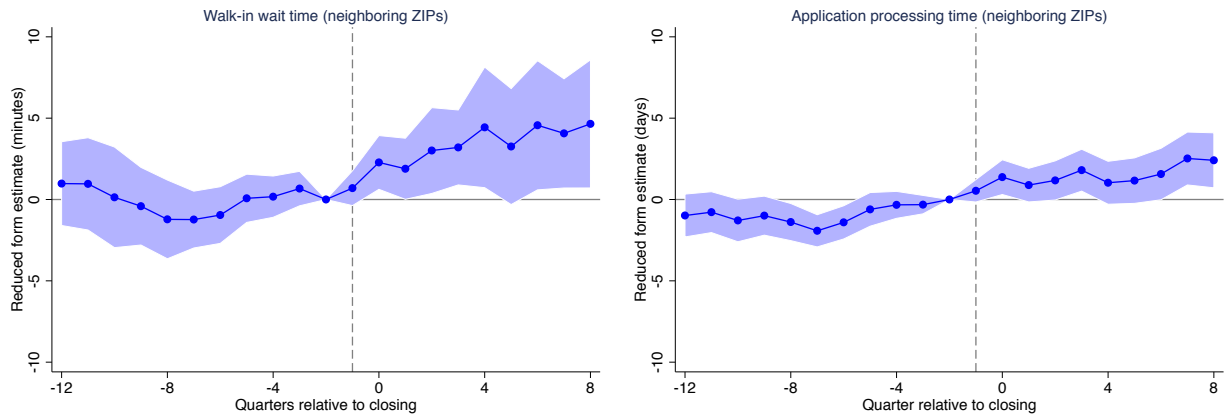
Notes: Figure plots estimates of δ_τ coefficients from equation (1) with local unemployment rate and population controls, where the dependent variable is the log number of disability applications (solid series) or the log number of disability recipients (dashed series). Shaded region is 95 percent confidence interval for disability applications (solid series). Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Figure A.7: Effect of Closings on Applications, Using Different Time Windows



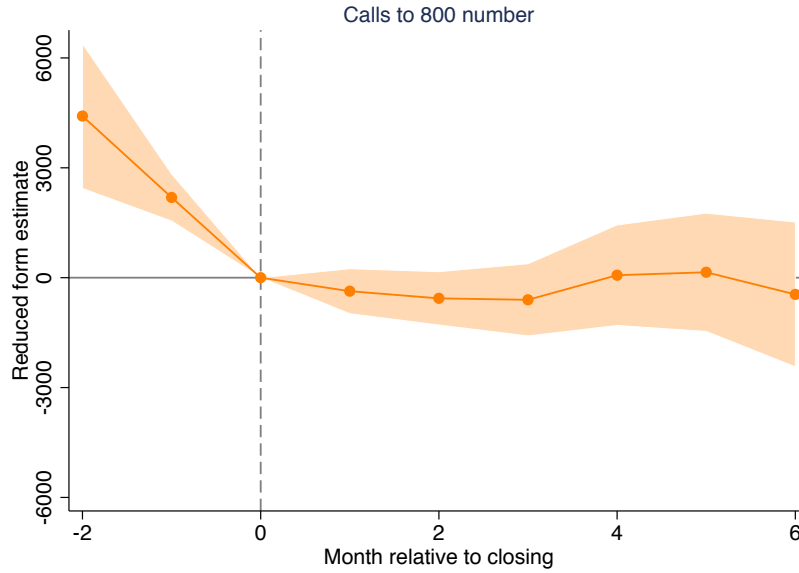
Notes: Figure plots estimates of δ_T coefficients from equation (1) for different minimum lengths of time between the treatment closing and control closings. The dependent variable is the log number of disability applications. Shaded region is 95 percent confidence interval. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Figure A.8: Effect of Closings on Measures of Field Office Congestion for Neighboring ZIPs



