Who Is Screened Out?

Application Costs and the Targeting of Disability Programs

Manasi Deshpande and Yue Li

Online Appendix

Model Demonstrating Theoretically Ambiguous Effect of Ordeals

Nichols and Zeckhauser (1982) hypothesize that application costs 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. We demonstrate here that the same neoclassical model that produces the Nichols and Zeckhauser (1982) hypothesis can also produce the opposite theoretical result if application costs are negatively correlated with ability—for example, if application costs involve cognitive costs instead of time costs.

Consider an economy with two types of individuals: those who are able (a) and those who are not able (d). Let u_w^a (u_w^d) denote the average utility of working for the able (not-able) type, and u_b^a (u_b^d) denote the utility of receiving benefits for the able (not-able) type. Let ϵ represent the idiosyncratic preference for working, with ϵ following a uniform distribution with range $[\underline{\epsilon}, \bar{\epsilon}]$ and density function $f(\epsilon) = \frac{1}{\bar{\epsilon}-\underline{\epsilon}}$.

The utility of working for type $i \in \{a, d\}$ is

$$u_w^i + \epsilon$$

while the utility of receiving benefits is

$$u_b^i - c^i$$

where c^i denotes the cost to type i of applying for benefits. Individuals would apply for benefits if and only if

$$u_b^i - c^i \geq u_w^i + \epsilon$$

or, equivalently,

$$\epsilon \leq u_b^i - c^i - u_w^i.$$

The mass of type i who apply for benefits is

$$\int_{\underline{\epsilon}}^{u_b^i - c^i - u_w^i} f(\epsilon) d\epsilon = \int_{\underline{\epsilon}}^{u_b^i - c^i - u_w^i} \frac{1}{\bar{\epsilon} - \underline{\epsilon}} d\epsilon = \frac{u_b^i - c^i - u_w^i - \underline{\epsilon}}{\bar{\epsilon} - \underline{\epsilon}}.$$

Now consider an ordeal that increases the application cost for type i from c^i to $c^i + \Delta c^i$. The resulting change in the mass of type i who apply for benefits is

$$\frac{u_b^i - (c^i + \Delta c^i) - u_w^i - \underline{\epsilon}}{\bar{\epsilon} - \underline{\epsilon}} - \frac{u_b^i - c^i - u_w^i - \underline{\epsilon}}{\bar{\epsilon} - \underline{\epsilon}} = \frac{-\Delta c^i}{\bar{\epsilon} - \underline{\epsilon}}.$$

Consider two cases:

- $\Delta c^d < \Delta c^a$: The increase in ordeals improves targeting by discouraging more able types than not able types from applying for benefits. This case reflects the Nichols and Zeckhauser (1982) hypothesis. If, for example, the ordeal takes the form of a time cost and able types have a higher opportunity cost of time, then the ordeal will improve targeting.

- $\Delta c^d > \Delta c^a$: The increase in ordeals worsens targeting by discouraging more not-able types than able types from applying for benefits. This case produces the opposite targeting result as Nichols and Zeckhauser (1982). If, for example, the ordeal takes the form of a cognitive cost (e.g., completing complicated paperwork) and not-able types have higher cognitive abilities, then the ordeal will worsen targeting.

Model Explaining Non-Monotonic Effects of Closings by Severity

The purpose of this model is to demonstrate the potentially non-monotonic effect of field office closings on applications by severity, based on our empirical finding that low-severity applicants are highly selected on the economic margin. Let potential disability applicants differ on two dimensions: health $h \in [0, 1]$ where $h = 1$ is the best health, and skills $s \in [0, 1]$ where $s = 1$ is the highest skills. Skills are negatively correlated with health in the potential applicant pool as a result of selection, which we model by making s a function of h, with $s'(h) < 0$. Wages (inclusive of the disutility of work) are determined by the function $w(s, h) = min\{h, s(h)\}$, meaning that poor health will be the binding constraint on wages for the highest severity individuals and skills will be the binding constraint on wages for the lowest severity individuals. Potential disability applicants apply if and only if

$$p(h)b + (1 - p(h))w(s, h) - \eta > w(s, h)$$
$$\iff p(h)[b - w(s, h)] > \eta$$

where b is the amount of disability benefits, $p(h)$ is the likelihood of being approved for benefits, with $p'(h) < 0$, and η is the cost of applying. We assume $b > w(s, h)$ since this is the interesting case.

Let $g(h) \equiv p(h)[b - w(s, h)]$. Consider an individual at the bottom of the health distribution, so that $h \ll s$. Then $g(h) = p(h)[b - h]$ and

$$\frac{\partial g(h)}{\partial h} = p'(h)[b - h] - p(h) < 0$$

since $p'(h) < 0$. The first term reflects that the likelihood of allowance is decreasing in health, and the second term reflects that the opportunity cost of applying is decreasing in health. Thus, when h is small (i.e., going from very high severity to high severity), $g(h)$ is unambiguously decreasing in h and so very high severity types are more likely to continue applying when application costs increase.

Now consider an individual at the top of the health distribution, so that $h \gg s$. Then $g(h) = p(h)[b - s(h)]$ and

$$\frac{\partial g(h)}{\partial h} = p'(h)[b - s(h)] - p(h)s'(h) \gtrless 0$$

since $p'(h) < 0$ and $s'(h) < 0$. The first term reflects that the likelihood of allowance is decreasing in health, but the second term reflects the selection effect that low severity types are more likely to be low-skilled. Thus, when h is large (i.e., going from medium severity to low severity), $g(h)$ could be increasing in h, in which case low severity types will be more likely to continue applying when application costs increase.

Figure A.17 provides a visual depiction of the model in which health h in the potential applicant pool has density $f(h)$. The benefit function $g(h)$ is non-monotonic in h because individuals in relatively good health (low h) are low-skilled and therefore also have a high value of disability benefits. The function $p(h)$ starts at $p(h) = 1$ at the very bottom of the health distribution (i.e., very high severity) and is decreasing in h. The line $Pr(R|A, \eta)$ indicates the average probability of allowance in the potential applicant pool at baseline, which depends on both $p(h)$ and $f(h)$. In the baseline case, the function $g(h)$ is everywhere above the application cost η, so all potential applicants apply for benefits. When application costs increase from η to $\eta' > \eta$, $g(h)$ is now below η' for some potential applicants in the middle of the health distribution, and so these medium-severity applicants no longer apply. Intuitively, targeting efficiency improves if the group that was screened out has a lower probability of allowance than the previous applicant pool, and it worsens if the group that was screened out has a higher probability of allowance than the previous applicant pool.

Social Welfare Calculations

Here we outline the calculations in Table 6 in detail. In Scenario 1, which reflects current government standards for eligibility, the "low" severity individuals are considered undeserving, while "medium," "high," and "very high" are considered deserving. In Scenario 2, the "low" and "medium" severity individuals are considered undeserving, while "high" and "very high" are considered deserving. In Scenario 3, the "low," "medium," and "high" severity individuals are considered undeserving, and only the "very high" are considered deserving.

Lower receipt for deserving individuals in closing ZIPs: For each scenario, we calculate the loss to society resulting from fewer deserving individuals receiving disability benefits, where the classification of deserving varies across scenarios. Here we illustrate the calculation for Scenario 1; the calculation is analogous for Scenarios 2 and 3 using different classifications of deserving. We calculate losses from lower receipt separately for SSDI adults, SSI adults, and SSI children. From Appendix Table A.20, the decline in SSDI receipt for the deserving in closing ZIPs is 14.8 percent. The mean number of DI allowances per quarter per ZIP is 10.9, and there are an average of 10 affected ZIPs per closing.[36] This amounts to an annual decline of 65 SSDI recipients as a result of the average closing. The average DI benefit is around \$1,300 per month. We also consider the value of Medicare: from the CPS, we estimate that approximately 20 percent of DI beneficiaries in the Medicare waiting period do not have health insurance, and we use the Finkelstein, Hendren and Luttmer (2015) estimate of the value of Medicaid (\$1600/year) as a conservative estimate for the value of Medicare for those without health insurance coverage. In addition, we assume—again, conservatively—that the discouraged applicant loses 2 years of benefits, meaning that the discouraged applicant eventually applies and receives disability benefits.

