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Who Is Screened Out? Application Costs and the Targeting of Disability Programs†

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We study the effect of application costs on the targeting of disability programs. We identify these effects using the closings of Social Security Administration field offices, which provide assistance with filing disability applications. Closings lead to a persistent 16 percent decline in the number of disability recipients in surrounding areas, with the largest effects for applicants with moderately severe conditions and low education levels. Disability applications fall by only 10 percent, implying that the closings reduce targeting efficiency based on current eligibility standards. Increased congestion at neighboring offices appears more important as a channel than higher travel or information costs. (*JEL* H55, I13, I18, J14)

Disability programs are large and expanding rapidly across the developed world. Social Security Disability Insurance (SSDI or DI), the insurance program for disabled workers in the United States, provided cash benefits and Medicare to nearly 9 million workers in 2015, up from 5 million in 2000. In addition, Supplemental Security Income (SSI) provided cash welfare and Medicaid eligibility to nearly 7 million low-income, disabled Americans, including 1.4 million children in 2015.[1] These programs aim to provide disability benefits to those—and only those—individuals who have severe disabilities and are in need of assistance.

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[1] Annual Statistical Report on the SSDI Program 2015; SSI Annual Statistical Report 2015. 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.

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 these application costs on the targeting of disability programs is ambiguous; hassles could screen out either those most in need or least in need, depending on how potential applicants respond to these costs. The application process is especially important for the targeting of disability programs because disability is difficult to observe and costly to verify. The government does not collect data on health or disability status outside of the disability determination process. If individuals with severe disabilities do not apply because the application process is too costly, the government has few other ways to identify them and provide benefits. Conversely, the government may want to design an application process that discourages low-severity individuals from applying, given the high administrative and time costs of determination.

In this paper, we address how application costs affect the targeting of disability programs. Nichols and Zeckhauser (1982) hypothesizes that application costs may improve targeting by screening out high-ability individuals with a high opportunity cost of time. In their model, the loss in productive efficiency from application hassles is more than offset by the gain in targeting efficiency. However, evidence from behavioral economics suggests that hassles may discourage those most in need (Bertrand, Mullainathan, and Shafir, 2004). Moreover, even a neoclassical framework like that of Nichols and Zeckhauser (1982) can produce the opposite theoretical result if application costs are negatively correlated with ability, which might occur, for example, if the application involves cognitive costs instead of time costs (see online Appendix).

We provide the first empirical analysis of the effects of such screening costs in the context of disability programs using variation in the timing of closings of Social Security Administration (SSA) field offices. These offices provide assistance with filing disability applications but do not make medical decisions about disability awards. 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. We employ a difference-in-difference 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 closing.[2] Using detailed SSA data on field office characteristics, we also evaluate the relative importance of different types of application costs induced by the closings, including travel time to assistance and congestion at neighboring field offices.

[2] In Section III, we present evidence that the timing of the closings is effectively random.

We find that field office closings reduce the number of disability applications by 10 percent (3.3 applications per zip code per quarter) and the number of recipients by 16 percent (2.6 "allowances," or final approvals, per zip code per quarter) in surrounding areas. Because these closings disproportionately discourage applications from individuals who would have been allowed into the program if they had applied, they reduce the targeting efficiency of disability programs based on current eligibility standards. The closings have the largest discouragement effects for those with moderately severe conditions, low education levels, and low pre-application earnings. The discouragement effects persist for at least two years after the closing, and they also occur in areas surrounding neighboring offices since those offices become more congested after the closing. The magnitude of the effects is large, suggesting an implied value of time of \$100 per hour for disability applicants at the margin of applying.

To better understand these effects, we examine the channels through which closings could affect application decisions, including congestion at neighboring field offices and travel time to neighboring offices.[3] We use walk-in wait time and application processing time as proxies for congestion; closings result in an average increase of 36 percent (4.8 minutes) in walk-in wait time, 12 percent (3.4 days) in processing time, and 70 percent (5.1 applications) in the number of applications that take longer than 40 days to process. To measure changes in travel times, we use calculations from Google Maps to estimate that driving time and public transit time to the nearest open field office increase by about 40 percent (10 minutes in driving time and 37 minutes in public transit time). Using an instrumental variables framework to decompose the decline in applications into various channels, we estimate that 54 percent of the reduction in applications is attributable to increased congestion at neighboring offices, 4 percent to increased driving distance, and 42 percent to other costs of switching field offices. One explanation for this result is that more local field office contacts occur by phone rather than in person, and congestion costs affect both modes of communication while transportation costs affect only in-person applicants. When we compare these estimates to the expected value of disability benefits, the estimates imply that potential applicants are willing to forgo \$670 in expected benefits to avoid increased congestion, \$50 to avoid greater driving distance, and \$510 to avoid other costs of switching offices.

Our results contribute to the literature on screening and targeting efficiency, both specifically in the context of SSA office closings and more broadly across social support programs. Most broadly, our findings stand in contrast to the Nichols and Zeckhauser (1982) hypothesis in that field office closings reduce both productive efficiency and targeting efficiency based on current eligibility standards for disability programs. Moreover, if these programs are also intended to address economic inequality, our results by socioeconomic status indicate that field office closings exacerbate the very inequality that disability programs are intended to reduce. Even in a world of online information and applications, in-person

[3] Note 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.

information and assistance still matter for applicants with low education and earnings levels.

More specifically to our context, we 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, the increased applicant time required to apply for disability, and applicant earnings decay from longer processing times. On the benefit side, we consider administrative savings from processing fewer applications and shuttering field offices, reductions in application costs for individuals who are discouraged from applying, and the cost of public funds saved from lower disability receipt for undeserving applicants. Using the government's *current* severity standards for eligibility and a conservative risk aversion parameter, we estimate a ratio of social costs to social benefits of field office closings of 5.4 to 1 and a total net social cost of all 118 closings of \$1.2 billion. However, when we use stricter severity standards, we find that closings have a smaller adverse impact on social welfare; for the extreme case in which only the most severe individuals are considered deserving, the closings have a net positive impact on social welfare. Finally, we use our welfare methodology to calculate net closing costs for each SSA field office and find that the actual closed offices have lower net closing costs than the average field office, but substantially higher net closing costs than the offices with the lowest cost to close.

The paper proceeds as follows. Section I reviews the literature on application costs and provides a conceptual framework to evaluate the effects of closings on targeting efficiency. In Section II, we describe the institutional context of Social Security field office closings and describe the administrative and programmatic data from the Social Security Administration. Section III outlines the empirical strategy, and Section IV presents estimates of the effect of closings on the take-up and targeting of disability programs. In Section V, we interpret our results on take-up and targeting and analyze the channels through which closings reduce disability applications. Section VI presents welfare calculations, and Section VII concludes.

I. Literature and Framework

A. *Literature and Contribution*

This paper makes two contributions to the literature on self-screening, and, in particular, whether the hassles (or "ordeals") associated with using benefits or services improve or worsen targeting. First, this is the first paper we are aware of to estimate the effect of application costs on the targeting efficiency of disability programs, a context in which the application process matters critically for targeting because the disability tag is difficult to observe.[4] As we discuss below, the theoretical effect of application costs on targeting efficiency

[4] Benítez-Silva et al. (1999) shows in a descriptive paper that disability applicants are in worse self-reported health than non-applicants.

is ambiguous, making this an empirical question. Second, this paper brings together for the first time detailed administrative data on applicants and specific features of field offices, allowing us to go beyond take-up and study both targeting efficiency and the channels through which closings discourage applicants. To examine targeting efficiency, 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, which allow us to quantify congestion at neighboring offices, and call volumes to the 800 information line, which shed light on the role of field offices in providing program information. We also calculate driving and public transportation times to field offices using Google Maps Application Programming Interfaces (APIs).

Several papers build the theoretical foundation for the effect of hassles 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. Kleven and Kopczuk (2011) considers these questions for a targeted program that uses a monitoring technology involving substantial information collection and complexity (e.g., disability determination). Nichols and Zeckhauser (1982) posits that hassles 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 hassles—to improve targeting efficiency. In the online Appendix, we show that the Nichols and Zeckhauser (1982) framework can be modified easily to include application costs that are negatively correlated with ability (e.g., a cognitive cost instead of a time cost) and then produce the result of worsening targeting. Bertrand, Mullainathan, and Shafir (2004) hypothesizes that, due to differential behavioral biases or information costs, hassles may in fact deter the individuals that society would like to target. The question of whether hassles improve or worsen targeting is ultimately an empirical one, and likely depends on the type of hassle and the characteristics of the marginal population.

Previous empirical work has estimated the effect of hassles (or their reduction) on program take-up, but with less attention to the question of targeting (see Currie 2006 for a review). In terms of take-up, high-intensity assistance and automatic enrollment have large effects on behavior (Bettinger et al. 2012, Madrian and Shea 2001), while more modest changes like office openings and electronic filing have smaller or zero effects (Rossin-Slater 2013, Kopczuk and Pop-Eleches 2007, Ebenstein and Stange 2010). Two recent papers address the targeting question more directly. Alatas et al. (2016) conducts a field experiment of requiring households in Indonesia to apply for a welfare program in person, rather than the status quo policy of automatic enrollment. Finkelstein and Notowidigdo (forthcoming) conducts a field experiment in the United States of providing assistance with SNAP enrollment to households that are likely eligible but not enrolled. Both papers find an inverse relationship between hassles and targeting efficiency. Alatas et al. (2016) finds that imposing the active enrollment requirement improves targeting efficiency by disproportionately screening out higher income households, while Finkelstein and Notowidigdo (2018) finds that providing assistance with SNAP enrollment reduces average benefit levels and increases average recipient health. In contrast, we find that application costs *reduce* targeting efficiency in the US disability context, as measured by the current disability standard and by socioeconomic status.

B. *Targeting Efficiency Framework*

Our goal is to estimate the effect of an increase in application costs on the targeting efficiency of disability programs and on social welfare. We define an improvement in targeting efficiency as follows: when application costs increase from η to $\eta' > \eta$, targeting efficiency increases if and only if $\Pr(R|A,\eta') > \Pr(R|A,\eta)$, where $\Pr(R|A,\eta)$ is the probability of receiving benefits conditional on applying for benefits at application cost η. The intuition behind this definition is that, assuming no change in adjudicator standards, the probability of acceptance increases when the applicant pool becomes more deserving. If $\Pr(R|A,\eta) \neq 0$, we can rewrite our definition of an improvement in targeting efficiency in terms of the empirical parameters that we estimate:

$$(1) \qquad 1 < \frac{\Pr(R|A,\eta')}{\Pr(R|A,\eta)} = \frac{\Delta_R + 1}{\Delta_A + 1},$$

where $\Delta_R \equiv \big(\Pr(R|\eta') - \Pr(R|\eta)\big)/\Pr(R|\eta)$ is the percent change in the number of disability recipients resulting from the closing and $\Delta_A \equiv \big(\Pr(A|\eta') - \Pr(A|\eta)\big)/\Pr(A|\eta)$ is the percent change in the number of disability applicants resulting from the closing. When a field office closes, targeting efficiency improves if the percent decline in disability receipt is less than the percent decline in disability applications.

Note that this definition assumes that the adjudicator's preferences for who is deserving or undeserving reflects societal preferences, taking the current screening technology as optimal. However, societal preferences may differ from adjudicator preferences. For example, if societal preferences are stricter than adjudicator preferences (i.e., society thinks the adjudicator allows undeserving applicants), then a reduction in take-up induced by a closing is more likely to increase social welfare. To account for societal preferences that may differ from adjudicator preferences, we also present changes in observable characteristics of applicants and recipients, including severity, disability type, education, pre-application earnings, and age. In Section VIC, we present a framework to calculate the change in social welfare from field office closings in different scenarios, one in which the current government severity standard for eligibility is optimal and alternative scenarios using a stricter severity standard.