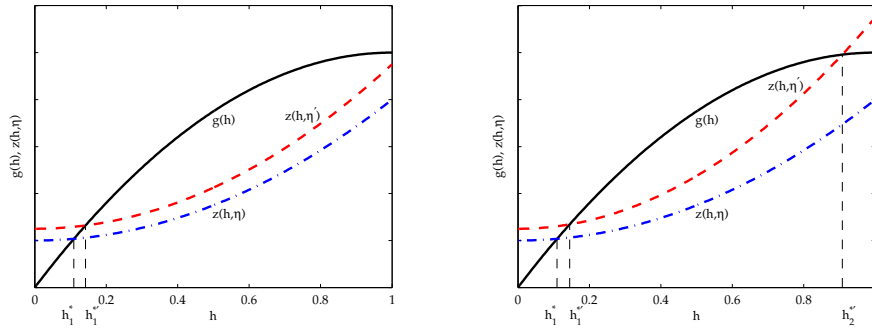
Notes: Figure plots estimates of δ_T coefficients from equation (3). The dependent variable is average walk-in wait time in minutes at nearest field office (left) or the average number of days it takes the field office to process a disability application (right). Shaded region is 95 percent confidence interval. Sample is ZIP codes whose nearest office is a neighbor of an office that closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. "Neighbor" office is defined as an office that is the second or third closest office of a ZIP code whose closest office closes. Regressions are weighted by application volume in the year before the closing.

Figure A.9: Effect of Closings on Calls to Social Security Administration 800 Phone Number



Notes: Figure plots estimates of δ_τ coefficients from equation (7), where the dependent variable is call volume from a given area code in a given month. Shaded region is 95 percent confidence interval.

Figure A.10: Conceptual Framework: Effect of Increase in Application Costs on Targeting



Left-hand-side graph shows an increase in application costs that unambiguously improves the targeting of disability programs by increasing the severity threshold at which individuals apply for benefits. Right-hand-side graph shows an increase in application costs that has an ambiguous effect on targeting, since it decreases the number of both low-severity and high-severity individuals who apply for benefits.

Table A.1: Summary Statistics of All Closing, Neighboring, and Unaffected ZIP Codes

	Closing ZIPs		Neighboring ZIPs		Unaffected ZIPs		T-test p-values		
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Closed vs. neighbor	Closed vs. unaffected	Neighbor vs. unaffected
ZIP characteristics (2000)									
Population	9,236	14,397	9,216	13,847	8,644	12,560	0.998	0.053	0.001
Poverty rate	13%	9%	13%	9%	13%	10%	0.857	0.377	0.052
Median income	\$39,567	\$18,850	\$39,130	\$16,948	\$39,584	\$15,957	0.394	0.966	0.066
Male	50%	4%	50%	4%	50%	4%	0.254	0.003	0.002
Female	50%	4%	50%	4%	50%	4%	0.254	0.003	0.002
White	83%	21%	83%	21%	86%	20%	0.516	0.000	0.000
Black	9%	18%	9%	17%	7%	15%	0.196	0.000	0.000
Hispanic	6%	12%	6%	11%	7%	14%	0.782	0.071	0.000
Other race	2%	12%	2%	11%	1%	14%	0.287	0.082	0.000
Age 0-19	27%	6%	28%	6%	28%	6%	0.002	0.000	0.000
Age 20-44	33%	8%	34%	7%	34%	6%	0.130	0.016	0.273
Age 45-64	24%	6%	24%	5%	24%	5%	0.007	0.017	0.469
Age 65+	15%	5%	15%	6%	14%	6%	0.008	0.000	0.000
HS dropout	20%	12%	20%	11%	22%	13%	0.949	0.000	0.000
HS graduate	34%	12%	34%	11%	35%	11%	0.403	0.000	0.000
Some college	26%	8%	26%	8%	26%	9%	0.002	0.164	0.001
College graduate	20%	16%	19%	14%	18%	13%	0.019	0.000	0.000
Never married	24%	9%	23%	9%	23%	9%	0.077	0.000	0.003
Currently married	58%	11%	58%	11%	59%	11%	0.381	0.000	0.000
Previously married	18%	6%	18%	6%	18%	6%	0.269	0.238	0.000
Walk-in wait time (2005)	7.28	7.62	8.89	8.97	8.84	8.27	0.000	0.000	0.601
Num. disability apps (2000)	71	140	76	143	70	128	0.171	0.685	0.000
N	1,867		7,491		22,553				