[36] We use the same set of ZIP codes for different programs (DI adult, SSI adult, SSI child) in the welfare calculations, and therefore the means reported in these calculations are different than the means reported in Appendix Table A.20.

Next we use equation (11), under different values of risk aversion, to calculate the value of transferring \$1 per month from the average taxpayer to the average SSDI recipient. For $\gamma = 1$, the expression $\frac{WTP}{b}\frac{1-\pi}{\pi}$ is 1.67, which means that the average SSDI recipient values the SSDI benefit and health insurance coverage 67 percent more than the average taxpayer (reflecting a higher marginal utility of income for a disabled individual net of the deadweight loss of taxation), so we multiply the total benefit by 0.67. The social value of SSDI benefits (including insurance coverage) foregone is therefore \$1.38 million.

We use an analogous analysis to calculate losses from the decline in SSI receipt. For SSI adults, the decline in receipt is 18 percent from Appendix Table A.20; there are 7.3 SSI adult recipients per quarter per ZIP and 10 affected ZIPs per closing, resulting in 53 fewer SSI adult recipients. The monthly SSI benefit is approximately \$700; from the CPS, we estimate that 50 percent of SSI adult recipients would not have health insurance without SSI. The calculation for SSI children is similar: a decline in receipt of 14.7 percent, an average of 3.2 SSI children per quarter per ZIP, 10 affected ZIPs per closing. This results in 19 fewer SSI child recipients. We assume that all SSI children would have health insurance without SSI. Under the same assumptions used for the SSDI calculations, the social value of SSI benefits (for adults and children combined) foregone is \$860,000.

Lower receipt for deserving individuals in neighboring ZIPs: We calculate losses from lower SSDI and SSI receipt in neighboring ZIPs in the same way that we calculate losses in closing ZIPs. The decline in neighboring ZIPs is 8.98 percent for deserving SSDI (average of 11.3 recipients per quarter per ZIP), 10.1 percent for SSI adults (average of 7.7 recipients per quarter per ZIP), and 11.1 percent for SSI children (average of 3.4 recipients per quarter per ZIP). There are an average of 61 neighboring ZIPs per closing, resulting in declines of 248 SSDI recipients, 190 SSI adult recipients, and 92 SSI child recipients per closing per year. Using the same methodology as above to calculate the value of the disability benefits to deserving disability recipients relative to the average taxpayer, we get a loss of \$5.28 million for SSDI and \$3.38 million for SSI. The neighboring ZIP losses are substantially larger than the closing ZIP losses because there are many more neighboring ZIPs than closing ZIPs.

Higher applicant time and earnings decay: We consider time costs from increased office congestion and longer travel time as well as earnings decay from longer processing times. We assume a 15-hour increase in application time from congestion (as we do in the implied value of time calculations) and use the estimate from Table 4 of a 0.2 hour increase in driving time. There are 10 affected ZIPs on average per closing, with an average of 35.7 applicants per ZIP per quarter who continue to apply after the closing. We assume a \$20/hour value of time and that one-half of applicants are actually affected by these costs (i.e., some applicants never interact with the field office). This gives 715 affected applicants per closing, with a total cost of \$214,000 for congestion costs and \$3,000 for travel costs for closed ZIPs. For neighboring ZIPs, we consider only congestion costs and estimate them at \$1.48 million using the same method.

To calculate earnings decay from longer processing time, we use the increase in processing time resulting from the closing from Table 4: 3.4 days for closing ZIPs and 1.8 days for neighboring ZIPs. Autor et al. (2017) estimate that a 2.4 month increase in processing time reduces annual employment by one percentage point. From this estimate, a one-day increase in processing translates into a 0.0139 percentage point reduction in employment, which amounts to \$2.78 annually assuming average annual earnings of \$20,000. We assume that this earnings decay lasts for a period of 10 years, so the average earnings decay is \$28 per additional day of processing time. We multiply this decay by the increase in processing days, and then multiply this amount by the number of adult applicants per ZIP, the number of affected ZIPs, and a 1/3 applicant rejection rate (since the earnings decay only applies to rejected applicants). These assumptions yield earnings decay costs of \$42,000 for closed ZIPs and \$150,000 for neighboring ZIPs.

Benefit savings from discouraging undeserving applicants: Under Scenario 1, no undeserving individuals receive disability benefits, so there are no savings from discouraging undeserving disability recipients. In Scenario 2 (Scenario 3), the medium-severity (medium- and high-severity) receive disability benefits despite being undeserving. Discouraging the undeserving from applying is a net social benefit under the assumption that undeserving recipients do not value disability benefits more than the average taxpayer, but financing their benefits still imposes a cost of public funds on society. Therefore, for Scenarios 2 and 3, we calculate the cost of public funds associated with financing disability benefits for undeserving individuals who would have received benefits but are discouraged from applying as a result of the closing. For each of the three groups (SSDI adults, SSI adults, and SSI children), we multiply our estimates of the percent decline in the number of undeserving recipients by the total number of undeserving recipients and the amount of cash and health insurance benefits, and then multiply this amount by 0.2 to reflect the cost of public funds.

Administrative savings from processing fewer applications: We start with the SSA's annual administrative budget of \$12 billion,[37] two-thirds of which is used to administer the disability

[37] See Social Security Administration FY 2017 Budget Overview.

programs.[38] We calculate from our data that field offices process approximately 4.4 million disability applications per year. This yields an estimated cost of $1,818 in processing costs per application. The reduction in applications is 10.0 percent for closing ZIPs (with 10 ZIPs on average per closing and 40 applicants per ZIP per quarter) and 4.6 percent for neighboring ZIPs (with 61 ZIPs on average per closing and 43 applicants per ZIP per quarter). We multiply the $1,800 in processing costs per application by the application decrease of 636 to get an estimated $1.16 million in administrative savings per closing. We multiply this amount by 1.2 to reflect the marginal cost of public funds.

Administrative savings from closing field office: According to a recent Congressional report, recent field office closings have saved $4 million over 10 years in lease costs.[39] We therefore estimate an annual savings of $400,000 per closing and multiply this amount by 1.2 to reflect the marginal cost of public funds.

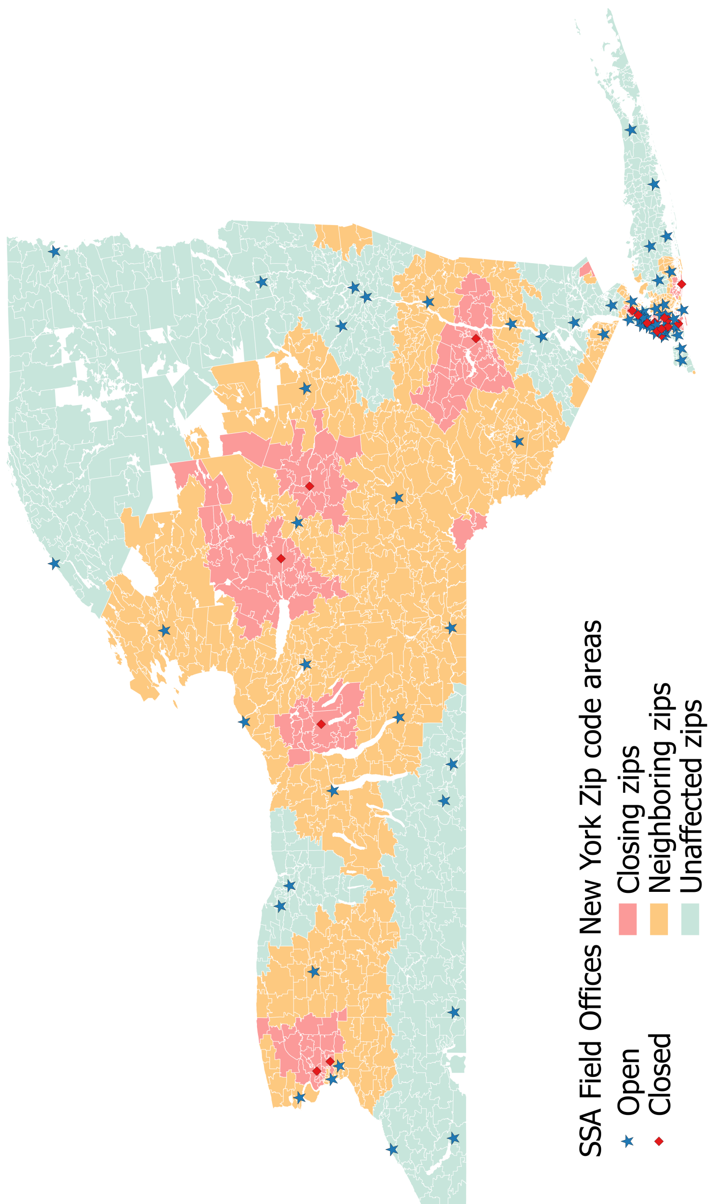
Application cost savings from discouraged applicants: Since we include foregone benefits of discouraged applicants in the costs of field office closings, we include application cost savings to discouraged applicants as a benefit of field office closings. As in "administrative savings from processing fewer applications," there are 636 fewer applicants between closing and neighboring ZIPs. We assume that applications take on average 40 hours to complete and the applicant value of time is $20 per hour. This amounts to $509,000 in applicant cost savings.