II. Institutional Context and Data

A. *Institutional Context*

The Social Security Administration administers the SSDI and SSI programs. SSDI and SSI have the same medical requirements but different nonmedical 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.[5] 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 nonmedical 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, if it meets the nonmedical requirements, to the state Disability Determination Services (DDS) office, where a disability examiner decides whether the applicant meets medical requirements. Note that field offices do not make medical decisions about an applicant's case. 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.

There are currently around 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. However, disability claims take up a disproportionately large amount of staff time, with two-thirds of SSA's administrative budget going to disability claims.[6] According to SSA testimony, "disability claims … are particularly time intensive as employees help claimants complete detailed forms about medications, treatment, medical testing, work history, and daily activities."[7] When a Social Security field office closes, most of the savings to the Social Security Administration are in the form of foregone rental costs. The staff from the office are generally given the opportunity to move to one of the other offices in the region.

[5] The SSI application became available online in April 2017, after our study period ends.

[6] Testimony of Jo Anne B. Barnhart, Commissioner, SSA, to the US House of Representatives, March 4, 2003. SSA's administrative budget reflects both field office and state DDS costs.

[7] Testimony of Nancy Berryhill, Deputy Commissioner for Operations, SSA, to Special Committee on Aging, US Senate, June 18, 2014.

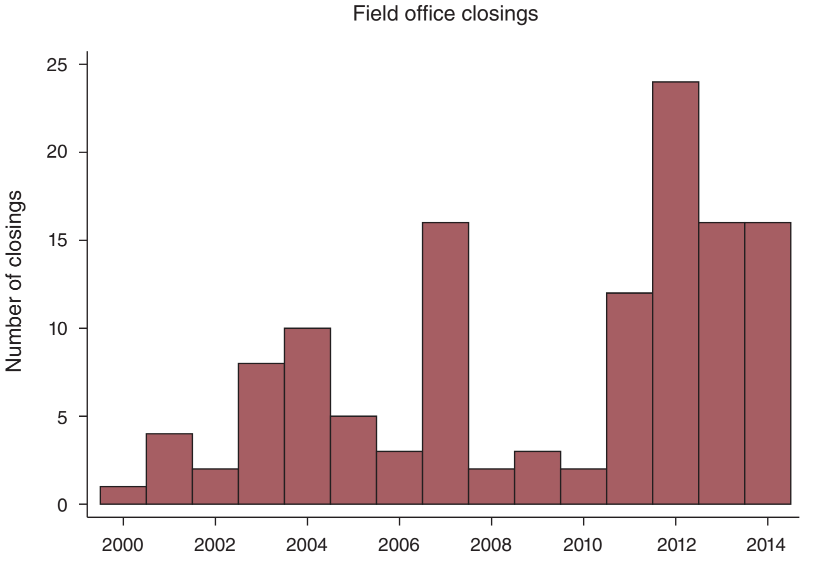

Figure 1. Timing of Field Office Closings

Note: Graph plots number of Social Security field offices closings in each year.

Source: Authors' tabulations based on Social Security Administration data

Since Social Security field offices assist with applications, the closing of these offices (weakly) increases 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 118 closings since that year, with approximately half of those closings occurring since 2009 (see Figure 1). According to testimony from the Senate Finance Committee, between 2000–2007, the Republican-held Congress cut appropriations to the Social Security Administration by a total of $1 billion below the President's budget request.[8] The spike in closings between 2011 and 2014 corresponds to the Budget Control Act of 2011, also known as budget sequestration, which included automatic federal spending cuts.

The obvious concern with using field office closings as variation in application costs 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.[9] To address this issue, we use areas that experience a closing in the future as controls

[8] "More Work, Less Resources: Social Security Field Offices Struggle to Deliver Service to the Public." Hearing before the Committee on Finance, United States Senate, 110th Congress Second Session, May 8, 2008.

[9] According 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 in online Appendix Table A.13 that smaller local populations, fewer applications, and more offices in close proximity predict a higher likelihood of an office closing, which suggests that the closings themselves are not as good as random. In Section IVC, we find that our estimates are robust to using unaffected zip codes as the control group and to using an event study design.

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. The Social Security Administration does not disclose its method for deciding which offices to close. In Section IVC, we demonstrate that the timing of the closings appears random (i.e., not predicted by observable characteristics), even though the closings themselves are not random. In addition, we demonstrate that there are no pre-trends in the outcome variables and that macroeconomic variables such as population and unemployment rate do not exhibit a break at the time of the closing.

B. *Data*

We use confidential administrative and program data from the Social Security Administration. We collect 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 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 the SSA's 800 phone number by area code by month from January 2014 to April 2016.

We use data on disability applicants and recipients from a number of sources created and maintained by the Social Security Administration. We start with the universe of disability applications with a disability examiner decision between 1990–2015 from the 831 files. The 831 files report 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 the applicant's zip code up to 2010. The 831 files include only applications that are assigned to and receive a decision from a disability examiner, and they exclude applications that result in technical denials (i.e., denials for nonmedical reasons). 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, has legal representation, has a representative payee, and has an email address. 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.

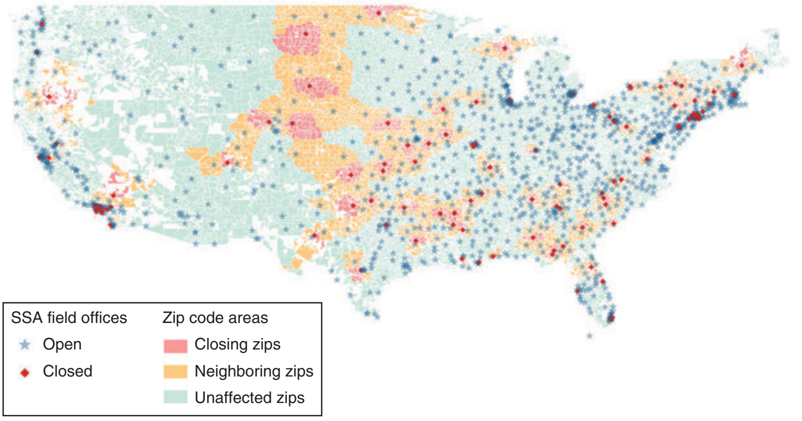

Figure 2. Map of Field Office Closings and Zip Code Classification in the United States

Notes: The map gives the locations of Social Security field offices, including both open and closed offices, as of 2016. In addition, the map codes different types of zip codes: zip codes where the nearest office was closed ("closing" zip codes), zip codes where the nearest office is the second or the third nearest field office of a closing zip code prior to the closing event ("neighboring" zip codes), and all remaining zip codes ("unaffected" zip codes).

Source: Authors' mapping based on Social Security Administration and Census Bureau data

We collapse the Social Security data by the zip code 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 zip codes. Figure 2 shows their boundaries. For each zip code, we use the geographic information system (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 the 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 code to its nearest, second nearest, and third nearest field offices for each quarter from 1990–2015. We classify zip codes into three categories: zip codes where the nearest office was closed ("closing" zip codes), zip codes where the nearest office is the second or the third nearest field office of a closing zip code prior to the closing event ("neighboring" zip codes), and all remaining zip codes ("unaffected" zip codes). Figure 2 shows the locations of all Social Security field offices since 2000 and demonstrates the classification of closing, neighboring, and unaffected zip codes. Online Appendix Figure A.7 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 and the American Community Survey. Since information at the zip code level is limited and 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 Commission; 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.

III. Empirical Strategy

To determine the appropriate empirical strategy, we test whether the field office closings appear to be random by predicting closings based on field office and area characteristics.[10] We find in online Appendix Table A.13 that some factors consistently predict the likelihood of a closing (columns 1–3). However, no observable characteristic consistently predicts the *timing* of a closing conditional on closing (columns 4–6). These results suggest that the *timing* of closings is effectively random even if the closings themselves are not, which motivates our main empirical strategy of exploiting only the timing of the closings.

For any given closing, we take zip codes that experience the current closing as treated zip codes, and zip codes that experience a closing in the future as control zip codes. Specifically, we construct our sample as follows. First, we create separate datasets for each of the 118 closings. In each dataset, zip codes that experience the current closing are labeled as treated zip codes, while zip codes that experience a closing more than two years in the future are labeled as control zip codes. Event quarters are specified relative to the quarter of the closing. Second, to eliminate zip codes with tiny populations, we drop zip codes (both treatment and control) with an average of fewer than four disability applications per quarter in the year before the closing.[11] Third, we append all 118 datasets into one dataset. We keep in the sample closings that occur too late to have future closings as controls. The resulting dataset has 1,110 closing zip codes and, in our main sample restricted to event quarters -12 to 8, a total of 1.0 million zip code quarters.

[10] According to congressional testimony, the SSA has not considered local economic or other conditions in deciding what offices to close ("Reduction in Face-to-Face Services at the Social Security Administration," US Senate Special Committee on Aging, Summary of Committee Staff Investigation, No Date). To examine whether local characteristics predict the *likelihood* of a closing for each year between 2000–2012, we use all open offices in a given year and estimate the following equation:

$$(2) \quad Closing_i = \alpha + \beta_1 Pop2000_i + \beta_2 Density_i + \beta_3 Apps_i + \beta_4 FOProcess_i + \beta_5 NumOffice_i + \beta_6 Wait_i + \epsilon_i,$$

where $Pop2000_i$ 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 previous year; $FOProcess_i$ is the application processing time for office i in the previous year; $NumOffice_i$ is the number of offices within 20 kilometers of office i before the closing; and $Wait_i$ is walk-in wait time for office i in the previous year (available only for 2006 and later). To examine whether local characteristics predict the *timing* of closing conditional on closing for each year between 2000–2012, we limit the sample to offices that are open in that year but will close in the future and estimate the following equation:

$$(3) \quad CloseYr_i = \alpha + \beta_1 Pop2000_i + \beta_2 Density_i + \beta_3 Apps_i + \beta_4 FOProcess_i + \beta_5 NumOffice_i + \beta_6 Wait_i + \epsilon_i,$$

where $CloseYr_i$ is the year in which office i closed. The results of both are shown in online Appendix Table A.13.

[11] For the subgroup analysis, we drop zip codes with an average of fewer than four disability applications in that subgroup per quarter in the year before the closing.

Table 1 presents the characteristics of zip codes that have an average of four or more disability applications per quarter in the year 2000, across closing, neighboring, and unaffected zip codes, as defined in Section IIB. The zip code means across the three groups are similar; the most apparent differences are that closing and neighboring zip codes have larger populations and more disability applications in the year 2000 than unaffected zip codes.[12]

The drop in applications in treatment zip codes after the closing is apparent even in the raw data (online Appendix Figure A.8), while control zip codes follow a smooth upward trend in applications. Online Appendix Table A.9 compares pre-closing characteristics of treatment and control zip codes and shows that they are similar on demographics, but treatment zip codes have higher walk-in wait times and more disability applications in the year before closing.

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

$$(4) \quad Y_{isct} = \alpha_i + \gamma_{st} + \delta_0 Treated_{ic} + \sum_{\tau} D_{ct}^{\tau} + \sum_{\tau} \delta_{\tau}(Treated_{ic} \times D_{ct}^{\tau}) + \epsilon_{isct},$$

where Y_{isct} is an outcome (e.g., number of disability applicants) for zip code i in state s for closing c in quarter t. The α_i are zip code fixed effects, and γ_{st} are calendar-quarter-by-state fixed effects.

The variable $Treated_{ic}$ is an indicator equal to 1 if zip code i is a treated (closing) zip code for closing c; notice that $Treated_{ic}$ is not colinear with the zip code fixed effects because the same zip code can appear as a control and a treated zip code in the data. 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 zip codes by the number of pre-closing applications for application regressions, and by the number of pre-closing recipients for receipt regressions. The coefficients of interest are the δ_{τ}; they represent the difference between treated and control zip codes in outcome Y, τ quarters after the closing. The graphs presented in the following sections plot the δ_{τ} estimates in event time.