Notes: Table presents summary statistics for all ZIP codes in the United States. Closing ZIPs are ZIPs whose nearest office closes. Neighboring ZIPs are ZIPs whose nearest office is the second or third closest office of a closing ZIP. Unaffected ZIPs are ZIPs that are neither closing nor neighboring ZIPs. "ZIP characteristics" are calculated from the 2000 Census, "Walk-in wait time" from Social Security Administration data (where 2005 is the earliest available year), and "Number of disability applications" from Social Security Administration data.

Table A.2: Summary Statistics of Treatment and Control ZIPs

	Treatment ZIPs		Control ZIPs		t-test
	Mean	Std Dev	Mean	Std Dev	p-values
ZIP characteristics (2000)					
Population	14,554	16,150	15,288	16,308	0.0020
Poverty rate	14%	10%	13%	9%	0.0000
Median income	\$41,576	\$18,734	\$43,074	\$18,589	0.0000
Male	49%	3%	49%	3%	0.5300
Female	51%	3%	51%	3%	0.5300
White	77%	24%	79%	22%	0.0000
Black	14%	21%	12%	20%	0.0000
Hispanic	7%	14%	8%	14%	0.1692
Other race	2%	14%	1%	11%	0.0000
Age 0-19	27%	6%	27%	6%	0.0000
Age 20-44	35%	7%	36%	7%	0.0000
Age 45-64	23%	4%	24%	4%	0.0000
Age 65+	14%	5%	14%	5%	0.0993
High school dropout	22%	12%	20%	11%	0.0000
High school graduate	32%	10%	31%	11%	0.0377
Some college	25%	6%	25%	6%	0.3945
College graduate	22%	17%	23%	17%	0.0000
Never married	26%	9%	26%	9%	0.0161
Currently married	55%	10%	55%	10%	0.2999
Previously married	19%	5%	19%	5%	0.0174
Walk-in wait time (year before closing)	14.9	11.1	13.6	10.4	0.0000
Num. disability apps (year before closing)	41.0	58.2	37.4	52.3	0.0000
N	4,824		186,052		

Notes: Table presents summary statistics for treatment and control ZIP codes, as described in Section 3. Treatment ZIPs are closing ZIPs (ZIPs whose nearest office closes) that experience the current closing, while control ZIPs are closing ZIPs that experience the closing at least two years in the future. "ZIP characteristics" are calculated from the 2000 Census, "Walk-in wait time" from Social Security Administration data, and "Number of disability applications" from Social Security Administration data.

Table A.3: Factors that Predict the Timing of Office Closings

	2000	2002	2004	2006	2008	2010	2012
Population (2000)	7.16e-06*	6.43e-06	3.48e-06	2.47e-07	2.75e-06*	1.61e-06	-7.04e-08
	(4.31e-06)	(4.00e-06)	(3.34e-06)	(3.78e-06)	(1.54e-06)	(1.47e-06)	(9.77e-07)
Pop. Density (2000)	0.000183	0.000163	0.000148*	9.10e-05*	6.95e-05	7.35e-05**	-0.000134***
	(0.000130)	(0.000131)	(8.13e-05)	(5.05e-05)	(4.44e-05)	(3.09e-05)	(3.51e-05)
Applications (previous year)	0.000417**	0.000345*	0.000129	0.000150	9.13e-05	1.43e-05	2.60e-05
	(0.000203)	(0.000202)	(0.000161)	(0.000110)	(6.81e-05)	(4.79e-05)	(2.91e-05)
Processing time (previous year)	-0.0125	-0.00432	-0.0107	0.00668	-0.00153	0.00960	0.00673
	(0.0376)	(0.0418)	(0.0406)	(0.0381)	(0.0219)	(0.0135)	(0.0106)
Num. offices < 20 mi	-0.0184	-0.0185	-0.0188	-0.00691	-0.0268	-0.0439***	0.0557***
	(0.0433)	(0.0425)	(0.0322)	(0.0231)	(0.0168)	(0.0152)	(0.0149)
Wait time (previous year)				0.00671	0.00905	0.0362	0.00151
				(0.0517)	(0.0106)	(0.0220)	(0.0228)
Observations	117	111	94	80	61	55	23