[38]"SSA's Administrative Costs by Funding Source–INFORMATION," Letter from Robert M. Rothenberg to Margaret Malone, Wayne Sulfridge, and David Warner, December 8, 1999.

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

Appendix Figures and Tables

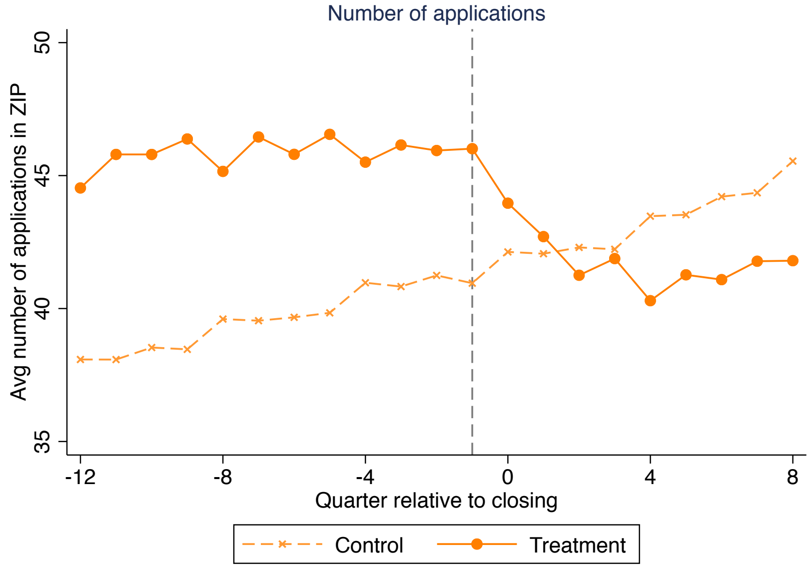
Figure A.7: Map of Field Office Closings and ZIP Classification in New York



Map gives the locations of Social Security field offices in New York state, including both open and closed offices as of 2016. In addition, map codes different types of ZIPs: ZIPs whose nearest office was closed ("closing" ZIPs), ZIPs whose nearest office is the second or the third nearest field office of a closing ZIP prior to the closing event ("neighboring" ZIPs), and all remaining ZIPs ("unaffected" ZIPs).

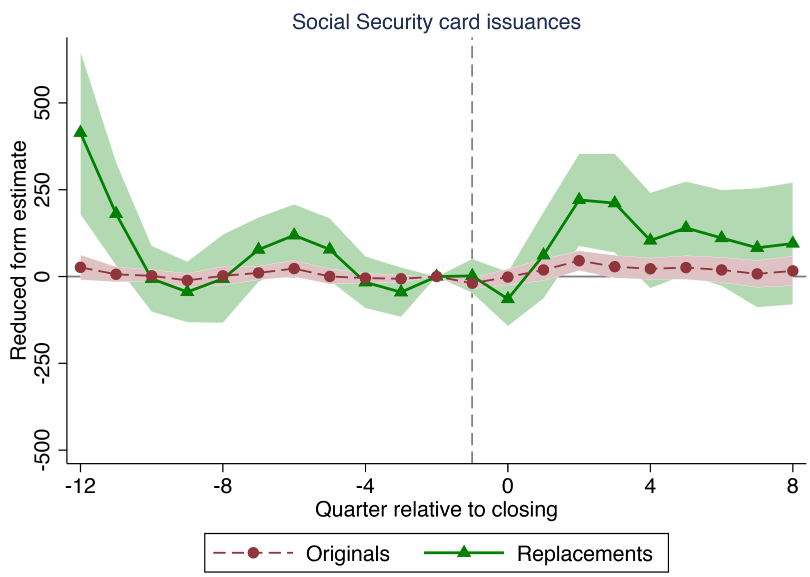
Source: Authors' mapping based on Social Security Administration and Census Bureau data

Figure A.8: Raw Plots of Number of Applications in Control and Treatment ZIPs



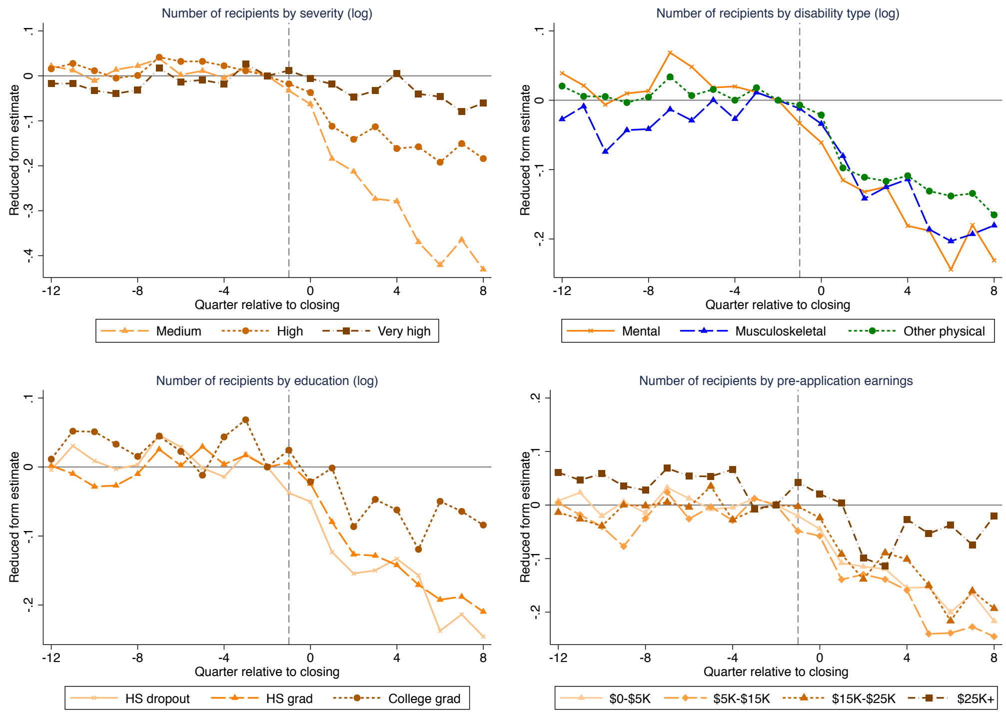
Notes: Figure plots raw (non-regression-adjusted) counts of applications in control and treatment ZIPs relative to the quarter of the closing. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least four disability applications per quarter in the year before the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

Figure A.9: Effect of Closings on Social Security Card Issuances



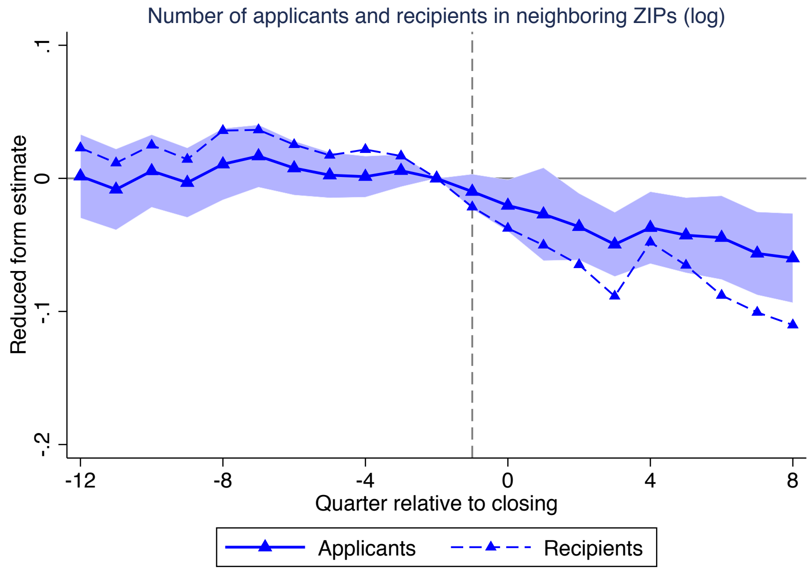
Notes: Figure plots estimates of the effect of the closing on Social Security card issuances in closing ZIPs in the event quarters before and after the closing. Specifically, the figure plots estimates of δ_τ coefficients from equation (4), which is a regression of the number of disability applicants by subgroup on ZIP 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 Social Security card issuances (either original or replacement) in a given ZIP and quarter. Shaded regions are 95 percent confidence intervals.