We cluster standard errors at the closing level (i.e., 118 clusters) since that is the level of our variation. Note that our strategy of using future closings as controls for current closings will result in the same zip code appearing multiple times in the data. Clustering at the closing level accounts for the repeated appearance of zip codes since zip codes are fully nested within closings.[13]

For table estimates, we estimate a pre-post version of equation (4):

$$(5) \quad Y_{isct} = \alpha_i + \gamma_{st} + \beta_0 Treated_{ic} + \sum_{\tau} D_{ct}^{\tau} + \beta\big(Treated_{ic} \times Post_{ct}\big) + \kappa\big(Treated_{ic} \times Zero_{ct}\big) + \epsilon_{isct},$$

[12] Online Appendix Table A.8 presents the same summary statistics for all zip codes in the United States.

[13] When one cluster level is fully nested in another cluster, the correct approach is to cluster at the higher level, which will result in more conservative standard errors (Cameron, Gelbach, and Miller 2011).

TABLE 1—SUMMARY STATISTICS OF CLOSING, NEIGHBORING, AND UNAFFECTED ZIP CODES IN SAMPLE

	Closing zip codes	Neighboring zip codes	Unaffected zip codes	*p*-values from *t*-tests		
	Mean (SD)	Mean (SD)	Mean (SD)	Closing vs. neighboring	Closing vs. unaffected	Neighboring vs. unaffected
Zip code characteristics (2000)						
Population	15,314	14,722	13,016	0.312	0.000	0.000
	(16,413)	(15,581)	(13,868)			
Poverty rate	14%	14%	13%	0.223	0.002	0.001
	(10%)	(9%)	(9%)			
Median income	\$41,199	\$40,431	\$40,439	0.246	0.119	0.716
	(\$18,214)	(\$16,753)	(\$15,410)			
Male	49%	49%	49%	0.385	0.000	0.000
	(3%)	(3%)	(3%)			
Female	51%	51%	51%	0.385	0.000	0.000
	(3%)	(3%)	(3%)			
White	76%	78%	83%	0.062	0.000	0.000
	(24%)	(23%)	(21%)			
Black	14%	13%	9%	0.130	0.000	0.000
	(21%)	(20%)	(17%)			
Hispanic	8%	8%	8%	0.954	0.836	0.774
	(14%)	(13%)	(15%)			
Other race	2%	2%	1%	0.321	0.001	0.000
	(14%)	(11%)	(13%)			
Age 0–19	27%	28%	28%	0.006	0.000	0.000
	(6%)	(5%)	(5%)			
Age 20–44	35%	35%	35%	0.952	0.002	0.000
	(7%)	(7%)	(6%)			
Age 45–64	23%	23%	23%	0.526	0.059	0.000
	(4%)	(4%)	(4%)			
Age 65+	14%	14%	13%	0.016	0.000	0.010
	(5%)	(5%)	(6%)			
High school dropout	22%	22%	22%	0.880	0.128	0.002
	(12%)	(11%)	(12%)			
High school graduate	31%	32%	33%	0.113	0.000	0.000
	(10%)	(10%)	(10%)			
Some college	25%	26%	26%	0.000	0.000	0.046
	(6%)	(7%)	(7%)			
College graduate	22%	21%	18%	0.014	0.000	0.000
	(16%)	(15%)	(13%)			
Never married	26%	25%	24%	0.043	0.000	0.000
	(9%)	(9%)	(8%)			
Currently married	55%	55%	58%	0.028	0.000	0.000
	(10%)	(11%)	(9%)			
Previously married	19%	19%	19%	0.340	0.000	0.000
	(5%)	(5%)	(5%)			
Walk-in wait time (minutes)	8.39	10.67	9.68	0.000	0.000	0.000
(2005)	(7.42)	(9.77)	(8.57)			
Quarterly disability applications	32	32	28	0.597	0.001	0.000
(2000)	(43)	(43)	(37)			
Observations	1,110	4,611	14,294			

Notes: Table presents summary statistics for zip codes with an average of at least four disability applications per quarter in the year 2000. The last three columns present *p*-values from the *t*-test of the difference in the characteristic between different types of zip codes. Closing zip codes are zip codes in which the closest office closes. Neighboring zip codes are zip codes in which the closest office is the second or third closest office to a closing zip code. Unaffected zip codes are zip codes that are neither closing nor neighboring zip codes. "Zip code characteristics" are calculated from the 2000 census, "walk-in wait time" from Social Security Administration data (where 2005 is the earliest available year), and "quarterly disability applications" from Social Security Administration data.

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). The identifying assumption of the difference-in-difference 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 zip codes as controls requires only that the timing of the closings be as good as random. Indeed, in Section IVC, we demonstrate that the timing of the closings appears to be effectively random (i.e., not predicted by observable characteristics) even though the closings themselves are not. In the figures presented in Section IV, we demonstrate that the treated and control zip codes exhibit parallel trends in the quarters before the closing in both number of applications and characteristics of disability applicants.

The main difference between our difference-in-difference strategy relative to a pure event study design is that the difference-in-difference model uses a control group to eliminate event time trends that do not appear in calendar time. For example, when SSA chooses which offices to close in a given year, it could be using population or application trends in previous years as a criterion in this decision; in that case, calendar time effects alone will not eliminate these pre-trends, and instead the model requires both calendar time effects and event time effects. In robustness checks, we find similar estimates of the treatment effect using an event study design, but the event study design has pre-trends. We choose the difference-in-differences as the main specification because it eliminates the pre-trend in disability applications from the pure event study.

IV. Estimates of the Effect of Closings on Applicants and Recipients

A. *Effect of Closings on Take-up*

Figure 3 shows the effect of field office closings on the log number of disability applications in closing zip codes, based on estimates from equation (4), where applications are assigned to quarter based on the date the application was filed. Notice that the treated and control zip codes exhibit parallel trends in disability applications prior to event quarter 0.[14] Disability applications fall by 10 percent as a result of a field office closing in closing zip codes (Table 2), and the fall in levels is 3.3 applications per zip code per quarter (online Appendix Table A.11). It takes

[14] Relative to the raw plot in online Appendix Figure A.8, the inclusion of state-by-quarter fixed effects eliminates the differential trend between treatment and control zip codes.

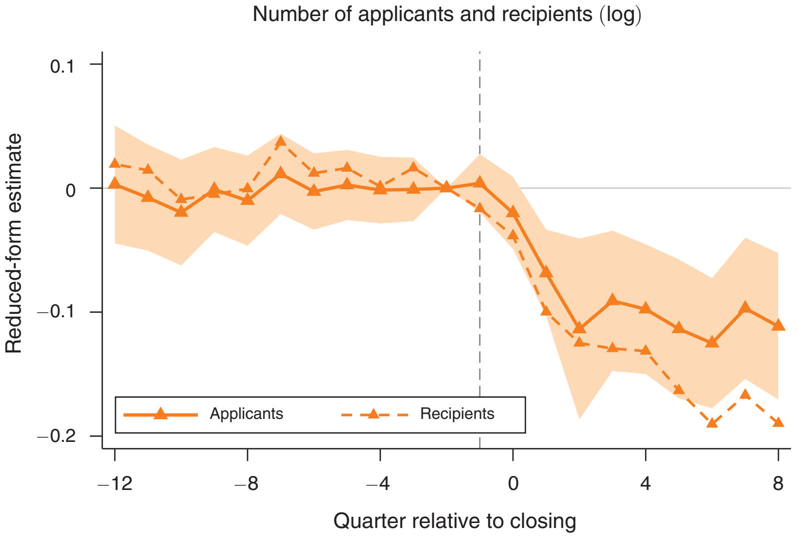

FIGURE 3. EFFECT OF CLOSINGS ON NUMBER OF DISABILITY APPLICATIONS AND ALLOWANCES

Notes: The figure plots estimates of the effect of the closing on applications (recipients) in closing zip codes in the event quarters before and after the closing. Specifically, the figure plots estimates of δ_τ coefficients from equation (4), which is a regression of the number of disability applicants (recipients) on zip code fixed effects, quarter-by-state fixed effects, a treatment indicator, event quarter indicators, and event quarter indicators interacted with the treatment indicator. The dependent variable is the log number of disability applications (solid series) or the log number of disability recipients (dashed series). The shaded region is the 95 percent confidence interval for disability applications (solid series). The sample is zip codes in which the nearest office closed after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application or recipient volume in the year before the closing.

two quarters after the closing for disability applications to reach a stable 10 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.

The decline in applications has different implications depending on whether it leads to a decline in the number of recipients. Figure 3 shows that the number of disability recipients declines by 16 percent in closing zip codes (Table 3), with allowances still assigned to quarter based on application date. This estimate is statistically different from the 10 percent decline in applications (online Appendix Table A.10). The decline in levels is 2.6 allowances per quarter per zip code (online Appendix Table A.11). The results imply that closings disproportionately discourage applications by those who would have been allowed by SSA adjudicators if they had applied.[15]

[15] When we cluster standard errors on closing date, the standard errors increase by 20 percent for log applicants and 60 percent for log recipients. The point estimates remain statistically significant at the 1 percent level.

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

	Count (log)			Proportion/average		
	Point estimate	Standard error	Control count	Point estimate	Standard error	Control mean
All	−0.100	(0.0288)	39.7			
Severity						
Low	−0.0483	(0.0295)	18.0	0.0278	(0.00444)	0.425
Medium	−0.338	(0.0503)	6.9	−0.0274	(0.00402)	0.184
High	−0.173	(0.0367)	8.5	−0.0118	(0.00318)	0.209
Very high	−0.0327	(0.0271)	6.2	0.0114	(0.00239)	0.183
Disability type						
Mental	−0.115	(0.0356)	12.3	−0.00522	(0.00376)	0.289
Musculoskeletal	−0.0576	(0.0298)	10.2	0.0101	(0.00255)	0.276
Other physical	−0.109	(0.0283)	17.2	−0.00485	(0.00353)	0.435
Education (years)				0.0666	(0.0201)	11.8
High school dropout	−0.142	(0.0275)	9.9			
High school graduate	−0.0740	(0.0280)	19.4			
College graduate	−0.0496	(0.0288)	2.4			
Pre-application earnings ($)				413.1	(202.0)	$15,362
$0–$5,000	−0.112	(0.0338)	18.7			
$5,000–$15,000	−0.0887	(0.0331)	8.9			
$15,000–$25,000	−0.0928	(0.0294)	5.0			
$25,000+	−0.0414	(0.0343)	7.0			
Language						
Speaks English	−0.0621	(0.0976)	24.9	0.00719	(0.0172)	0.623
Does not speak English	−0.107	(0.0530)	14.7			
Age (years)				0.469	(0.118)	40.7
18–34	−0.126	(0.0339)	7.9			
35–49	−0.130	(0.0292)	12.9			
50+	−0.0489	(0.0262)	13.1			
Applicant behavior						
Files online	0.135	(0.0682)	2.8	0.0374	(0.00741)	0.075
Files in person or by phone	−0.194	(0.0319)	36.9			
Provides email address	0.260	(0.0795)	4.2	0.0455	(0.00953)	0.111
No email address	−0.158	(0.0309)	35.4			
Has representation	0.264	(0.0711)	2.2	0.0325	(0.00545)	0.054
No representation	−0.139	(0.0297)	37.4			

Notes: 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 (5), which is a regression of log applications for a subgroup on zip code fixed effects, quarter-by-state fixed effects, a treatment indicator, event quarter indicators, an interaction between the treatment indicator and a "post" indicator (coefficient of interest β), and an interaction between the treatment indicator and an "event year zero" indicator. The second set of columns presents estimates of β for the same equation, where the dependent variable is the proportion of applicants with that characteristic (for indicator variables like severity, disability type, applicant behavior, and language) or the average of the characteristic across applicants (for continuous variables like education, earnings, and 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 "control count" is the number of individuals in the control zip code in a category, and "control mean" is the mean characteristic in the control group. The sample is zip codes in which the nearest office closed after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing. Standard errors are in parentheses.