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates from equation (5) of the effect of various observable office characteristics on the timing of the closing. Population density is population per squared kilometer of the office's service area. The sample is all SSA field offices that are open in the given year and will close by 2014, and the dependent variable is the year in which an office closes. Standard errors in parentheses.

Table A.4: P-values from Tests of Statistical Differences Across Subgroups

	Application level	Allowance level
Allowance vs. application		0.0128
Severity		
Low vs. medium	0.0001	N/A
Low vs. high	0.0198	N/A
Low vs. very high	0.0551	N/A
Medium vs. high	0.0047	0.0081
Medium vs. very high	0.0000	0.0000
High vs. very high	0.0000	0.0001
Disability type		
Mental vs. musculoskeletal	0.0058	0.0303
Mental vs. other physical	0.9914	0.0407
Musculoskeletal vs. other physical	0.0078	0.8807
Education		
HS dropout vs. HS grad	0.4181	0.3835
HS dropout vs. college grad	0.0917	0.1305
HS grad vs. college grad	0.1140	0.0041
Age		
18-34 vs. 35-49	0.9764	0.0270
18-34 vs. 50+	0.0967	0.2180
35-49 vs. 50+	0.0628	0.0003

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table presents p-values of t-tests for differences in estimates in Tables 2 and 3 across subgroups. The specifications are given by equation (2) estimated for different subgroups.

Table A.5: Estimates of the Effect of Closings in Early vs. Late Time Periods

	Early closing ($\leq 2011Q2$)			Late closing ($>2011Q2$)		
	Pt. Est.	Std. Err.	N	Pt. Est.	Std. Err.	N
Applications						
All	-0.0926*	(0.0515)	998,802	-0.140***	(0.0178)	23,020
DI adults	-0.0619	(0.0407)	831,957	-0.0991***	(0.0178)	19,594
SSI adults	-0.118**	(0.0566)	691,362	-0.189***	(0.0251)	16,502
SSI children	-0.133	(0.0974)	452,865	-0.197***	(0.0422)	11,722
Initial allowances						
All	-0.0423	(0.0473)	926,699	-0.151***	(0.0266)	21,717
DI adults	-0.0126	(0.0382)	774,318	-0.118***	(0.0206)	18,621
SSI adults	-0.0678	(0.0551)	630,264	-0.138***	(0.0344)	15,435
SSI children	-0.0543	(0.0747)	390,740	-0.235***	(0.0571)	10,669
Final allowances						
All	-0.0464	(0.0461)	998,802	-0.275***	(0.0316)	23,020
DI adults	-0.0281	(0.0365)	831,957	-0.281***	(0.0319)	19,594
SSI adults	-0.0654	(0.0577)	691,362	-0.289***	(0.0376)	16,502
SSI children	-0.0506	(0.0768)	452,865	-0.251***	(0.0498)	11,722

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table presents estimates of the effect of field office closings on log applications, log initial allowances, and log final allowances, specifically estimates of β from equation (2). The first set of columns gives estimates for closings that occurred before or during 2011Q2, and the second set of columns gives estimates for closings that occurred after 2011Q2. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.6: Estimates of the Effect of Closings Using Alternative Distance Measures