Figure A.10: Effect of Closings on Number of Disability Allowances, by Subgroup



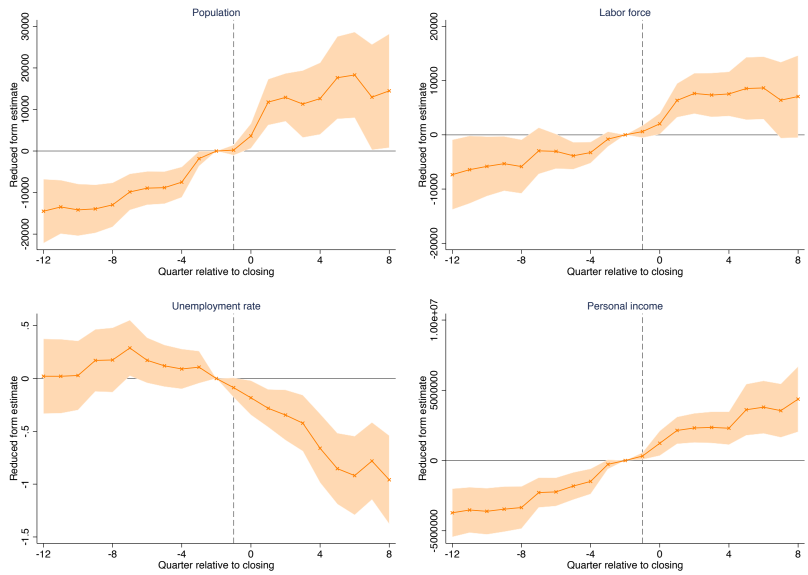
Notes: Figures plot estimates of the effect of the closing on disability allowances by subgroup in closing ZIPs in the event quarters before and after the closing. Specifically, the figures plot estimates of δ_τ coefficients from equation (4), which is a regression of the number of disability allowances on ZIP 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 allowances by subgroup. Sample is ZIP codes whose 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.

Figure A.11: Effect of Closings on Number of Disability Applications and Allowances for Neighboring ZIPs



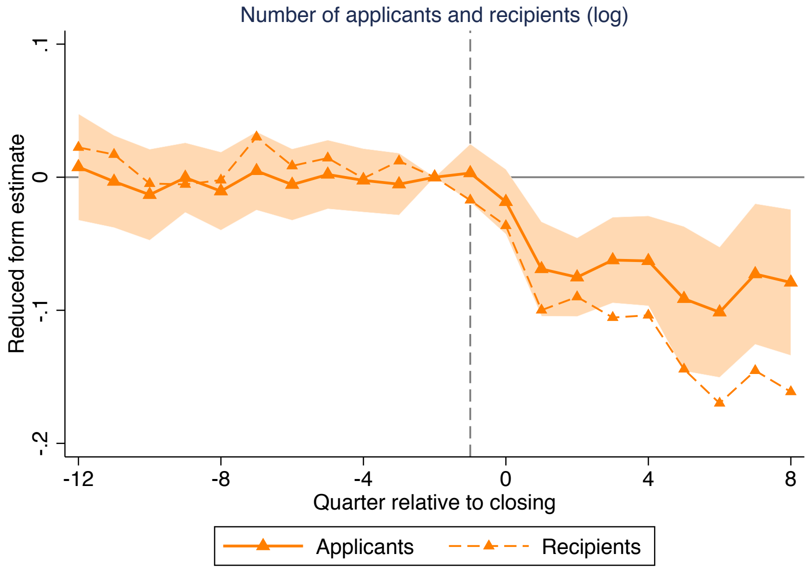
Notes: Figure plots estimates of the effect of the closing on disability applications and allowances in neighboring ZIPs in the event quarters before and after the closing. Specifically, the figure plots estimates of δ_τ coefficients from equation (4) but with the $Treated_i$ indicator replaced by a $TreatedNbr_i$ indicator. This is a regression of the number of disability applicants and allowances on ZIP fixed effects, quarter-by-state fixed effects, a treated neighbor indicator, event quarter indicators, and event quarter indicators interacted with the treated neighbor indicator. The dependent variable is the log number of disability applications (solid series) or the log number of disability recipients (dashed series). Shaded region is 95 percent confidence interval for disability applications (solid series). Sample is ZIP codes whose nearest office is a neighbor of an office that closes after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. "Neighboring" ZIPs are ZIPs whose nearest office is the second or third closest office of a closing ZIP prior to the closing event. Regressions are weighted by application (recipient) volume in the year before the closing.

Figure A.12: Differential Trends in Macroeconomic Conditions Between Control and Treatment ZIPs



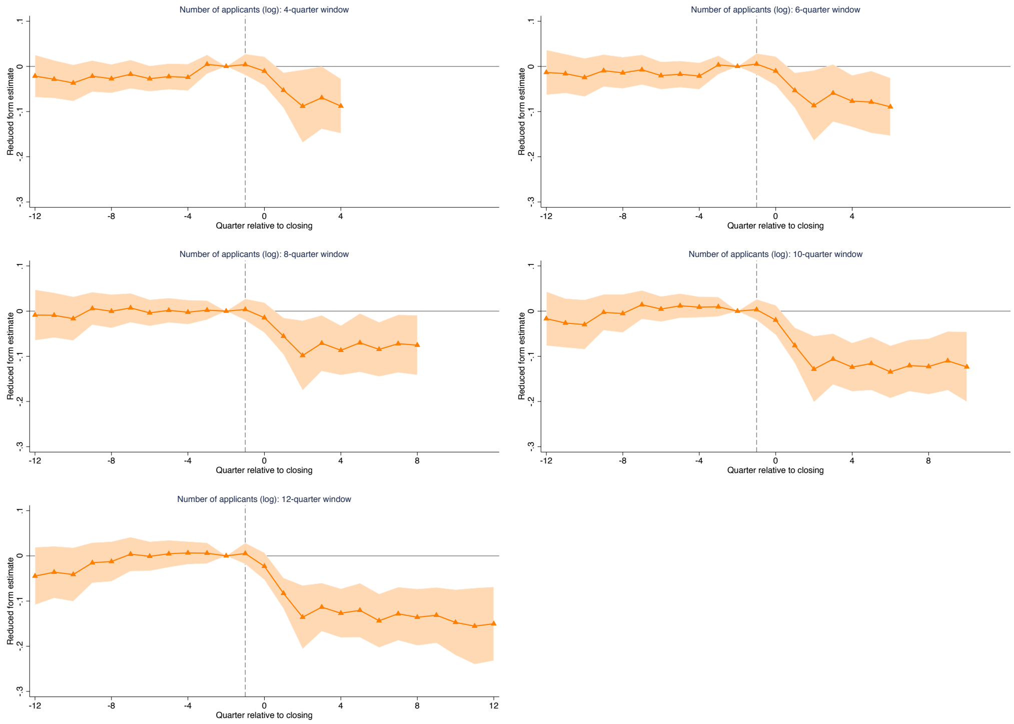
Notes: Figures plot falsification test estimates of the effect of the closing on macroeconomic variables in the quarters before and after the closing. Specifically, the figures plot the estimates of δ_τ coefficients from equation (4), which is a regression of the number of disability applicants by subgroup on ZIP fixed effects, quarter-by-state fixed effects, a treatment indicator, event quarter indicators, and event quarter indicators interacted with the treatment indicator. The dependent variables are the macroeconomic measures indicated. Shaded region is 95 percent confidence interval. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Figure A.13: Effect of Closings on Applications and Allowances, Controlling for Local Economic Conditions