We also examine the effects of the closing on neighboring zip codes, which are zip codes in which the nearest office is the second or third closest office of a closing zip code prior to the closing event. We estimate equations analogous to (4) and (5), replacing the $Treated_{ic}$ indicator with a $TreatedNbr_{ic}$ indicator that is equal to 1 if zip code i is a neighboring zip code for closing c and 0 otherwise. The number of applications falls by 4.6 percent and the number of recipients falls by 9.3 percent,

Table 3—Estimates of the Effect of Closings on Disability Receipt

	Count (log)			Proportion/average		
	Point estimate	Standard error	Control count	Point estimate	Standard error	Control mean
All	−0.155	(0.0301)	21.7			
Severity						
Low	N/A			N/A		
Medium	−0.319	(0.0484)	6.9	−0.0417	(0.00689)	0.329
High	−0.165	(0.0351)	8.5	−0.00376	(0.00532)	0.359
Very high	−0.0287	(0.0255)	6.2	0.0455	(0.00647)	0.312
Disability type						
Mental	−0.190	(0.0358)	6.9	−0.0120	(0.00338)	0.289
Musculoskeletal	−0.129	(0.0354)	5.1	0.00279	(0.00325)	0.252
Physical	−0.132	(0.0280)	9.7	0.00924	(0.00386)	0.459
Education (years)				0.0197	(0.0281)	11.9
High school dropout	−0.180	(0.0314)	5.1			
High school graduate	−0.153	(0.0321)	10.6			
College graduate	−0.0931	(0.0278)	1.6			
Pre-application earnings ($)				516.2	(249.3)	$18,328
$0–$5,000	−0.154	(0.0338)	9.0			
$5,000–$15,000	−0.168	(0.0384)	4.5			
$15,000–$25,000	−0.134	(0.0327)	3.1			
$25,000+	−0.0948	(0.0312)	5.1			
Age (years)				0.510	(0.145)	43.0
18–34	−0.210	(0.0336)	3.1			
35–49	−0.255	(0.0386)	6.1			
50+	−0.0908	(0.0279)	9.3			

Notes: The first set of columns presents estimates of the effect of field office closings on log allowances by subgroup, specifically estimates of β from equation (5), which is a regression of log allowances for a subgroup on zip code fixed effects, quarter-by-state fixed effects, a treatment indicator, event quarter indicators, an interaction between the treatment indicator and a "post" indicator (coefficient of interest β), and an interaction between the treatment indicator and an "event year zero" indicator. The second set of columns presents estimates of β for the same equation, where the dependent variable is the proportion of recipients with that characteristic (for indicator variables like severity, disability type, applicant behavior, and language) or the average of the characteristic across recipients (for continuous variables like education, earnings, and age). Earnings and education estimates include only adult allowances. The "control count" is the number of individuals in the control zip code in a category, and "control mean" is the mean characteristic in the control group. "Low" severity is not applicable at the allowance level because low severity is defined as being denied. The sample is zip codes in which the nearest office closes after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by recipient volume in the year before the closing. Standard errors are in parentheses.

with persistent effects (Table 4 and online Appendix Figure A.11). We present evidence in Section V that neighboring offices become more congested after the closing, which could explain these declines.

B. *Effect of Closings on Targeting*

Who is screened out by higher application costs? We measure effects on targeting in two ways. First, we estimate the effect of the closings on applicants and recipients separately for each subgroup (first set of columns in Tables 2 and 3) and test for statistical differences across subgroups (see online Appendix Table A.10). Second, we estimate 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

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

	Closing zip code			Neighboring zip code		
	Point estimate	Standard error	Control mean	Point estimate	Standard error	Control mean
Applications (log)	−0.100	(0.0288)	39.7	−0.0460	(0.0134)	42.5
Recipients (log)	−0.155	(0.0301)	21.7	−0.0928	(0.0146)	22.6
Congestion measures						
FO processing time	3.426	(0.732)	28.8	1.764	(0.515)	28.4
Apps with processing time > 40 days	5.052	(1.551)	7.3	3.245	(0.739)	7.6
Walk-in wait times	4.842	(1.199)	13.6	3.211	(0.991)	16.3
Travel cost measures						
Driving time	10.43	(1.691)	23.5			
Driving distance	12.83	(1.423)	24.3			
Transit time	37.45	(6.617)	89.4			

Notes: The table presents estimates of the effect of field office closings on log applications, log allowances, and measures of application costs for closing and neighboring zip code. Specifically, the table presents estimates of β from equation (5), which is a regression of the dependent variable on zip code fixed effects, quarter-by-state fixed effects, a treatment indicator, event quarter indicators, an interaction between the treatment indicator and a "post" indicator (coefficient of interest β), and an interaction between the treatment indicator and an "event year zero" indicator. For the neighboring zip code regressions, the treatment indicator is replaced by an indicator for being a neighboring zip code of that closing. A closing zip code is a zip code in which the nearest office closes. A neighboring zip code is a zip code in which the nearest office is the second or third closest office of a closing zip code. 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 code centroid. The sample is zip codes in which the nearest office closed after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application or recipient volume in the year before the closing. Standard errors are in parentheses.

(2010) (second set of columns in Tables 2 and 3). While the proportion/average estimates summarize overall effects of the closings on a characteristic, the estimates by subgroup provide a more detailed picture of the effects of the closings. This analysis rests on the assumption, discussed in detail in Section IVC, 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. We categorize applicants into four severity categories: those 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 labeled "medical improvement expected" or "medical improvement possible" ("high" severity), and those allowed at the initial level and labeled "medical improvement not expected" ("very high" severity).[16] Whether field office closings disproportionately discourage higher severity or lower severity applicants is ex ante ambiguous: higher severity applicants may face higher costs of reaching a neighboring office or applying through other means because

[16] SSA'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).

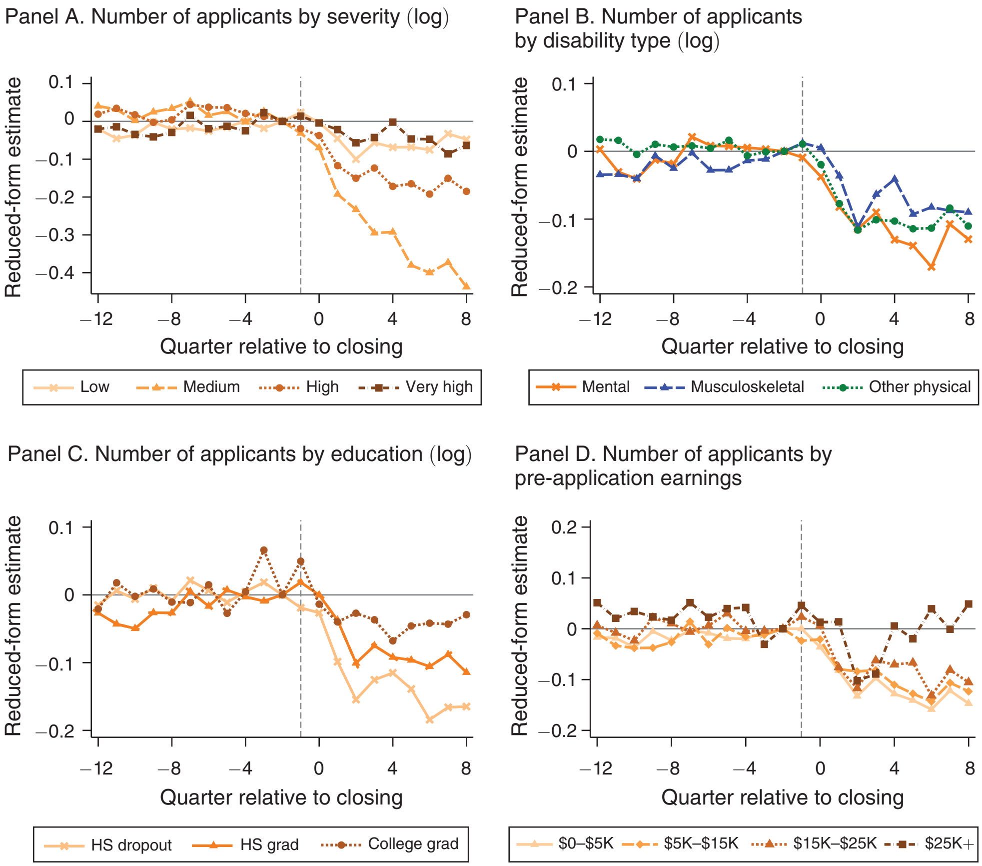

Figure 4. Effect of Closings on Number of Disability Applications, by Subgroup

Notes: The figure plots estimates of the effect of the closing on applications by subgroup in closing zip codes in the event quarters before and after the closing. Specifically, the figure plots estimates of δ_τ coefficients from equation (4), which is a regression of the number of disability applicants by subgroup on zip code fixed effects, quarter-by-state fixed effects, a treatment indicator, event quarter indicators, and event quarter indicators interacted with the treatment indicator. The dependent variable is the log number of disability applications by subgroup. The sample is zip codes whose nearest office closed after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

of their health, while less severely disabled applicants may no longer find it worth applying given the increase in application costs. As shown in Figure 4, we find that the decline in applications is non-monotonic in severity, with smaller effects for low-severity (4.8 percent) and very high-severity (3.3 percent) applicants, and larger effects for medium-severity (34 percent) and high-severity (17 percent) applicants. The differences across severity subgroups are statistically significant, except for low versus very high.[17]

Another observable measure of health is disability type. We categorize applicants into three disability types based on the body system code on their

[17] We also split "low" severity into "low, appeal" and "low, no appeal" and find that the estimates are economically similar (8.5 percent and 4.5 percent, respectively) and statistically indistinguishable.

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.[18] The decline in applications is nearly twice as large for mental conditions (12 percent) and physical conditions (11 percent) compared to musculoskeletal (6 percent) conditions, and this difference is statistically significant. However, at the recipient level, the closings reduce mental conditions the most (19 percent), with smaller effects on musculoskeletal (13 percent) and other physical (13 percent) conditions.

Turning to socioeconomic status, we estimate the effects of the closings by education and pre-application earnings. 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 4 and Table 2, applications decline by 14 percent for high school dropouts, by 7 percent for high school graduates, and by 5 percent for college graduates. These differences are significant and carry over to the recipient level. The effects of the closings are also decreasing in pre-application earnings, which we measure as annual earnings in the five years prior to the year of application. Applications decline by 11 percent in the lowest earnings category ($0-$5,000) but by just 4 percent for the highest earnings category (above $25,000), and these estimates are statistically different from each other. The result of these differential effects is that average annual pre-application earnings increase by $410, or 2.7 percent, after a closing.

Finally, with respect to age, we find that older applicants are less discouraged than younger applicants, with applications declining by 5 percent for those older than 50 years and 13 percent for younger applicants. These differences are statistically significant.

We also estimate the effects in levels, with results in online Appendix Table A.11. Taking the point estimates at face value, we find that for every 10 low-severity potential applicants who are discouraged from applying due to a closing, the closing also discourages 20 medium-severity applicants, 14 high-severity applicants, and 0.4 very high-severity applicants. Similarly, for every 10 college graduates discouraged from applying, 133 high school dropouts and 136 high school graduates are discouraged.[19]

All disability programs experience substantial declines in the number of applicants, but the point estimates for the adult SSI (14 percent) and child SSI

[18] The "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.

[19] Of 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 very high severity is a positive 0.05. For this reason, in online Appendix Table A.12, we also estimate the effect of field office closings on characteristics jointly. 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 medium- and high-severity conditions. College graduates do not experience large declines in any severity category, and similarly, very high-severity potential applicants experience small declines regardless of education category. Effects by education-by-disability-type cells are also consistent with the separate education and disability type estimates.

(15 percent) programs are twice as large as those for the adult SSDI (7 percent) program (online Appendix Table A.19). 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, such as the online application or third-party representation.[20] We find that the number of applicants who file online *increases* by 14 percent and is mostly driven by high school graduates (online Appendix Table A.18). The closing increases the number of applicants with representation by a statistically significant 26 percent, though only a small fraction—5.4 percent—of applicants are represented at baseline.