Distance measure	Applications			Allowances		
	Pt. Est.	Std. Err.	N	Pt. Est.	Std. Err.	N
Straight-line distance	-0.110***	(0.0300)	1,021,822	-0.134***	(0.0312)	1,021,822
Driving time	-0.102***	(0.0298)	931,551	-0.128***	(0.0314)	931,551
30-km fixed radius	-0.126***	(0.0380)	816,046	-0.142***	(0.0371)	816,046
60-km fixed radius	-0.111***	(0.0302)	991,024	-0.131***	(0.0313)	991,024
90-km fixed radius	-0.110***	(0.0301)	1,012,573	-0.133***	(0.0313)	1,012,573

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table presents estimates of the effect of field office closings on log applications and log allowances, specifically estimates of β from equation (2), using different measures of distance: straight-line distance from ZIP centroid to the closed office, driving time from ZIP centroid to the closed office, and radii of different lengths around the closed office. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.7: Estimates of the Effect of Closings by Geographic Measures

	Pt. Est.	Std. Err.	N
Population density			
Low (rural)	-0.136***	(0.0463)	348,928
Medium	-0.104***	(0.0288)	254,999
High (urban)	-0.0949***	(0.0232)	417,895
Distance to own office			
Low (< 10 km)	-0.110***	(0.0300)	330,031
Medium (10-30 km)	-0.0972**	(0.0371)	335,560
High (>30 km)	-0.0990**	(0.0419)	297,978
Distance to neighboring office			
Low	-0.105***	(0.0255)	356,618
Medium	-0.0532	(0.0439)	253,683
High	-0.138***	(0.0387)	353,268

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table presents estimates of the effect of field office closings on log applications and log allowances, specifically estimates of β from equation (2), by different measure of geography. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.8: Estimates of the Effect of Closings by Measures of Information

	Pt. Est.	Std. Err.	N
Proportion on disability			
Low	-0.0154	(0.0363)	216,908
Medium	-0.122***	(0.0220)	503,747
High	-0.165**	(0.0703)	293,208
Proportion applying for disability			
Low	-0.147***	(0.0556)	298,205
Medium	-0.0902***	(0.0257)	321,127
High	-0.147***	(0.0470)	402,490
Chetty et al. (2013) information			
Low	-0.100***	(0.0229)	193,959
Medium	-0.0974*	(0.0506)	466,590
High	-0.120**	(0.0556)	354,347
Num. broadband providers			
Low	-0.125***	(0.0342)	45,075
Medium	-0.114***	(0.0255)	130,758
High	-0.0668***	(0.0193)	182,421
Num. broadband-connected households			
Low	-0.150***	(0.0354)	62,794
Medium	-0.0448	(0.0407)	93,862
High	-0.0721***	(0.0206)	201,598

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table presents estimates of the effect of field office closings on log applications, specifically estimates of β from equation (2), by potential measures of information. Proportion on disability is the ratio of individuals on SSI or SSDI in a county to the county's population. Number of applications is the fraction of the ZIP's population applying for disability between 1996 and 2000. The Chetty et al. (2013) measure is the amount of bunching of self-employed individuals at EITC kinks, which the authors estimate by ZIP-3 and interpret as a measure of EITC knowledge. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.9: Estimates of the Effect of Closings on Online Applications by Education Subgroup

	Pt. Est.	Std. Err.
Online applications		
All	0.0710	(0.0565)
High school dropouts	0.00394	(0.0578)
High school graduates	0.0568	(0.0549)
College graduates	0.103***	(0.0331)
Non-online applications		
All	-0.150***	(0.0338)
High school dropouts	-0.161***	(0.0341)
High school graduates	-0.134***	(0.0324)
College graduates	-0.0917**	(0.0401)
N	1,021,822	

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table presents estimates of the effect of field office closings on log online applications and log non-online applications, specifically estimates of β from equation (2), by education subgroup. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.10: Estimates of the Effects of Application Costs on Disability Applications