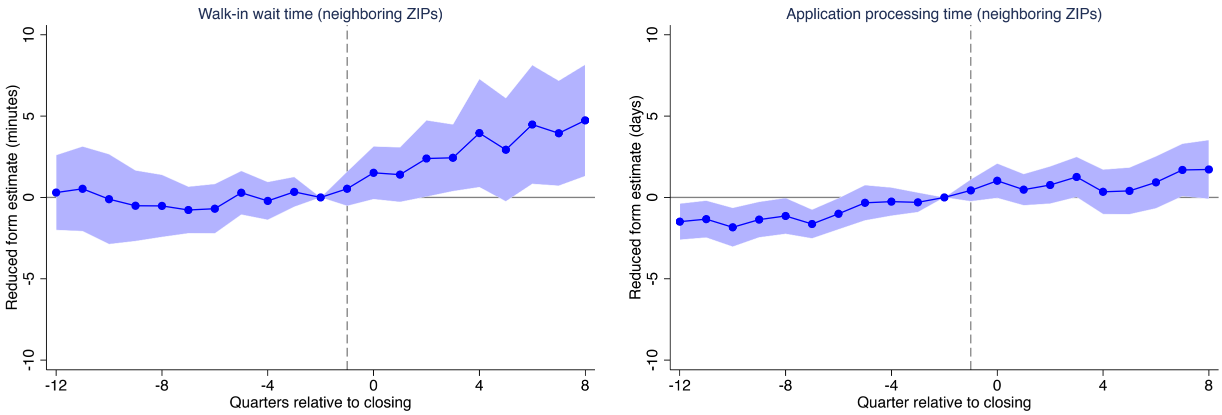
Notes: Figure plots estimates of the effect of the closing on applications and allowances in closing ZIPs in the event quarters before and after the closing, controlling for macroeconomic variables. Specifically, the figure plots estimates of δ_τ coefficients from equation (4), which is a regression of the number of disability applicants or allowances on ZIP fixed effects, quarter-by-state fixed effects, a treatment indicator, event quarter indicators, and event quarter indicators interacted with the treatment indicator, plus local unemployment rate and population controls. The dependent variable is the log number of disability applications (solid series) or the log number of disability recipients (dashed series). Shaded region is 95 percent confidence interval for disability applications (solid series). Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application (recipient) volume in the year before the closing.

Figure A.14: Effect of Closings on Applications, Using Different Time Windows



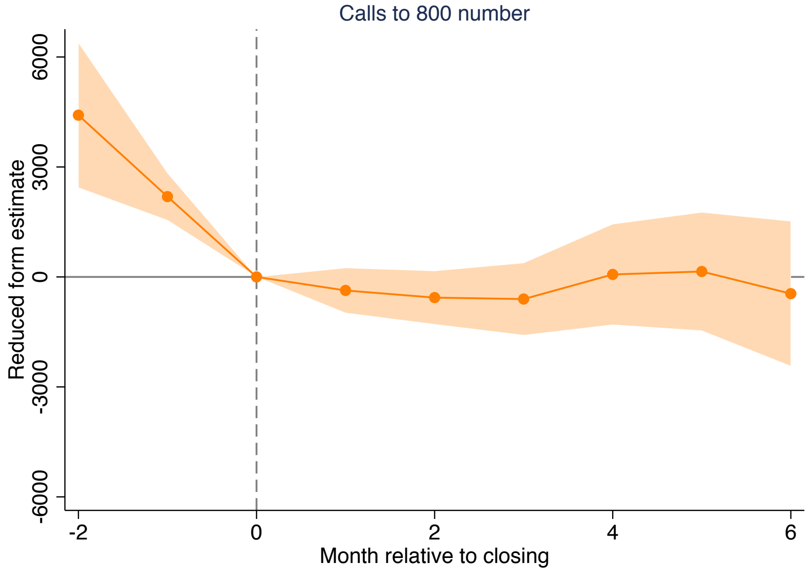
Notes: Figures plot estimates of the effect of the closing on applications in closing ZIPs in the event quarters before and after the closing. Specifically, the figures plot estimates of δ_τ coefficients from equation (4) for different minimum lengths of time between the treatment closing and control closings. The dependent variable is the log number of disability applications. Shaded region is 95 percent confidence interval. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.

Figure A.15: Effect of Closings on Measures of Field Office Congestion for Neighboring ZIPs



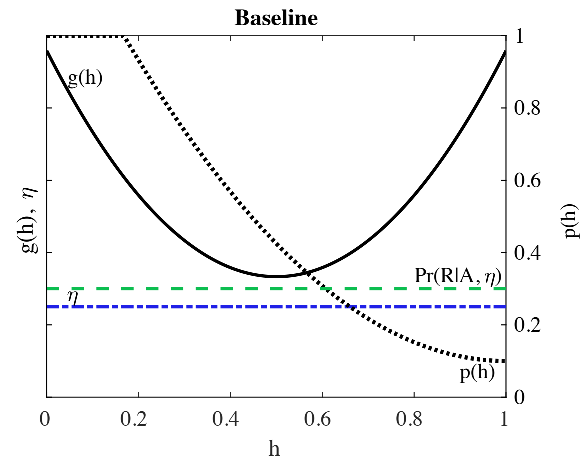
Notes: Figures plot estimates of the effect of the closing on walk-in wait time (left) and application processing time (right) in neighboring ZIPs in the event quarters before and after the closing. Figures plot estimates of δ_τ coefficients from equation (4) where $Treated_{ic}$ is replaced with $TreatedNbr_{ic}$. The dependent variable is average walk-in wait time in minutes at nearest field office (left) or the average number of days it takes the field office to process a disability application (right). Shaded region is 95 percent confidence interval. Sample is ZIP codes whose nearest office is a neighbor of an office that closes after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. "Neighbor" office is defined as an office that is the second or third closest office of a ZIP code whose closest office closes. Regressions are weighted by application volume in the year before the closing.

Figure A.16: Effect of Closings on Calls to Social Security Administration 800 Phone Number



Notes: Figure plots estimates of the effect of the closing on calls to the SSA 800 phone number in closing area codes in the event quarters before and after the closing. Specifically, the figure plots estimates of δ_τ coefficients from equation (7), where the dependent variable is call volume from a given area code in a given month. Shaded region is 95 percent confidence interval.

Figure A.17: Model of Non-Monotonic Effects by Severity



Notes: Figure presents a model that explains non-monotonic effects by severity. The left-hand graph shows baseline conditions, with health h on the x-axis, where $h = 1$ is the best health. Measured on the right axis are the individual probability of allowance $p(h)$ and the average probability of allowance for those who apply $Pr(R|A, \eta)$. Measured on the left axis are the benefits of application $g(h)$ and the line η is the cost of application. As explained in the Appendix, the function $g(h)$ is non-monotonic because poor-health (high-severity) applicants value benefits because of poor health, while good-health (low-severity) applicants value benefits because they are negatively selected on skills. At baseline, everyone applies since $g(h)$ is everywhere above η. The right-hand graph shows what happens when application costs increase from η to η'. Individuals in the middle of the health distribution are screened out, while those at either end continue applying.