C. *Robustness*

The identifying assumption of the difference-in-difference design is that control and treatment zip codes would experience parallel trends in outcomes in the absence of the field office closing. As seen in Figures 3 and 4, control and treatment zip codes 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 zip codes (e.g., local economic shock or drop in population), and those changes in economic conditions could lead to changes in the number and composition of residents in those zip codes. To probe this threat, we put macroeconomic variables on the left-hand side of equation (4) and find (in online Appendix Figure A.12) smooth trends through the closing date in population (increasing), labor force (increasing), unemployment rate (declining), and personal income (increasing). The absence of major trend breaks suggests that the changes in the number and composition of applicants and recipients are not caused by macroeconomic shocks. We also augment equations (4) and (5) to include controls for the local unemployment rate and population and find no change in the estimates (online Appendix Figure A.13).[21]

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

$$Y_{isct} = \alpha_i + \gamma_{st} + \sum_{\tau} \delta_{\tau} D_{ct}^{\tau} + \epsilon_{isct}, \tag{6}$$

where we estimate one version that includes unaffected zip codes as controls and another version that includes only closing zip codes. For control (unaffected) zip codes, all D_{ct}^{τ} are set to zero. For treatment (closing) zip codes, the D_{ct}^{τ} are equal to one when the quarter is τ quarters after (or before, if negative) the closing. Figure 5

[20] We also estimate the effects of field office closings on Social Security card issuances and find null effects, as shown in online Appendix Figure A.9.

[21] Another potential threat is that control zip codes (those that experience their own closing at least two years later) could be neighboring zip codes of the closing for which they serve as a control. Since, as we show, neighboring zip codes also experience effects from the closing, using neighboring zip codes 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 zip codes are neighbors, and the estimates do not change when we exclude neighbors from the sample.

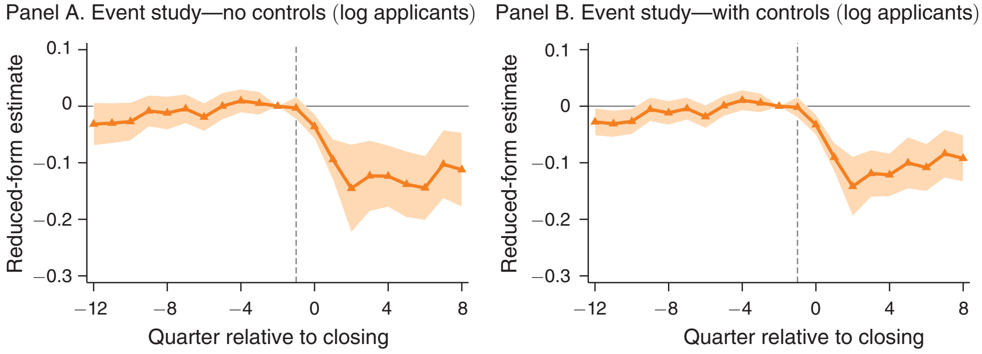

FIGURE 5. ROBUSTNESS: EVENT STUDY SPECIFICATIONS, WITH AND WITHOUT UNAFFECTED ZIP CODES

Notes: The figure plots estimates of the effect of the closing on applications in closing zip codes in the event quarters before and after the closing, using an event study specification with and without controls. Specifically, the figures plot estimates of δ_τ coefficients from equation (6), which is a regression of the number of disability applications on zip code fixed effects, quarter-by-state fixed effects, and event quarter indicators. The dependent variable is the log number of disability applications. The left graph includes only closing zip codes, while the right graph also includes unaffected zip codes, which help to identify the quarter-by-state fixed effects. For both, the sample contains only zip codes with an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

shows the event study regression with and without control zip codes. Both versions show a small upward pre-trend but give estimates of the application drop of similar magnitude to the main specification (11.4 percent without controls and 9.0 percent with controls). In addition, we estimate the effects of the closing using the difference-in-difference specification with 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 online Appendix Figure A.14).

Since our distance measure determines how zip codes are classified, we probe the robustness of our main results (using straight-line distance) to two other methods, using driving time and defining closing zip codes as zip codes within a certain radius (as measured by straight-line distance) of the field office. The estimates (given in online Appendix Table A.14) are within 10 percent of the main estimates for applications and within 15 percent of the main estimates for recipients.

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, for example, the closings affect the likelihood that an applicant is classified as high severity, then the change in severity composition reflects not only differential responsiveness of severity types to the closing, but also a change in the likelihood of being classified as a given severity type. First, it is important to reiterate that the closings do not affect the state DDS offices that make the initial decisions on disability cases and determine severity classification and disability type. According to our calculations, the decline in applications from a single 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. Within DDS offices, cases are assigned to disability examiners in an effectively random way and not based on geography, so assignment is not correlated with being a closing zip code.[22] Second, the state DDS office is responsible for conducting quality control on the applications it receives and remanding incomplete applications back to the field office for further development. Third, institutional details and our own observations of field office interactions do not indicate that field office workers ask leading questions or otherwise try to influence the state DDS decision in preparing the application. Still, it is possible that field office assistance affects the number or type of medical conditions listed and thereby affects severity or disability type classifications, and we cannot rule out this possibility. 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.

V. Evidence on Channels for Closings Effects

A. *Congestion, Travel Times, and Information*

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 the next field office; and other channels, including the costs of acquiring program information and network effects.

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. Based on estimating equation (4), Figure 6 shows that for closing zip codes the closing causes an increase of 36 percent (4.8 minutes) in walk-in wait time, 12 percent (3.4 days) in application processing time, and 70 percent (5.1 applications) in the number of applications with a processing time greater than 40 days.[23] Neighboring zip codes experience

[22] See, e.g,. Maestas, Mullen, and Strand (2013) for a description of the assignment system. Even if examiners observe a zip code after being assigned a case, it is unlikely that they know which zip codes are located near office closings. Examiners are instructed to use only SSA's medical and vocational guidelines to decide cases.

[23] We also estimate effects on the number of field office staff per capita in the service area of the zip code's nearest 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.

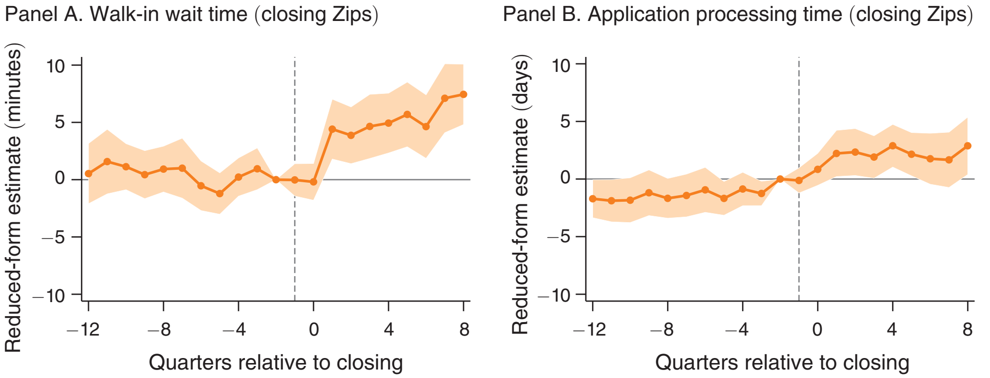

Figure 6. Effect of Closings on Measures of Field Office Congestion

Notes: The figure plots estimates of the effect of the closing on walk-in wait time (left) and application processing time (right) in closing zip codes in the event quarters before and after the closing. Specifically, the figures plot estimates of δ_τ coefficients from equation (4), which is a regression of the dependent variable on zip code fixed effects, quarter-by-state fixed effects, a treatment indicator, event quarter indicators, and event quarter indicators interacted with the treatment indicator. The dependent variable is average walk-in wait time in minutes at the nearest field office (left) or the average number of days it takes the field office to process a disability application (right). The shaded region is the 95 percent confidence interval. The sample is zip codes in which the nearest office closes after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

similarly large increases in congestion measures (see Table 4 and online Appendix Figure A.15). Note that these measures are merely proxies for overall congestion, which can take many forms, including less time for assistance and lower quality of assistance. We expect congestion to affect not only in-person interactions with the field office, but also the larger number of interactions that occur by phone since applicants are generally directed to their local field office phone line for assistance.[24]

Travel Times.—We use calculations from Google Maps to estimate increases in driving distance, driving time, and public transportation time. Using estimating equation (5), 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, 13 kilometers in driving distance, and 37 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. As another measure of the importance of distance, we estimate effects by distance to own (closed) office and distance to neighboring office. We find little heterogeneity with respect to either distance measure (online Appendix Table A.16), suggesting that distance is less important than other channels in affecting disability applications.

[24] Writing in *The Atlantic*, Kwerel (2016) describes her experience applying for disability benefits: "I often waited on hold for 45 minutes at a time. . . On two occasions, I spent more than three hours waiting in line to speak to someone, not including the time I took one look at the jammed waiting room, turned around, and went home."

This is likely because travel times affect only potential applicants who visit an office in person, but not those who interact by phone.

Information.—Another potential mechanism for the effect of closings on applications is the cost of acquiring program information. 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 an office. Although we do not have direct measures of information acquisition costs, we find evidence, shown in online Appendix Figure A.16, that the closings stem a downward trend in call volumes to SSA's 800 number, which handles inquiries regarding disability applications and other Social Security matters.[25] This suggests that field offices, when open, provide information about SSA programs.[26]

B. *Decomposition of Channels*

We use an instrumental variables framework to decompose the decline in applications into three channels: congestion at the neighboring office, travel time, and other costs of switching offices. The other costs of switching offices could include several components: the effect of physical proximity to an SSA office (e.g., potential applicants inquire about benefits because they see the SSA sign), effort to figure out where the next office is and how to get there, the destruction of relationships between the field office and local health care providers or schools, match quality between the field office staff and local population (e.g., on race or other demographics), and updating by potential applicants about the likelihood of rejection or the difficulty of interacting with the system in the future. The structural equation of interest is the following:

$$(8) \quad Y_{isct} = \alpha_i + \gamma_{st} + \beta Congestion_{ict} + \kappa Distance_{ict} + \delta NewOffice_{ict} + \epsilon_{isct},$$

where Y_{isct} is the number of applications in zip code i in state s for closing c in quarter t; $Congestion_{ict}$ is processing time at the office that is closest to zip code i in quarter t; $Distance_{ict}$ is the driving distance between zip code i and its closest office in quarter t; and $NewOffice_{ict}$ is an indicator for whether zip code i has a different

[25] We 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:

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

where Y_{it} is call volume from area code i in month t, α_i is area code fixed effects, and μ_t is 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} is 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.

[26] In online Appendix Table A.17, we estimate effects with respect to measures of information, such as the proportion of the area receiving or applying for disability; the Chetty, Friedman, and Saez (2013) earned income tax credit (EITC) information measure; and broadband access.

closest office than it did earlier in the sample period. The $NewOffice_{ict}$ variable captures the other costs of the closing besides congestion and distance.

We estimate first-stage and reduced-form event study specifications of the form

$$(9) \quad Y'_{isct} = \alpha_i + \gamma_{st} + \delta_0 Post_t + \delta_1 (Post_t \times Rural_{ic}) + \kappa_1 (Post_t \times \mathbf{Z}_{ic}) + \xi_{isct},$$

where Y'_{isct} is the number of applications (for the reduced form) or the endogenous variable (for the first stage) in zip code i in state s for closing c in quarter t; $Post_t$ is an indicator for quarters after the closing; $Rural_{ic}$ is an indicator for rural zip codes; and $\mathbf{Z}_{ic}$ is a matrix of instrument(s). We use instruments that provide plausibly exogenous variation in congestion and distance, and we allow the effects of the closing to vary for urban versus rural areas. The instruments for $Congestion_{ict}$ include:

- $ProcessDiff_{isc}$: difference between the processing time at the now-closest office and the processing time at the previously closest (closed) office, both measured in the four quarters before the closing;
- $AppDiff_{ic}$: difference between the pre-closing number of applications from zip codes in the now closest office's new service area and the pre-closing number of applications from zip codes in the now closest office's original service area (i.e., change in demand for field office services);
- $StaffDiff_{ic}$: difference between the number of staff in the now closest office after the closing and the number of staff in the now closest office before the closing (i.e., change in supply of field office services).