	First stage		Log applications	
	Wait time (min)	Distance (km)	RF	IV
Diff. in pre-closing wait times	0.489*** (0.0766)		-0.000649 (0.00204)	
Diff. in pre-closing distances		0.993*** (0.00650)	-0.000188 (0.000373)	
Wait time				-0.00142 (0.00395)
Distance				-0.000284 (0.000315)
N	471,413	963,569	875,663	441,763

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table presents first stage estimates from equations (9) and (10), reduced form estimates, and IV estimates from equation (8). The first stage for wait time gives the effect of the difference in pre-closing wait time of the now-closest office and previously-closest office on wait time (in minutes), and analogously for the first stage for distance (in kilometers). The reduced form estimates give the effect of the instruments on log disability applications. The IV estimates give the effect of wait time and distance on log disability applications. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Wait time data are not available for all offices in all quarters, so the sample size falls when wait time is the dependent variable. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.11: Estimates of the Effect of Closings on Log Applications by Program

	DI adult		SSI adult		SSI children	
	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.
All	-0.0738***	(0.0245)	-0.146***	(0.0340)	-0.146**	(0.0580)
Severity						
Low	-0.0218	(0.0272)	-0.133***	(0.0342)	-0.120*	(0.0651)
Medium	-0.240***	(0.0476)	-0.263***	(0.0528)	-0.0531	(0.0406)
High	-0.0832**	(0.0351)	-0.198***	(0.0455)	-0.169***	(0.0567)
Very high	-0.0354	(0.0268)	-0.0361	(0.0343)	-0.000533	(0.0183)
Disability type						
Mental	-0.0857***	(0.0291)	-0.141***	(0.0395)	-0.149**	(0.0580)
Musculoskeletal	-0.0354	(0.0273)	-0.157***	(0.0367)		
Other physical	-0.0757***	(0.0251)	-0.109***	(0.0363)	-0.123**	(0.0566)
Education (years)						
HS dropout	-0.0876***	(0.0270)	-0.154***	(0.0354)		
HS graduate	-0.0660***	(0.0250)	-0.122***	(0.0285)		
College graduate	-0.00502	(0.0261)	-0.0500*	(0.0284)		
Pre-application earnings						
\$0-\$5,000	-0.0784*	(0.0454)	-0.169***	(0.0470)		
\$5,000-\$15,000	-0.0832	(0.0549)	-0.127**	(0.0567)		
\$15,000-\$25,000	-0.0189	(0.0696)	-0.0285	(0.0683)		
\$25,000+	0.0375	(0.0696)	-0.0269	(0.0603)		
Age (years)						
0-9					-0.124**	(0.0572)
10-17					-0.166***	(0.0580)
18-34	-0.0758**	(0.0292)	-0.154***	(0.0384)		
35-49	-0.0782***	(0.0271)	-0.159***	(0.0366)		
50+	-0.0617***	(0.0229)	-0.125***	(0.0324)		

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates of the effect of field office closings on log applications by program, specifically estimates of β from equation (2). Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three applications in the relevant program per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.12: Estimates of the Effect of Closings on Log Allowances by Program