Table A.8: Summary Statistics of All Closing, Neighboring, and Unaffected ZIP Codes

	Closing ZIPs		Neighboring ZIPs		Unaffected ZIPs		p-values from t-tests		
							Closing vs. neighboring	Closing vs. unaffected	Neighboring vs. unaffected
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev			
ZIP characteristics (2000)									
Population	9,178	14,380	9,306	13,933	8,615	12,519	0.675	0.061	0.000
Poverty rate	13%	10%	13%	10%	13%	10%	0.829	0.040	0.001
Median income	$39,346	$18,762	$39,056	$17,020	$39,626	$15,928	0.608	0.466	0.019
Male	50%	4%	50%	4%	50%	4%	0.542	0.019	0.003
Female	50%	4%	50%	4%	50%	4%	0.542	0.019	0.003
White	83%	22%	83%	21%	86%	20%	0.476	0.000	0.000
Black	9%	18%	9%	18%	7%	15%	0.646	0.000	0.000
Hispanic	6%	12%	6%	11%	6%	14%	0.795	0.084	0.006
Other race	2%	13%	2%	11%	1%	14%	0.368	0.009	0.001
Age 0-19	27%	6%	28%	6%	28%	6%	0.003	0.000	0.000
Age 20-44	33%	8%	34%	7%	34%	6%	0.032	0.019	0.630
Age 45-64	24%	6%	24%	5%	24%	5%	0.001	0.007	0.131
Age 65+	15%	5%	15%	6%	14%	6%	0.006	0.000	0.000
HS dropout	20%	12%	20%	11%	22%	13%	0.935	0.000	0.000
HS graduate	34%	12%	34%	11%	35%	11%	0.359	0.000	0.000
Some college	26%	8%	26%	8%	26%	9%	0.004	0.086	0.036
College graduate	20%	16%	19%	14%	18%	13%	0.019	0.000	0.000
Never married	24%	10%	23%	9%	23%	9%	0.084	0.000	0.000
Currently married	58%	11%	58%	11%	59%	11%	0.471	0.000	0.000
Previously married	18%	6%	19%	6%	18%	6%	0.186	0.198	0.000
Walk-in wait time (min) (2005)	7.19	7.53	8.86	9.00	8.85	8.24	0.000	0.000	0.926
Qrtrly. disability apps (2000)	18	36	19	36	17	32	0.114	0.477	0.000
N	1,921		7,550		22,445				

Notes: Table presents summary statistics for all ZIP codes in the United States. The last three columns present p-values from the t-test of the difference in the characteristic between different types of ZIP codes. Closing ZIPs are ZIPs whose closest office closes. Neighboring ZIPs are ZIPs whose closest office is the second or third closest office of a closing ZIP. Unaffected ZIPs are ZIPs that are neither closing nor neighboring ZIPs. "ZIP characteristics" are calculated from the 2000 Census, "walk-in wait time" from Social Security Administration data (where 2005 is the earliest available year), and "quarterly disability applications" from Social Security Administration data.

Table A.9: Summary Statistics of Treatment and Control ZIPs

	Treatment ZIPs		Control ZIPs		p-values
	Mean	Std Dev	Mean	Std Dev	from t-test
ZIP characteristics (2000)					
Population	14,581	16,186	14,646	16,276	0.923
Poverty rate	14%	10%	14%	10%	0.722
Median income	$41,759	$18,828	$41,883	$18,566	0.874
Male	49%	3%	49%	3%	0.848
Female	51%	3%	51%	3%	0.848
White	77%	24%	78%	24%	0.628
Black	13%	21%	13%	20%	0.551
Hispanic	7%	14%	8%	14%	0.951
Other race	2%	14%	2%	14%	0.999
Age 0-19	27%	6%	27%	6%	0.794
Age 20-44	35%	7%	35%	7%	0.965
Age 45-64	23%	4%	23%	4%	0.953
Age 65+	14%	5%	14%	5%	0.836
HS dropout	21%	11%	21%	11%	0.489
HS graduate	32%	10%	32%	11%	0.842
Some college	25%	6%	25%	6%	0.987
College graduate	22%	17%	22%	17%	0.733
Never married	26%	9%	26%	9%	0.786
Currently married	55%	10%	55%	10%	0.886
Previously married	19%	5%	19%	5%	0.987
Walk-in wait time (min) (year before closing)	15.17	11.05	12.60	8.38	0.000
Qrtrly. disability apps (year before closing)	41	58	35	49	0.007
N	1,181		1,121		

Notes: Table presents summary statistics for treatment and control ZIP codes, as described in Section III. The last column presents p-values from the t-test of the difference in the characteristic between treatment and control ZIP codes. Treatment ZIPs are closing ZIPs (ZIPs whose nearest office closes) that experience the current closing, while control ZIPs are closing ZIPs that experience the closing at least two years in the future. Since ZIPs can serve as a control for multiple closings, for control ZIPs we calculate the walk-in wait time and disability application summary statistics by averaging values in the year before the closing across all closings for which that ZIP is a control ZIP. "ZIP characteristics" are calculated from the 2000 Census, "walk-in wait time" from Social Security Administration data (where 2005 is the earliest available year), and "quarterly disability applications" from Social Security Administration data.

Table A.10: p-values from Tests of Statistical Differences Across Subgroups

	Application level	Allowance level
Allowance vs. application	0.0000	
Severity		
Low vs. medium	0.0000	N/A
Low vs. high	0.0000	N/A
Low vs. very high	0.8277	N/A
Medium vs. high	0.0000	0.0000
Medium vs. very high	0.0000	0.0000
High vs. very high	0.0000	0.0000
Disability type		
Mental vs. musculoskeletal	0.0022	0.0033
Mental vs. other physical	0.7049	0.0017
Musculoskeletal vs. other physical	0.0009	0.9671
Education		
HS dropout vs. HS grad	0.0003	0.0748
HS dropout vs. college grad	0.0000	0.0008
HS grad vs. college grad	0.0384	0.0047
Pre-application earnings ($)		
$0-$5,000 vs. $5,000-$15,000	0.6301	0.1076
$0-$5,000 vs. $15,000-$25,000	0.6081	0.8528
$0-$5,000 vs. $25,000+	0.0182	0.0385
$5,000-$15,000 vs. $15,000-$25,000	0.8492	0.0164
$5,000-$15,000 vs. $25,000+	0.0150	0.0033
$15,000-$25,000 vs $25,000+	0.0042	0.0289
Age		
18-34 vs. 35-49	0.6532	0.0177
18-34 vs. 50+	0.0000	0.0000
35-49 vs. 50+	0.0000	0.0000

Notes: Table presents p-values of t-tests for differences in estimates in Tables 2 and 3 across subgroups using seemingly unrelated regression. The specifications are given by equation (5) estimated for different subgroups.

Table A.11: Estimates of the Effect of Closings on Log and Level Applications and Allowances by Subgroup

	Applications					Receipt				
	Log estimates		Level estimates			Log estimates		Level estimates		
	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.	Mean	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.	Mean
All	-0.100***	(0.0288)	-3.319***	(1.027)	39.7	-0.155***	(0.0301)	-2.612***	(0.626)	21.7
Severity										
Low	-0.0483	(0.0295)	-0.741	(0.490)	18.0	N/A		N/A		
Medium	-0.338***	(0.0503)	-1.483***	(0.298)	6.9	-0.319***	(0.0484)	-1.499***	(0.300)	6.9
High	-0.173***	(0.0367)	-1.069***	(0.300)	8.5	-0.165***	(0.0351)	-1.078***	(0.300)	8.5
Very high	-0.0327	(0.0271)	-0.0264	(0.122)	6.2	-0.0287	(0.0255)	-0.0349	(0.122)	6.2
Disability type										
Mental	-0.115***	(0.0356)	-1.385***	(0.408)	12.3	-0.190***	(0.0358)	-1.061***	(0.246)	6.9
Musculoskeletal	-0.0576*	(0.0298)	-0.456*	(0.240)	10.2	-0.129***	(0.0354)	-0.544***	(0.155)	5.1
Physical	-0.109***	(0.0283)	-1.478***	(0.456)	17.2	-0.132***	(0.0280)	-1.006***	(0.264)	9.7
Education (years)										
HS dropout	-0.142***	(0.0275)	-1.260***	(0.277)	9.9	-0.180***	(0.0314)	-0.785***	(0.161)	5.1
HS graduate	-0.0740***	(0.0280)	-1.289***	(0.489)	19.4	-0.153***	(0.0321)	-1.293***	(0.327)	10.6
College graduate	-0.0496*	(0.0288)	-0.0950	(0.0604)	2.4	-0.0931***	(0.0278)	-0.181***	(0.0541)	1.6
Pre-application earnings										
$0-$5,000	-0.112***	(0.0338)	-2.031***	(0.658)	18.7	-0.154***	(0.0338)	-1.226***	(0.340)	9.0
$5,000-$15,000	-0.0887***	(0.0331)	-0.802***	(0.261)	8.9	-0.168***	(0.0384)	-0.689***	(0.161)	4.5
$15,000-$25,000	-0.0928***	(0.0294)	-0.371***	(0.121)	5.0	-0.134***	(0.0327)	-0.381***	(0.0983)	3.1
$25,000+	-0.0414	(0.0343)	-0.130	(0.137)	7.0	-0.0948***	(0.0312)	-0.317***	(0.100)	5.1
Age (years)										
18-34	-0.126***	(0.0339)	-0.913***	(0.236)	7.9	-0.210***	(0.0336)	-0.502***	(0.1000)	3.1
35-49	-0.130***	(0.0292)	-1.299***	(0.318)	12.9	-0.255***	(0.0386)	-0.998***	(0.191)	6.1
50+	-0.0489*	(0.0262)	-0.543*	(0.301)	13.1	-0.0908***	(0.0279)	-0.765***	(0.250)	9.3

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Table presents estimates of the effect of field office closings on log and level applications and allowances by subgroup, specifically estimates of β from equation (5), which is a regression of log applications for a subgroup on ZIP 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 a "event year zero" indicator. The "mean" columns report the average for the control group over the post-closing period. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application (recipient) volume in the year before the closing. Standard errors in parentheses.