The instrument for $Distance_{ict}$ is the difference between driving distance from zip code i to the now closest office and the driving distance from zip code i to the previously closest office ($DistanceDiff_{ic}$).[27] By construction, $NewOffice_{ict} \equiv Post_t$, and we assume that $NewOffice_{ict}$ is exogenous so it does not require a separate first stage.

The first-stage, reduced-form, ordinary least squares (OLS), and IV estimates are given in Table 5, with all estimated on the sample of closing and neighboring zip codes. For the congestion first stage, we estimate that a 1-day difference in pre-closing processing times between the closest and second closest office predicts a statistically significant 0.64-day increase in processing time after the closing; a 1-application difference between the second-closest office's new and old service areas predicts a statistically significant 0.01-day increase in processing time after the closing; and a 1-person increase in staff after the closing relative to before predicts an insignificant 0.01-day increase in processing time. For the driving distance first stage, a 1-kilometer difference in driving distance predicts, not surprisingly, a 1-kilometer increase in driving distance after the closing.

[27] We use the *difference* in processing times as the instrument instead of just pre-closing processing time at the now-closest office because processing times are spatially correlated; a high processing time at the now-closest office predicts a high processing time at the previously closest office, and therefore does a poor job predicting the increase in processing time that the zip code experiences after the closing. Similarly, we use the difference in driving distances because distances are spatially correlated; they are longer in rural areas than urban areas.

Table 5—IV Estimates of the Effect of Different Application Costs on Disability Applications

	First stage							
	Driving distance	Processing time	Red. form log(app)	OLS log(app)	IV log(app)	OLS Δ in log(app)	IV Δ in log(app)	% based on IV
Post × *DistanceDiff*	0.995	0.00438	−0.00127					
	(0.00325)	(0.0134)	(0.000486)					
Post × *ProcessDiff*	−0.00439	0.636	−0.00576					
	(0.0107)	(0.0715)	(0.00234)					
Post × *AppDiff*	2.25e-05	0.0110	−0.000559					
	(6.27e-05)	(0.00421)	(0.000172)					
Post × *StaffDiff*	0.000769	0.0112	0.00315					
	(0.000772)	(0.0517)	(0.00190)					
Post	−0.00146	1.647	−0.0458	−0.0600	−0.0323	−0.060	−0.032	42
	(0.0180)	(0.538)	(0.0175)	(0.0167)	(0.0176)			
Post × *Rural*	−0.0204	−1.298	0.00877	0.0162	−0.00434	0.000	0.000	0.1
	(0.0866)	(0.558)	(0.0210)	(0.0230)	(0.0231)			
Driving distance (km)				−0.00118	−0.00128	−0.003	−0.003	4
				(0.000499)	(0.000533)			
Processing time (days)				−0.00752	−0.0181	−0.017	−0.042	54
				(0.00153)	(0.00401)			
p-value on joint F-test	0.0000	0.0000						
Observations	100,880	105,617	104,591	100,880	100,880			

Notes: The table presents first-stage estimates from equation (9), reduced-form estimates from equation (9), and OLS and IV estimates from equation (8). The first stage for processing time (a measure of congestion) gives the effect on processing time of three instruments: (i) *ProcessDiff*, the difference between the processing time at the now closest office and the processing time at the previously closest (closed) office, both measured in the four quarters before the closing; (ii) *AppDiff*, the difference between the pre-closing number of applications from zip codes in the now closest office's new service area and the pre-closing number of applications from zip codes in the now closest office's original service area; and (iii) *StaffDiff*, the difference between the number of staff in the now closest office after the closing and the number of staff in the now closest office before the closing. The first stage for driving distance gives the effect on driving distance of the difference in kilometers between driving distance from the zip code to the now closest office and the driving distance from the zip code to the previously closest office. The reduced-form estimates give the effect of the instruments on log disability applications. The IV estimates give the effect of processing time (i.e., congestion), distance, and other costs of office switching (i.e., *Post*) on log disability applications. The sample is closing zip codes (whose nearest office closes after 2000) and neighboring zip codes (whose second or third closest office closes after 2000) and that have an average of at least four disability applications per quarter in the year before the closing. The *Post* × *ProcessDiff* and *Post* × *DistanceDiff* are 0 for neighboring zip codes. Regressions are weighted by application volume in the year before the closing. Standard errors are in parentheses.

The IV estimates in Table 5 indicate that every additional day of processing time (which proxies for other types of congestion) reduces disability applications by 1.8 percentage points, every additional kilometer of driving distance from a field office reduces applications by 0.1 percentage points, and other costs of office switching reduce applications by 3.2 percentage points. All of these estimates are significant. Scaling these estimates up by the actual changes after the closing, we find that increased congestion accounts for 4.2 percentage points of the decline in applications (54 percent), driving distance for 0.3 percentage points of the decline (4 percent), and the fixed cost of switching offices for 3.2 percentage points of the decline (42 percent). When we compare these estimates to the expected value of benefits, the estimates imply that potential applicants are willing to pay around \$660 to avoid increased congestion, \$50 to avoid greater driving distance, and

\$560 to avoid switching offices.[28] When we implement the IV decomposition for disability recipients rather than disability applicants, we find that congestion explains 43 percent of the decline in recipients (versus 54 percent for applicants), driving distance explains 2 percent (versus 4 percent), and other costs of office switching explain 55 percent (versus 42 percent). Although the differences between applicants and recipients are not statistically significant, the point estimates suggest that congestion matters more for applicants who will be rejected than for applicants who will be accepted. Note that the OLS estimates underestimate the effect of congestion by an order of magnitude and overestimate the effect of office switching, likely because offices that experience higher congestion are in areas with higher demand for disability benefits.

VI. Interpretation and Welfare Implications of Field Office Closings

A. *Interpreting Effects on Take-up*

We find in the previous section that field office closings reduce disability applications by 7 percent for SSDI adults and 14 percent for SSI adults, and reduce disability receipt by 15 percent for SSDI adults and 18 percent for SSI adults. These are large effects, with our back-of-the-envelope calculations implying a value of time of approximately \$100 per hour for both SSI and DI applicants. This implied value of time is consistent with Alatas et al. (2016), whose estimates suggest an implied value of time of about \$20 per hour in the Indonesian context, where wages are several times lower than in the United States.[29]

How do the effects of field office closings compare to the effects of hassles in other contexts? From a review of the literature, our estimates are smaller than the effects of changing defaults and providing high-intensity assistance, but much larger than the effects of opening offices or offering electronic filing.[30] 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

[28] To calculate willingness to pay, we assume, conservatively, that those who do not apply because of the closing lose an average monthly benefit of \$1,000 (averaged over DI and SSI) for two years. With an overall two-thirds probability of allowance, the expected benefit of applying is \$16,000. From the estimates in Table 5, congestion reduces the probability of applying by 4.2 percent, driving distance by 0.3 percent, and office switching by 3.2 percent. Multiplying these percentage declines by \$16,000 yields \$660, \$50, and \$560, respectively.

[29] To calculate implied value of time in our setting, we assume, conservatively, that DI applicants who do not apply because of the closing lose two years of DI benefits, which average \$1,300 per month. With an overall two-thirds 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 we assume that 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 $(0.07 \times \$20{,}800)/15 = \$97$. By similar logic, and using the 15 percent decline and \$700 per month in benefits, the value of time for SSI recipients is \$105. We calculate an implied value of time in Alatas et al. (2016) as follows. They find a 15 percent decline in the take-up of benefits with an estimated \$700 NPV, in response to an estimated half-day increase in travel and wait time. If we assume a 5 hour increase in time to apply, the implied value of time is $(0.15 \times \$700)/5 = \$21$.

[30] Bettinger et al. (2012) estimates a 29 percent increase in college completion from providing assistance with the free application for federal student aid (FAFSA), while Madrian and Shea (2001) estimate a 130 percent increase in 401(k) enrollment from automatically enrolling individuals. Quasi-experimental estimates of hassle 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) estimates a 12 percent increase in EITC claiming from electronic filing, and Ebenstein and Stange (2010) finds no effect of internet-based UI claiming on take-up.

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 application reductions from closings versus earnings gains or health shocks are likely different.[31]

The $100 per hour implied value of time is much larger than the monetary opportunity cost of time for low- and medium-wage individuals, especially SSI applicants, who by definition have low income and assets. Why are the effects on take-up so large? We find in Section V that about half of the decline in applications is attributable to congestion costs and the other half to other costs unrelated to congestion or travel. But this decomposition does not explain why the *level* of costs is so large. There are several potential explanations for the large implied value of time. First, potential applicants may have difficulty finding alternative sources of assistance after a closing because of credit constraints and legal restrictions. In principle, potential applicants could promise a third party some fraction of their disability benefits if their application is approved, but government regulations restrict compensation to third party representatives of disability applicants.[32] Second, potential applicants may exhibit present bias, in which they underweight the large benefits of applying and overweight the additional costs of applying resulting from the closing. Third, field office closings may reduce awareness about disability programs, either because the office itself provides this information or because local organizations that refer people to field offices do not update their materials immediately. Field offices themselves stopped doing community outreach in the late 1990s. Finally, the closings may cause potential applicants to update their beliefs about the disability system. After experiencing a closing and resulting inconveniences, potential applicants may adjust their beliefs about the probability of rejection or about the difficulty of interacting with the system in the future.

B. *Interpreting Effects on Targeting*

We apply the definition of targeting efficiency based on adjudicator preferences from Section IB to our results.[33] We use our estimates of the percent decline

[31] Black, Daniel, and Sanders (2002) studies the effects of the coal boom and bust on disability payments. They estimate that a 10 percent increase in earnings reduces DI payments by 3–4 percent and SSI payments by 4–7 percent. Duggan and Imberman (2009) decomposes DI program growth from 1984–2003 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 (2018) estimates suggest that having a chronic severe condition increases the likelihood of disability receipt by 88 percent relative to a chronic non-severe condition.

[32] Federal regulations require that fees are the smaller of 25 percent of past due benefits or the amount of the fee set by SSA (Code of Federal Regulations §404.1730). Third-party representation is much less common at the initial level than at the appeals level, when applicants receive more "past due benefits" if their case is approved.

[33] Although equation (1) is expressed as a change in probabilities and our estimates are changes in levels, we can show that they are equivalent. Let $n_i(R|\eta)$ denote the number of recipients in zip code i given application cost η, and let w_i denote the population of zip code i, where we normalize $\sum_i w_i = 1$. Since $\Pr(R|\eta) = \sum_i n_i(R|\eta)/\sum_i(w_i) = \sum_i n_i(R|\eta)$, then

$$\frac{\Pr(R|\eta') - \Pr(R|\eta)}{\Pr(R|\eta)} = \frac{\sum_i n_i(R|\eta') - \sum_i n_i(R|\eta)}{\sum_i n_i(R|\eta)} = \frac{\sum_i \frac{n_i(R|\eta') - n_i(R|\eta)}{n_i(R|\eta)} n_i(R|\eta)}{\sum_i n_i(R|\eta)} = \sum_i \frac{n_i(R|\eta') - n_i(R|\eta)}{n_i(R|\eta)} \frac{n_i(R|\eta)}{\sum_i n_i(R|\eta)},$$

in applications and recipients to calculate the targeting efficiency ratio from equation (1):

$$\frac{\Delta_R + 1}{\Delta_A + 1} = \frac{-0.155 + 1}{-0.100 + 1} < 1.$$

We calculate bootstrapped standard errors for this ratio and find that it is statistically different from 1 at the 1 percent level. This ratio leads us to conclude, at odds with the Nichols and Zeckhauser (1982) hypothesis, that field office closings worsen targeting based on current government eligibility standards. In Section VIC, we consider the implications of stricter severity standards.