	DI adult		SSI adult		SSI children	
	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.
All	-0.119***	(0.0275)	-0.154***	(0.0382)	-0.128**	(0.0498)
Severity						
Low	N/A		N/A		N/A	
Medium	-0.216***	(0.0441)	-0.238***	(0.0496)	-0.0468	(0.0437)
High	-0.0797**	(0.0336)	-0.194***	(0.0450)	-0.134**	(0.0516)
Very high	-0.0309	(0.0259)	-0.0352	(0.0345)	-0.000654	(0.0198)
Disability type						
Mental	-0.117***	(0.0288)	-0.139***	(0.0418)	-0.153***	(0.0511)
Musculoskeletal	-0.0948***	(0.0317)	-0.124***	(0.0432)		
Other physical	-0.0898***	(0.0262)	-0.143***	(0.0385)	-0.0462	(0.0532)
Education (years)						
HS dropout	-0.0767***	(0.0284)	-0.139***	(0.0409)		
HS graduate	-0.125***	(0.0298)	-0.131***	(0.0332)		
College graduate	-0.0314	(0.0241)	-0.0175	(0.0239)		
Pre-application earnings						
\$0-\$5,000	-0.0823**	(0.0412)	-0.182***	(0.0490)		
\$5,000-\$15,000	-0.0989*	(0.0594)	-0.131**	(0.0610)		
\$15,000-\$25,000	-0.0483	(0.0596)	-0.00901	(0.0490)		
\$25,000+	-0.00292	(0.0636)	-0.0260	(0.0442)		
Age (years)						
0-9					-0.101**	(0.0505)
10-17					-0.158***	(0.0497)
18-34	-0.0642**	(0.0273)	-0.126***	(0.0406)		
35-49	-0.159***	(0.0349)	-0.187***	(0.0448)		
50+	-0.0895***	(0.0252)	-0.141***	(0.0388)		

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates of the effect of field office closings on log allowances by program, specifically estimates of β from equation (2). Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three applications in the relevant program per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.13: Estimates of the Effect of Closings on Log and Level Applications and Allowances by Subgroup

	Applications					Receipt				
	Log estimates		Level estimates		Mean	Log estimates		Level estimates		Mean
	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.		Pt. Est.	Std. Err.	Pt. Est.	Std. Err.	
Severity										
Low	-0.0841**	(0.0322)	-5.598*	(3.032)	18.0	N/A		N/A		
Medium	-0.269***	(0.0518)	-3.387***	(0.834)	6.9	-0.244***	(0.0478)	-2.989***	(0.782)	6.9
High	-0.161***	(0.0393)	-2.980**	(1.342)	8.5	-0.149***	(0.0371)	-2.597**	(1.246)	8.5
Very high	-0.0477	(0.0302)	-0.404	(0.614)	6.2	-0.0412	(0.0286)	-0.292	(0.607)	6.2
Disability type										
Mental	-0.116***	(0.0351)	-4.329**	(1.874)	12.3	-0.152***	(0.0341)	-2.347***	(0.889)	6.9
Musculoskeletal	-0.0656**	(0.0318)	-2.158*	(1.299)	10.2	-0.109***	(0.0358)	-1.102*	(0.636)	5.1
Physical	-0.116***	(0.0309)	-5.894***	(2.193)	17.2	-0.110***	(0.0311)	-2.428**	(1.054)	9.7
Education (years)										
HS dropout	-0.130***	(0.0316)	-3.675***	(1.310)	9.9	-0.123***	(0.0338)	-1.500**	(0.638)	5.1
HS graduate	-0.0882***	(0.0264)	-4.130**	(1.906)	19.4	-0.124***	(0.0298)	-2.314**	(0.914)	10.6
College graduate	-0.0398	(0.0311)	-0.0584	(0.204)	2.4	-0.0509	(0.0318)	-0.126	(0.138)	1.6
Pre-application earnings										
\$0-\$5,000	-0.136***	(0.0473)	-7.147**	(3.366)	17.0	-0.152***	(0.0488)	-3.278***	(1.210)	7.8
\$5,000-\$15,000	-0.119**	(0.0570)	-1.543	(1.567)	8.6	-0.134**	(0.0630)	-0.889	(0.672)	4.4
\$15,000-\$25,000	-0.0448	(0.0757)	-0.341	(0.782)	4.8	-0.0590	(0.0670)	-0.186	(0.422)	3.0
\$25,000+	0.0111	(0.0743)	0.116	(0.813)	6.7	-0.0116	(0.0703)	0.0292	(0.517)	5.0
Age (years)										
18-34	-0.118***	(0.0350)	-2.996***	(1.126)	7.9	-0.133***	(0.0358)	-0.751**	(0.326)	3.1
35-49	-0.116***	(0.0318)	-3.702***	(1.401)	12.9	-0.185***	(0.0397)	-1.768***	(0.666)	6.1
50+	-0.0886***	(0.0266)	-2.757*	(1.490)	13.1	-0.108***	(0.0290)	-2.122**	(1.018)	9.3