Table A.12: Correlations Across Diagnosis, Severity, and Education Subgroups and Estimates Within Fine Subgroup

Correlations among diagnosis, severity, and education categories

	Diagnosis			Severity			
	Mental	Musc	Other phys	Low	Med	High	V. high
Sev: low	0.00	0.05	-0.05				
Sev: med	-0.10	0.12	-0.02				
Sev: high	0.19	-0.18	-0.01				
Sev: very high	-0.10	-0.01	0.10				
Ed: HS dropout	0.03	-0.01	-0.01	0.04	-0.03	-0.01	-0.01
Ed: HS grad	-0.03	0.03	0.00	-0.01	0.03	0.00	-0.02
Ed: coll grad	0.00	-0.03	0.03	-0.06	0.01	0.02	0.05

Estimates of effect of closings on applications within subgroups

	Diagnosis			Severity			
	Mental	Musc	Other phys	Low	Med	High	V. high
Sev: low	-0.0461	-0.000750	-0.0801***				
	(0.0408)	(0.0282)	(0.0302)				
Sev: med	-0.223***	-0.283***	-0.281***				
	(0.0413)	(0.0500)	(0.0464)				
Sev: high	-0.168***	-0.0653**	-0.154***				
	(0.0381)	(0.0283)	(0.0387)				
Sev: very high	-0.101***	0.0224	-0.0148				
	(0.0261)	0.0224	(0.0267)				
Ed: HS dropout	-0.151***	-0.0829***	-0.145***	-0.104***	-0.261***	-0.162***	-0.0280
	(0.0348)	(0.0260)	(0.0309)	(0.0278)	(0.0437)	(0.0377)	(0.0259)
Ed: HS grad	-0.0824**	-0.0356	-0.0936***	-0.00818	-0.296***	-0.166***	-0.0239
	(0.0350)	(0.0318)	(0.0290)	(0.0287)	(0.0510)	(0.0371)	(0.0305)
Ed: coll grad	-0.0290*	-0.0111	-0.0406	0.0231	-0.0618***	-0.0493***	-0.00476
	(0.0150)	(0.0203)	(0.0257)	(0.0202)	(0.0197)	(0.0138)	(0.0176)

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The top panel presents correlations across severity, diagnosis, and education subgroups. The bottom panel presents estimates of the effect of field office closings on log applications by fine subgroup (e.g., low severity and high school graduate), specifically estimates of β from equation (5), which is a regression of log applications for a subgroup on ZIP 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 a "event year zero" indicator. Sample is ZIP codes whose 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. Standard errors in parentheses.

Table A.13: Factors that Predict Office Closings or Timing of Closings

	Office ever closes			Timing of closing		
	2000	2006	2012	2000	2006	2012
Population (2000)	-2.40e-07***	-1.33e-07***	-6.94e-08**	7.16e-06*	2.47e-07	-7.04e-08
	(4.86e-08)	(4.43e-08)	(2.98e-08)	(4.31e-06)	(3.78e-06)	(9.77e-07)
Pop. Density (2000)	2.28e-06	5.18e-06	7.29e-06	0.000183	9.10e-05*	-0.000134***
	(7.06e-06)	(7.01e-06)	(4.90e-06)	(0.000130)	(5.05e-05)	(3.51e-05)
Applications (previous year)	-1.20e-05***	-4.81e-06***	-9.13e-07	0.000417**	0.000150	2.60e-05
	(2.65e-06)	(1.28e-06)	(6.31e-07)	(0.000203)	(0.000110)	(2.91e-05)
Processing time (previous year)	0.000286	0.000794	0.000599	-0.0125	0.00668	0.00673
	(0.00106)	(0.00105)	(0.000814)	(0.0376)	(0.0381)	(0.0106)
Num. offices $<$ 20 km	0.00394**	0.00340*	-0.000630	-0.0184	-0.00691	0.0557***
	(0.00175)	(0.00174)	(0.000829)	(0.0433)	(0.0231)	(0.0149)
Wait time (previous year)		-0.00155**	0.000587		0.00671	0.00151
		(0.000763)	(0.000812)		(0.0517)	(0.0228)
Observations	1,331	1,288	1,235	117	80	23

Notes: *** p<0.01, ** p<0.05, * p<0.1. Columns 1-3 present estimates from equation (2) of how observable office characteristics predict the likelihood of closing for the offices that are still open in the year indicated in the column heading. The sample is all SSA field offices that are open in the given year, and the dependent variable is whether the office closes. Columns 4-6 present estimates from equation (3) of how observable office characteristics predict the timing of a closing conditional on eventually closing, for the offices that are still open in the year indicated in the column heading. The sample is all SSA field offices that are open in the given year but will close by 2014, and the dependent variable is the year in which an office closes. Population density is population per square kilometer of the office's service area. Standard errors in parentheses.

Table A.14: Estimates of the Effect of Closings Using Alternative Distance Measures

	Applications		Allowance	
Distance measure	Pt. Est.	Std. Err.	Pt. Est.	Std. Err.
Straight line	-0.100***	(0.0288)	-0.155***	(0.0301)
Driving time	-0.103***	(0.0258)	-0.153***	(0.0296)
30-km fixed	-0.0902***	(0.0307)	-0.131***	(0.0307)
60-km fixed	-0.0931***	(0.0294)	-0.135***	(0.0297)
90-km fixed	-0.0942***	(0.0290)	-0.138***	(0.0292)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates of the effect of field office closings on log applications and log allowances using different measures of distance. Specifically, the table presents estimates of β from equation (5), which is a regression of log applications for a subgroup on ZIP 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 a "event year zero" indicator. The measures of distance are as follows: straight-line distance from ZIP centroid to the closed office, driving time from ZIP centroid to the closed office, and radii of different lengths around the closed office. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least four disability applications per quarter in the year before the closing. Regressions are weighted by application (recipient) volume in the year before the closing. Standard errors in parentheses.

Table A.15: Correlations Between Severity and Earnings in the Two Years Before Application

	Average earnings in 2 years before application			
	\$0-\$5K	\$5K-\$15K	\$15K-\$25K	\$25K+
Sev: low	0.14	0.01	-0.06	-0.16
Sev: med	-0.12	0.05	0.06	0.08
Sev: high	0.05	-0.05	-0.02	0.00
Sev: very high	-0.12	-0.02	0.05	0.15

Notes: Table presents correlations between severity and average earnings for disability applicants in the main sample in the two years before application.

Table A.16: Estimates of the Effect of Closings by Geographic Measures

	Pt. Est.	Std. Err.	N
Population density			
Low (rural)	-0.106***	(0.0264)	343,060
Medium	-0.0777**	(0.0316)	250,760
High (urban)	-0.0860***	(0.0298)	407,067
Distance to own office			
Low ($<$10 km)	-0.101***	(0.0295)	317,842
Medium (10-30 km)	-0.104***	(0.0346)	327,001
High ($>$30 km)	-0.0719***	(0.0242)	297,759
Distance to neighboring office			
Low	-0.0964***	(0.0309)	346,434
Medium	-0.0630*	(0.0336)	247,045
High	-0.0996***	(0.0283)	349,123

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates of the effect of field office closings on log applications and log allowances by different measures of geography. Specifically, the table presents estimates of β from equation (5), which is a regression of log applications for a subgroup on ZIP 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 a "event year zero" indicator. Sample is ZIP codes whose 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. Standard errors in parentheses.