Using observable characteristics to assess targeting efficiency, the effects of the closing on disability applications are non-monotonic in severity, with smaller effects for low- and very high-severity applicants and larger effects for medium- and high-severity applicants. Excluding the low-severity group, we could explain the results by severity with the hypothesis that the value of the benefits is increasing in severity and the opportunity cost of applying is decreasing in severity. But why do low-severity applicants continue to apply? We find evidence that low-severity applicants are a highly selected group, being much more likely than the other severity groups to have experienced zero or low earnings in the two years before they apply (see online Appendix Table A.15). In the online Appendix, we present a model that explains the non-monotonic effects by severity by incorporating both a health effect and a selection effect on the skills margin.

C. *Welfare Implications of Field Office Closings*

We calculate the change in social welfare resulting from the field office closings under different scenarios. In scenario 1, we calculate effects on social welfare using current government standards for who is deserving; specifically, we assume that low-severity individuals (as defined in Section III) are not deserving of disability benefits, while medium-, high-, and very high-severity individuals are deserving of disability benefits. We assume in the baseline scenario that disability adjudicator decisions are perfect, meaning that all disability recipients are deserving of benefits and all rejected applicants are undeserving. In scenario 2, we calculate effects on social welfare using eligibility standards that are *stricter* than the current government standards, in particular that both low- and medium-severity individuals are undeserving while high- and very high-severity individuals are deserving. In scenario 3, we assume that all but very high-severity individuals are undeserving. Scenarios 2 and 3 assume a type II error at baseline (i.e., adjudicator allows undeserving applicants) but no type I error at baseline.

In the costs of the closings, we consider the foregone value of benefits to deserving recipients, the value of lost time from increased travel and wait times, and the lost earnings from the increase in processing times based on estimates from Autor et al. (2015). In the benefits of the closings, we consider cost of public

which is the recipient-weighted average change in recipients across zip codes that we estimate. The case for applicants is analogous.

funds savings from fewer undeserving applicants receiving benefits, administrative savings from processing fewer applications, administrative savings from foregone office rent, and time savings to discouraged applicants. We do not consider losses to non-disability applicant visitors to the field office.

We make several assumptions to determine the value of providing disability benefits to a disability recipient relative to the average taxpayer. To calculate this value, we assume that (state-invariant) utility takes the form of constant relative risk aversion (CRRA) and depends only on consumption (c), which is equal to income (y):

$$u(c) = u(y) = \begin{cases} \frac{y^{1-\gamma} - 1}{1-\gamma} & \text{if } \gamma \neq 1 \\ \ln(y) & \text{if } \gamma = 1 \end{cases}, \tag{10}$$

where γ is the coefficient of relative risk aversion. We calculate the willingness to pay of healthy workers for disability insurance by equalizing expected utility across states:

$$\pi u(y_d + b) + (1-\pi)u(y_h) = \pi u(y_d) + (1-\pi)u(y_h + WTP), \tag{11}$$

where π is the probability of becoming disabled, y_d is the income of a person with a disability, b is the disability benefit amount, y_h is the income of a healthy worker, and WTP is the willingness to pay of the healthy worker to equalize expected utility across states. Then the value of disability benefits to disability recipients relative to the average taxpayer is

$$\frac{WTP}{b}\frac{1-\pi}{\pi}.$$

We use this ratio to determine the value of foregone benefits to deserving recipients who are discouraged from applying for disability benefits as a result of the closings.[34] We assume, conservatively, that discouraged applicants lose only two years of disability benefits as a result of the closings and include a conservative value of health insurance for those who would not have health insurance without disability benefits. We provide more details about these assumptions in the online Appendix.

Table 6 presents the cost-benefit analysis estimates, with detailed calculations in the online Appendix. In scenario 1, which uses current government standards for eligibility (all but low-severity individuals are deserving), we find using $\gamma = 1$ that total costs of a closing are around \$12.8 million per year, with the vast majority of this loss coming from the value of benefits to recipients. Total benefits are around \$2.4 million per year, mostly in the form of administrative savings from processing fewer applications. Putting these figures together, we find that the total net social cost

[34] For y_h, we use the Congressional Budget Office's estimate of the average after-tax, before-transfer household income for the middle quintile of \$44,000. Based on the Meyer and Mok (2018) estimate that after-tax, pre-transfer household income is 40 percent lower two years after disability onset for chronic, severe disabilities, we assume y_d is \$26,500. We assume $\pi = 0.09$ based on the Meyer and Mok (2018) estimate of the probability of experiencing a chronic, severe disability.

Table 6—Welfare Calculations: Social Costs and Benefits of Field Office Closings

	Scenario 1 (current): M, H, VH deserving		Scenario 2: H, VH deserving		Scenario 3: VH deserving	
	$\gamma = 1$	$\gamma = 4$	$\gamma = 1$	$\gamma = 4$	$\gamma = 1$	$\gamma = 4$
Cost of closing (thousands)						
Lower receipt for deserving in closing zip codes	\$2,200	\$22,400	\$900	\$8,600	\$100	\$900
Lower receipt for deserving in neighboring zip codes	\$8,700	\$86,700	\$3,800	\$38,000	\$200	\$1,800
Higher applicant time and earnings decay	\$1,900	\$1,900	\$1,900	\$1,900	\$1,900	\$1,900
Total	\$12,800	\$111,000	\$6,600	\$48,500	\$2,200	\$4,600
Benefits of closing (thousands)						
Benefit savings from discouraging undeserving	\$0	\$0	\$2,000	\$2,000	\$3,300	\$3,300
Administrative savings from processing fewer applicants	\$1,400	\$1,400	\$1,400	\$1,400	\$1,400	\$1,400
Administrative savings from closing field office	\$500	\$500	\$500	\$500	\$500	\$500
Application cost savings from discouraged applicants	\$500	\$500	\$500	\$500	\$500	\$500
Total	\$2,400	\$2,400	\$4,400	\$4,400	\$5,700	\$5,700
Ratio of costs to benefits	5.4	46.7	1.5	11.2	0.4	0.8

Notes: The table presents estimates of costs and benefits of field office closings, in thousands of dollars. Scenario 1 uses current government eligibility standards in which severity groups "medium (M)," "high (H)," and "very high (VH)" (defined in Section IV) are considered deserving of disability benefits. Scenario 2 uses higher severity standards in which only severity groups "high" and "very high" are considered deserving. Scenario 3 uses the highest severity standards in which only severity group "very high" is considered deserving. On the costs side, "lower receipt for deserving" in closing and neighboring zip codes is calculated using CRRA utility with different values of the risk aversion parameter γ ($\gamma = 1$ and $\gamma = 4$). "Higher applicant time" is calculated by using an increase of 15 hours in time required to complete the application (assumption), an increase of 0.2 hours of travel time (from Table 4), and a value of time of \$20 per hour (assumption). "Earnings decay" is calculated using an increase in processing time of 3.4 (1.8) days for closing (neighboring) zip codes (from Table 4) and an earnings decline of \$28 per day for adults (from Autor et al. 2015). On the benefits side, "benefit savings from discouraging undeserving" is calculated using the amount of disability benefits paid to undeserving applicants. "Administrative savings from processing fewer applicants" is calculated by multiplying the decline in applications by \$1,818, the marginal cost of processing an application based on authors' calculations. "Administrative savings from closing field office" is the amount saved on rent as reported by the Social Security Administration. "Application cost savings from discouraged applicants" is the time and earnings saved by discouraged applicants from not applying using the same assumptions as "higher applicant time and earnings decay." See the online Appendix for detailed explanation of calculations.

of all 118 closings is \$1.2 billion, and that social costs outweigh social benefits by a ratio of 5.4 to 1, mostly because of the large loss in social welfare from discouraging applicants who would have been allowed had they applied. As the table shows, the ratio of costs to benefits is substantially higher for larger values of γ.

In scenario 2, we assume that high- and very high-severity applicants are deserving while low- and medium-severity applicants are not. Relative to scenario 1, the costs of the closings are smaller under scenario 2 because medium-severity individuals, who are strongly discouraged from applying by the closings, are no longer considered deserving. The benefits of the closings are larger under scenario 2 because society saves the cost of public funds that goes into paying the benefits of discouraged medium-severity individuals. The ratio of costs to benefits of the closings falls to 1.5 for $\gamma = 1$.

In scenario 3, the most extreme scenario, we assume that only the very high-severity applicants are deserving. The costs of the closings under scenario 3 are smaller for two reasons. First, as in scenario 2, the loss of benefits to discouraged medium- and high-severity individuals is no longer a social cost. Second, the very-high-severity group is the least discouraged by closings from applying for disability benefits. Under scenario 3, the closings *increase* social welfare, with a ratio of costs to benefits of 0.4 using $\gamma = 1$.

Finally, we use the methodology above to calculate the cost of closing each of the 1,331 SSA field offices in our sample that were open in the year 1999. The goal of this exercise is to determine, looking forward from 1999, which closings would have had the lowest costs to society, based on an extrapolation from our estimates. To calculate the cost of lower disability receipt to deserving recipients, we combine our estimates of the effects of office closings by subgroup with data on the number of recipients in each subgroup in closing and neighboring zip codes for each potential closing. We define subgroup cells as program (i.e., DI adult, SSI adult, and SSI child) by severity (low, medium, high, very high). We calculate all other costs and benefits in the same way as the methodology presented above, and we assume current government standards for eligibility (i.e., scenario 1) and a coefficient of relative risk aversion (γ) of 1.

We first order the 1,331 offices in ascending order by net closing cost in 1999. Table 7 gives the results of this exercise, with closing costs and characteristics for the average office in the first column, for the 118 actual closed offices in the second column, for the 118 lowest closing cost offices in the third column, and for the 20 future lowest closing cost offices (among those still open in 2014) in the final column. We find that the average closing cost of the 118 closed offices was less than the average closing cost of all offices in 1999, meaning that the selection process for deciding closings was better than random in terms of social welfare. However, the 118 closed offices still had an average closing cost more than double that of the 118 *lowest closing cost* offices, which were less costly because they were more rural and had smaller service area populations.[35] The final column shows that the average closing cost for the 20 future lowest closing cost offices among offices still open in 2014 was less than one fourth of the net closing costs of the actual closings. In general, we find substantial heterogeneity in closing costs across field offices, meaning that the selection of future office closings matters for minimizing the social costs of these closings.

VII. 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. We find that the closings of Social Security field offices,

[35] The 118 lowest closing cost offices include 23 of the 118 actual closed offices.

Table 7—Welfare Calculations: Net Closing Costs for All Field Offices

	All offices	Actual 118 closings	Lowest cost 118 closings	Future 20 low-cost closings
Average closing characteristics				
Average net cost of closing (thousands)	$9,048	$6,941	$2,652	$1,515
Number of closing zip codes	25	17	23	20
Number of neighboring zip codes	144	109	119	109
Number of applicants in closing zip codes	1,486	978	571	362
Number of applicants in neighboring zip codes	8,151	7,059	2,823	2,126
Number of offices within 20 km	4.9	10.5	4.8	2.0
Average applicant characteristics				
Years of education	11.2	11.2	11.3	11.2
Fraction DI adult	46%	45%	47%	48%
Fraction SSI adult	41%	42%	42%	43%
Fraction SSI child	13%	13%	11%	10%
Fraction low severity	47%	46%	45%	45%
Fraction medium severity	17%	16%	17%	19%
Fraction high severity	20%	20%	19%	17%
Fraction very high severity	16%	18%	19%	20%

Notes: The table presents the average net cost of closing for different sets of offices, calculated using the method from Table 6, but using a baseline year of 1999 for the number of applications. The sets of offices are as follows: all SSA field offices that were open in 1999 ("all offices"), the 118 field offices that were closed between 2000–2014 ("actual 118 closings"), the 118 offices with the lowest closing costs as calculated in 1999 ("lowest cost 118 closings"), and the 20 offices that were still open in 2014 and have the lowest closing costs as estimated using the methodology in Section VIC ("future 20 low-cost closings"). The table also reports summary statistics for each set of offices using 1999 as the baseline year. The closing costs for the actual closings are lower than those estimated in Table 6 because the number of applications nearly doubled between 1999 and the baseline years used in Table 6. See Section VIC for a detailed explanation of calculations.

which provide assistance with disability applications, reduce the number of disability applications by 10 percent and the number of recipients by 16 percent in neighborhoods whose nearest office closes, and have smaller but sizable effects in neighborhoods around neighboring offices. 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 valuable to disability applicants and are instrumental for 10 percent of applicants in the decision to apply. 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. 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 and earnings. Future decisions about field office placement could consider the distributional consequences of closings. Third, application costs have particular significance in the context of disability programs, since health status is available to the disability agency only if the individual applies. If application costs discourage truly disabled individuals from applying, as we find in this paper, the disability agency has few other ways to identify these individuals and provide them with benefits.