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates of the effect of field office closings on log and level applications and allowances by subgroup, specifically estimates of β from equation (2). The "mean" columns report the average for the control group over the post-closing period. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.14: Estimates of the Effect of Closings on Log and Level Applications and Allowances by Finer Subgroup

	Applications					Receipt				
	Log estimates		Level estimates			Log estimates		Level estimates		
	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.	Mean	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.	Mean
Severity by education										
Low/med, HS dropout	-0.139***	(0.0324)	-2.910***	(0.952)	6.58	-0.169***	(0.0396)	-0.778***	(0.270)	1.79
High, HS dropout	-0.124***	(0.0427)	-0.639**	(0.288)	1.55	-0.116***	(0.0414)	-0.595**	(0.271)	1.60
Very high, HS dropout	-0.00485	(0.0314)	-0.123	(0.234)	1.70	-0.00255	(0.0302)	-0.122	(0.235)	1.75
Low/med, HS graduate	-0.0831***	(0.0281)	-3.303**	(1.426)	12.88	-0.212***	(0.0450)	-1.622***	(0.436)	4.16
High, HS graduate	-0.123***	(0.0397)	-0.637*	(0.364)	3.17	-0.114***	(0.0376)	-0.569	(0.350)	3.26
Very high, HS graduate	-0.0459	(0.0289)	-0.184	(0.337)	3.14	-0.0368	(0.0283)	-0.112	(0.341)	3.23
Low/med, college grad	-0.0104	(0.0275)	-0.0267	(0.136)	1.28	-0.0328	(0.0198)	-0.0977	(0.0603)	0.48
High, college grad	-0.0245	(0.0166)	-0.0793	(0.0487)	0.49	-0.0239	(0.0173)	-0.0779	(0.0516)	0.50
Very high, college grad	0.0127	(0.0206)	0.0474	(0.0578)	0.61	0.0153	(0.0210)	0.0506	(0.0589)	0.62
Disability type by education										
Mental, HS dropout	-0.136***	(0.0374)	-0.976**	(0.462)	2.76	-0.101**	(0.0406)	-0.442*	(0.234)	1.48
Musc., HS dropout	-0.0791**	(0.0333)	-0.928**	(0.428)	2.91	-0.0562	(0.0340)	-0.273	(0.210)	1.44
Other phys., HS dropout	-0.122***	(0.0323)	-1.768***	(0.632)	4.17	-0.0938***	(0.0332)	-0.779**	(0.332)	2.22
Mental, HS graduate	-0.0810**	(0.0342)	-1.165**	(0.581)	4.78	-0.103***	(0.0338)	-0.588***	(0.220)	2.65
Musc., HS graduate	-0.0512*	(0.0306)	-1.088	(0.732)	6.03	-0.108***	(0.0334)	-0.818**	(0.400)	3.08
Other phys., HS grad	-0.0980***	(0.0286)	-1.870**	(0.835)	8.39	-0.107***	(0.0308)	-0.897*	(0.469)	4.94
Mental, college grad	-0.0118	(0.0199)	-0.0570	(0.0691)	0.64	-0.0176	(0.0175)	-0.0798	(0.0520)	0.44
Musc., college grad	-0.00721	(0.0237)	-0.0364	(0.0811)	0.57	-0.00686	(0.0167)	-0.0308	(0.0504)	0.34
Other phys., college grad	-0.000691	(0.0307)	0.0347	(0.113)	1.17	-0.000320	(0.0238)	-0.0144	(0.0735)	0.83

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table presents estimates of the effect of field office closings on log and level applications and allowances by subgroup, specifically estimates of β from equation (2). The "mean" columns report the average for the control group over the post-closing period. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.