Table A.17: Estimates of the Effect of Closings by Measures of Information

	Pt. Est.	Std. Err.	N
Proportion on disability			
Low	-0.0690	(0.0462)	210,811
Medium	-0.0826***	(0.0249)	497,235
High	-0.119*	(0.0689)	285,806
Proportion applying for disability			
Low	-0.0385	(0.0310)	298,132
Medium	-0.0852***	(0.0269)	321,310
High	-0.155***	(0.0455)	381,445
Chetty et al. (2013) EITC information measure			
Low	-0.0491	(0.0465)	193,545
Medium	-0.0905**	(0.0384)	457,254
High	-0.137***	(0.0518)	344,119
Num. broadband providers			
Low	-0.181***	(0.0361)	44,254
Medium	-0.156***	(0.0299)	129,070
High	-0.110***	(0.0209)	176,733
Num. broadband-connected households			
Low	-0.205***	(0.0308)	62,069
Medium	-0.0837**	(0.0403)	91,971
High	-0.116***	(0.0198)	196,017

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates of the effect of field office closings on log applications by potential measures of information. Specifically, the table estimates of β from equation (5), which is a regression of log applications for a subgroup on ZIP 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 a "event year zero" indicator. Proportion on disability is the ratio of individuals on SSI or SSDI in a county to the county's population. Number of applications is the fraction of the ZIP's population applying for disability between 1996 and 2000. The Chetty et al. (2013) measure is the amount of bunching of self-employed individuals at EITC kinks, which the authors estimate by ZIP-3 and interpret as a measure of EITC knowledge. Sample is ZIP codes whose 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. Standard errors in parentheses.

Table A.18: Estimates of the Effect of Closings on Online Applications by Education Subgroup

	Pt. Est.	Std. Err.
Online applications		
All	0.135**	(0.0682)
High school dropouts	0.0429	(0.0476)
High school graduates	0.139**	(0.0586)
College graduates	0.0484*	(0.0279)
Non-online applications		
All	-0.194***	(0.0319)
High school dropouts	-0.217***	(0.0320)
High school graduates	-0.188***	(0.0318)
College graduates	-0.148***	(0.0313)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates of the effect of field office closings on log online applications and log non-online applications by education subgroup. Specifically, the table presents estimates of β from equation (5), which is a regression of log applications for a subgroup on ZIP 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 a "event year zero" indicator. Sample is ZIP codes whose 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. Standard errors in parentheses.

Table A.19: Estimates of the Effect of Closings on Log Applications by Program

	DI adult			SSI adult			SSI children		
	Pt. Est.	Std. Err.	Cntrl. Ct.	Pt. Est.	Std. Err.	Cntrl. Ct.	Pt. Est.	Std. Err.	Cntrl. Ct.
All	-0.0681***	(0.0233)	20.6	-0.143***	(0.0318)	22.0	-0.152**	(0.0588)	11.4
Severity									
Low	0.0283	(0.0260)	7.7	-0.111***	(0.0310)	11.9	-0.112*	(0.0612)	4.9
Medium	-0.318***	(0.0478)	5.2	-0.319***	(0.0551)	3.1	-0.0932**	(0.0413)	0.5
High	-0.124***	(0.0303)	3.3	-0.229***	(0.0415)	4.0	-0.155**	(0.0609)	5.5
Very high	-0.0256	(0.0261)	4.3	-0.0260	(0.0276)	3.0	-0.00893	(0.0162)	0.4
Disability type									
Mental	-0.0985***	(0.0287)	4.2	-0.143***	(0.0395)	7.1	-0.133**	(0.0630)	6.9
Musculoskeletal	-0.0312	(0.0260)	6.9	-0.100***	(0.0328)	5.7			
Other physical	-0.0728***	(0.0235)	9.5	-0.159***	(0.0330)	9.3	-0.153***	(0.0539)	4.4
Education (years)									
HS dropout	-0.110***	(0.0236)	4.5	-0.171***	(0.0323)	8.1			
HS graduate	-0.0626**	(0.0246)	12.5	-0.107***	(0.0318)	11.7			
College graduate	-0.0231	(0.0247)	2.0	-0.0672***	(0.0223)	0.9			
Pre-application earnings									
\$0-\$5,000	-0.0664**	(0.0325)	4.1	-0.140***	(0.0341)	12.7			
\$5,000-\$15,000	-0.0727**	(0.0288)	5.9	-0.128***	(0.0379)	5.2			
\$15,000-\$25,000	-0.0720***	(0.0249)	3.9	-0.103***	(0.0320)	2.3			
\$25,000+	-0.0257	(0.0281)	6.7	-0.0709*	(0.0420)	1.8			
Age (years)									
0-9							-0.134**	(0.0579)	7.8
10-17							-0.152**	(0.0615)	3.5
18-34	-0.0964***	(0.0287)	3.5	-0.157***	(0.0368)	6.6			
35-49	-0.0992***	(0.0247)	7.6	-0.177***	(0.0329)	8.7			
50+	-0.0321	(0.0238)	9.4	-0.0817***	(0.0298)	6.6			

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Table presents estimates of the effect of field office closings on log applications by program, specifically estimates of β from equation (5), which is a regression of log applications on ZIP 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 a "event year zero" indicator. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least four applications in the relevant program per quarter in the year before the closing (at least three for SSI child). Regressions are weighted by application volume in the year before the closing. Standard errors in parentheses.

Table A.20: Estimates of the Effect of Closings on Log Allowances by Program

	DI adult			SSI adult			SSI children		
	Pt. Est.	Std. Err.	Cntrl. Ct.	Pt. Est.	Std. Err.	Cntrl. Ct.	Pt. Est.	Std. Err.	Cntrl. Ct.
All	-0.148***	(0.0270)	12.8	-0.180***	(0.0348)	10.1	-0.147***	(0.0529)	6.5
Severity									
Low		N/A			N/A			N/A	
Medium	-0.292***	(0.0453)	5.2	-0.295***	(0.0522)	3.1	-0.0846*	(0.0453)	0.5
High	-0.121***	(0.0291)	3.3	-0.218***	(0.0420)	4.0	-0.138**	(0.0534)	5.5
Very high	-0.0194	(0.0252)	4.3	-0.0235	(0.0275)	3.0	-0.0113	(0.0164)	0.4
Disability type									
Mental	-0.181***	(0.0297)	2.6	-0.206***	(0.0392)	3.6	-0.137**	(0.0596)	4.2
Musculoskeletal	-0.124***	(0.0327)	4.0	-0.121***	(0.0365)	2.2			
Other physical	-0.117***	(0.0256)	6.2	-0.155***	(0.0336)	4.4	-0.119***	(0.0414)	2.3
Education (years)									
HS dropout	-0.143***	(0.0272)	2.6	-0.182***	(0.0372)	3.7			
HS graduate	-0.157***	(0.0308)	7.8	-0.151***	(0.0356)	5.2			
College graduate	-0.0690***	(0.0232)	1.4	-0.0389**	(0.0167)	0.5			
Pre-application earnings									
$0-$5,000	-0.116***	(0.0313)	1.8	-0.178***	(0.0355)	5.7			
$5,000-$15,000	-0.163***	(0.0352)	3.3	-0.152***	(0.0393)	2.2			
$15,000-$25,000	-0.128***	(0.0311)	2.6	-0.0780***	(0.0284)	1.2			
$25,000+	-0.0889***	(0.0259)	5.1	-0.0613**	(0.0281)	1.0			
Age (years)									
0-9							-0.122**	(0.0515)	4.6
10-17							-0.157***	(0.0563)	1.8
18-34	-0.137***	(0.0269)	1.5	-0.189***	(0.0361)	2.4			
35-49	-0.236***	(0.0357)	4.2	-0.236***	(0.0416)	3.5			
50+	-0.0806***	(0.0260)	7.1	-0.108***	(0.0341)	4.2			

Notes: *** p<0.01, ** p<0.05, * p<0.1. Table presents estimates of the effect of field office closings on log allowances by program, specifically estimates of β from equation (5), which is a regression of log allowances on ZIP 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 a "event year zero" indicator. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least four applications in the relevant program per quarter in the year before the closing (at least three for SSI child). Regressions are weighted by recipient volume in the year before the closing. Standard errors in parentheses.