In terms of normative implications, Nichols and Zeckhauser (1982) hypothesizes that hassles 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 hassles 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.

REFERENCES

Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A. Olken, Ririn Purnamasari, and Matthew Wai-Poi. 2016. "Self-Targeting: Evidence from a Field Experiment in Indonesia." *Journal of Political Economy* 124 (2): 371–427.

Autor, David H., Nicole Maestas, Kathleen J. Mullen, and Alexander Strand. 2015. "Does Delay Cause Decay? The Effect of Administrative Decision Time on the Labor Force Participation and Earnings of Disability Applicants." NBER Working Paper 20840.

Benítez-Silva, Hugo, Moshe Buchinsky, Hiu Man Chan, John Rust, and Sofia Sheidvasser. 1999. "An Empirical Analysis of the Social Security Disability Application, Appeal, and Award Process." *Labour Economics* 6 (2): 147–78.

Bertrand, Marianne, Sendhil Mullainathan, and Eldar Shafir. 2004. "A Behavioral-Economics View of Poverty." *American Economic Review* 94 (2): 419–23.

Besley, Timothy, and Stephen Coate. 1992. "Workfare versus Welfare: Incentive Arguments for Work Requirements in Poverty-Alleviation Programs." *American Economic Review* 82 (1): 249–61.

Bettinger, Eric P., Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu. 2012. "The Role of Application Assistance and Information in College Decisions: Results from the H&R Block FAFSA Experiment." *Quarterly Journal of Economics* 127 (3): 1205–42.

Black, Dan, Kermit Daniel, and Seth Sanders. 2002. "The Impact of Economic Conditions on Participation in Disability Programs: Evidence from the Coal Boom and Bust." *American Economic Review* 92 (1): 27–50.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. 2011. "Robust Inference with Multiway Clustering." *Journal of Business and Economic Statistics* 29 (2): 238–49.

Chetty, Raj, John N. Friedman, and Emmanuel Saez. 2013. "Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings." *American Economic Review* 103 (7): 2683–2721.

Currie, Janet. 2006. "The Take-Up of Social Benefits." In *Public Policy and Income Distribution*, edited by Alan J. Auerbach, David Card, and John M. Quigley, 80–148. New York: Russell Sage Foundation.

Deshpande, Manasi, and Yue Li. 2019. "Who Is Screened Out? Application Costs and the Targeting of Disability Programs: Dataset." *American Economic Journal: Economic Policy*. https://doi.org/10.1257/pol.20180076.

Duggan, Mark, and Scott A. Imberman. 2009. "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*, edited by David M. Cutler and David A. Wise, 337–80. Chicago: University of Chicago Press.

Ebenstein, Avraham, and Kevin Stange. 2010. "Does Inconvenience Explain Low Take-up? Evidence from Unemployment Insurance." *Journal of Policy Analysis and Management* 29 (1): 111–36.

Einav, Liran, Amy Finkelstein, and Mark R. Cullen. 2010. "Estimating Welfare in Insurance Markets Using Variation in Prices." *Quarterly Journal of Economics* 125 (3): 877–921.

Fadlon, Itzik, and Torben Heien Nielsen. 2015. "Family Labor Supply Responses to Severe Health Shocks." NBER Working Paper 21352.

Finkelstein, Amy, and Matthew J. Notowidigdo. Forthcoming. "Take-up and Targeting: Experimental Evidence from SNAP." *Quarterly Journal of Economics*.

Golosov, Mikhail, and Aleh Tsyvinski. 2006. "Designing Optimal Disability Insurance: A Case for Asset Testing." *Journal of Political Economy* 114 (2): 257–79.

Gruber, Jonathan, Phillip Levine, and Douglas Staiger. 1999. "Abortion Legalization and Child Living Circumstances: Who Is the 'Marginal Child'?" *Quarterly Journal of Economics* 114 (1): 263–91.
Guryan, Jonathan. 2004. "Desegregation and Black Dropout Rates." *American Economic Review* 94 (4): 919–43.
Kleven, Henrik Jacobsen, and Wojciech Kopczuk. 2011. "Transfer Program Complexity and the Take-Up of Social Benefits." *American Economic Journal: Economic Policy* 3 (1): 54–90.
Kopczuk, Wojciech, and Cristian Pop-Eleches. 2007. "Electronic Filing, Tax Preparers and Participation in the Earned Income Tax Credit." *Journal of Public Economics* 91 (7–8): 1351–67.
Kwerel, Laura. 2016. "The Hell of Applying for Government Benefits." *The Atlantic*, June 12. (accessed February 28, 2017).
Madrian, Brigitte C., and Dennis F. Shea. 2001. "The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior." *Quarterly Journal of Economics* 116 (4): 1149–87.
Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. 2013. "Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects." *American Economic Review* 103 (5): 1797–1829.
Meyer, Bruce D., and Wallace K. C. Mok. 2018. "Disability, Earnings, Income and Consumption." *Journal of Public Economics* 171: 51–69.
Nichols, Donald, Eugene Smolensky, and T. Nicolaus Tideman. 1971. "Discrimination by Waiting Time in Merit Goods." *American Economic Review* 61 (3): 312–23.
Nichols, Albert L., and Richard J. Zeckhauser. 1982. "Targeting Transfers through Restrictions on Recipients." *American Economic Review* 72 (2): 372–77.
Rossin-Slater, Maya. 2013. "WIC in Your Neighborhood: New Evidence on the Impacts of Geographic Access to Clinics." *Journal of Public Economics* 102: 51–69.

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10. Gabrielle Pepin. 2022. The effects of welfare time limits on access to financial resources: Evidence from the 2010s. *Southern Economic Journal* **88**:4, 1343-1372. [Crossref]
11. Delia Furtado, Kerry L. Papps, Nikolaos Theodoropoulos. 2022. Who Goes on Disability when Times are Tough? The Role of Work Norms among Immigrants. *European Economic Review* **143**, 103983. [Crossref]
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18. Henry Bundy. 2022. “I’m Just Sitting Now. Wondering.”: Surviving the Wait for Disability. *Medical Anthropology* **41**:1, 94-106. [Crossref]
19. Sarah S. Stith. 2022. Effects of work requirements for food assistance eligibility on disability claiming. *IZA Journal of Labor Economics* **11**:1. . [Crossref]
20. Tatiana Homonoff, Jason Somerville. 2021. Program Recertification Costs: Evidence from SNAP. *American Economic Journal: Economic Policy* **13**:4, 271-298. [Abstract] [View PDF article] [PDF with links]
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22. Pengju Zhang, Ling Zhu. 2021. Does the ACA Medicaid Expansion Affect Hospitals’ Financial Performance?. *Public Finance Review* **49**:6, 779-814. [Crossref]
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25. Rik Peeters, Mauricio I. Dussauge Laguna. 2021. Acting out or playing along: A typology of citizens' low trust responses to public organizations. *Governance* **34**:4, 965-981. [Crossref]
26. Michael Anne Kyle, Austin B. Frakt. 2021. Patient administrative burden in the US health care system. *Health Services Research* **56**:5, 755-765. [Crossref]
27. Wei Tang. 2021. Decentralization and development of small cites: Evidence from county-to-city upgrading in China. *China Economic Quarterly International* **1**:3, 191-207. [Crossref]
28. Daniel Waldinger. 2021. Targeting In-Kind Transfers through Market Design: A Revealed Preference Analysis of Public Housing Allocation. *American Economic Review* **111**:8, 2660-2696. [Abstract] [View PDF article] [PDF with links]
29. Mariana Chudnovsky, Rik Peeters. 2021. The unequal distribution of administrative burden: A framework and an illustrative case study for understanding variation in people's experience of burdens. *Social Policy & Administration* **55**:4, 527-542. [Crossref]
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31. Lene Aarøe, Martin Baekgaard, Julian Christensen, Donald P. Moynihan. 2021. Personality and Public Administration: Policymaker Tolerance of Administrative Burdens in Welfare Services. *Public Administration Review* **81**:4, 652-663. [Crossref]
32. Michael A. Kuhn. 2021. Electronic Benefit Transfer and Food Expenditure Cycles. *Journal of Policy Analysis and Management* **40**:3, 744-773. [Crossref]
33. Robert W. Hahn, Robert D. Metcalfe. 2021. Efficiency and Equity Impacts of Energy Subsidies. *American Economic Review* **111**:5, 1658-1688. [Abstract] [View PDF article] [PDF with links]

34. Melissa S. Kearney, Brendan M. Price, Riley Wilson. 2021. Disability Insurance in the Great Recession: Ease of Access, Program Enrollment, and Local Hysteresis. *AEA Papers and Proceedings* **111**, 486-490. [Abstract] [View PDF article] [PDF with links]

35. Anna M H Price, Anna Zhu, Huu N J Nguyen, Diana Contreras-Suárez, Natalie Schreurs, Jade Burley, Kenny D Lawson, Margaret Kelaher, Raghu Lingam, Rebekah Grace, Shanti Raman, Lynn Kemp, Susan Woolfenden, Sharon Goldfeld. 2021. Study protocol for the Healthier Wealthier Families (HWF) pilot randomised controlled trial: testing the feasibility of delivering financial counselling to families with young children who are identified as experiencing financial hardship by community-based nurses. *BMJ Open* **11**:5, e044488. [Crossref]

36. D. James Greiner, Ellen Lee Degnan, Thomas Ferriss, Roseanna Sommers. 2021. Using random assignment to measure court accessibility for low-income divorce seekers. *Proceedings of the National Academy of Sciences* **118**:14. . [Crossref]

37. Garrett Anstreicher. 2021. Does increasing health care access reduce disability insurance caseloads? Evidence from the rural United States. *Health Economics* **30**:4, 786-802. [Crossref]

38. Ha Trong Nguyen, Huong Thu Le, Luke B Connelly. 2021. Who's declining the “free lunch”? New evidence from the uptake of public child dental benefits. *Health Economics* **30**:2, 270-288. [Crossref]

39. Kajal Lahiri, Jianting Hu. 2021. Productive efficiency in processing social security disability claims: a look back at the 1989–95 surge. *Empirical Economics* **60**:1, 419-457. [Crossref]

40. Dan Han, Aayush Khadka, Margaret McConnell, Jessica Cohen. 2020. Association of Unexpected Newborn Deaths With Changes in Obstetric and Neonatal Process of Care. *JAMA Network Open* **3**:12, e2024589. [Crossref]

41. Pei Li, Yi Lu, Jin Wang. 2020. The effects of fuel standards on air pollution: Evidence from China. *Journal of Development Economics* **146**, 102488. [Crossref]

42. Julian Christensen, Lene Aarøe, Martin Baekgaard, Pamela Herd, Donald P. Moynihan. 2020. Human Capital and Administrative Burden: The Role of Cognitive Resources in Citizen-State Interactions. *Public Administration Review* **80**:1, 127-136. [Crossref]

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