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The Effect of Lower Transaction Costs on Social Security Disability Insurance Application Rates and Participation

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Abstract:
Transaction costs pose significant barriers to participation in public programs. We analyze how Social Security Disability Insurance (SSDI) application behavior was affected by iClaim, a 2009 innovation that streamlined the online application process. We use a difference-in-differences design to compare application rates before and after 2009 across counties with varying degrees of access to high-speed internet. We estimate that counties with internet connectivity one standard-deviation above the mean experienced a 1.6 percent increase in SSDI applications, and a 2.8 percent increase in appeals after the reform. We estimate that the increase in applications due to iClaim can explain 15 percent of the overall increase in applications between 2008 and 2011. Higher exposure to the online application led to a slightly larger increase in SSDI awards, meaning there was a small but significant increase in the overall award rate. Application rates increased the most in rural areas, while appeals and awards had more significant increases in urban areas. These results suggest that the online application reduced transaction costs on applicants, and the lower costs improved the overall targeting efficiency of the application process.
(Keywords: disability insurance; internet connectivity; transaction costs)

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1. INTRODUCTION

Policymakers often rely on complex screening mechanisms to balance the efficiency and effectiveness of a public program. By "tagging" a smaller group of individuals as those in most need of the program, the government can transfer a larger benefit to a more targeted group (Akerlof, 1978). However, a complex screening mechanism also introduces significant transaction costs for applicants, and the transaction costs themselves can screen out potential program participants (Currie, 2006). Because individuals experience higher and lower costs depending on their circumstances, these transaction costs can result in non-targeted individuals receiving benefits, and targeted individuals being excluded from the program (Diamond and Sheshinski, 1995; Kleven and Kopczuk, 2011).

Social Security Disability Insurance (SSDI) is a public program with particularly large up-front application costs: the application process requires a sufficient work history to be SSDI-insured, extensive medical documentation of a disability that will last at least 12 months, proof that this disability inhibits one's ability to work, and a waiting period of at least 5 months after the onset of the disability (Office of Research, Evaluation and Statistics, 2017). In addition to the volume of information required to qualify for benefits, the nuances of the application process can often be confusing, in particular for individuals with lower levels of education or mental impairments. These factors mean that not only are the transaction costs of SSDI entry high, but they could be highest for those most in need of the benefits. In this paper, we analyze how application and acceptance to the SSDI program were affected by an innovation that reduced transaction costs in the application process.

In 2009, the Social Security Administration (SSA) introduced a new and improved version of the online application process called iClaim. Prior to the introduction of iClaim, the majority of SSDI applications were filed in person in a local field office, although it was also possible to apply over the phone. After the introduction of iClaim, applicants could complete the initial application from home, outside of business hours, and without relying on transportation to get to the field office. Additionally, iClaim allowed people to view the application and learn about the requirements before deciding to submit it, rather than potentially making multiple trips or phone calls to the field office to gather all the required documentation. Finally, iClaim also allowed individuals and any third-party preparers to file their appeals paperwork online, lowering the cost of appealing considerably. As shown in Figure 1, online applications increased dramatically following the change, from 15 percent of all initial applications in 2008 to 23 percent just a year later, and to more than 50 percent by 2014.

We contribute to the literatures on disability insurance and transaction costs by evaluating the impact of this significant improvement in the online application process, assessing how a change in transaction costs affects application and participation in SSDI. Using county-level data from SSA, we employ a difference-in-differences strategy to compare SSDI applications, acceptances and appeals before and after 2009 across counties that had more or less access to high speed internet, as measured by data from the Federal Communication Commission (FCC).

We find that counties with internet access one standard deviation above the mean experienced an increase in applications of approximately 1.6 percent after the introduction of iClaim, and our estimate can explain 15 percent of the increase in applications for the average county between 2008 and 2011. There is a corresponding increase in appeals of 2.8 percent. The particularly large increase in appeals suggests that the online application may have induced more individuals to appeal than would have in the absence of the online system. Additionally, we find that awards increased by a slightly larger magnitude than applications, meaning the introduction of iClaim led to a small but significant increase in the award rate. We explore heterogeneity in these patterns by geographic area and broad age categories and find that the largest effect on applications occurred among applicants over 55, while appeal effects were largest for applicants under 30, and award effects were largest for applicants ages 30-44. Additionally, we find that the impact on applications is larger in rural areas while the impact on appeals and awards is larger in urban areas. These results suggest that the iClaim policy lowered application and appeals costs, but for different segments of the population.

The rest of the paper proceeds in the following way. Section 2 discusses the previous literature on disability insurance, with a focus on changes to costs for applicants, and presents a simple theoretical framework. Section 3 discusses the data we use for the project, and how we construct our measure of internet access, while Section 4 presents our research design. Section 5 presents our main results, and Section 6 concludes.

2. TRANSACTION COSTS AND TAKEUP OF PUBLIC PROGRAMS

2.1 Prior Literature

There is a substantial literature on take-up of public programs and the associated transaction costs. Ordeals such as administrative burden and categorical eligibility requirements ("tagging") impose larger costs on ineligible applicants than on intended recipients, and have been argued to be an effective mechanism for sorting out "impostors" (Akerlof, 1978; Nichols and Zeckhauser, 1982). However, tagging can increase monitoring costs and introduce the potential for errors in determining whether or not applicants are eligible. Categorical eligibility requirements could also lead individuals to feign eligibility for the program by overstating their need or changing behavior to meet the requirement. Despite the challenges posed by ordeals and categorical eligibility, however, the optimal design of a public benefits program likely includes some degree of complexity, so long as the welfare gains of more efficient screening exceeds the associated costs (Kleven and Kopczuk, 2011; Diamond and Sheshinski, 1995).

An empirical literature considers the impact of various transaction costs in SSDI. Early work by Parsons (1991) finds that an increase in initial denial rates, which impose longer overall wait times and reduce impostors' probability of receiving benefits, reduces subsequent applications. More recently, research has found that increases in transaction costs via field office closures lead to a 16 percent decline in disability applications and 10 percent decline in allowances (Deshpande and Li, 2017), while declines in transaction costs through the dissemination of the Social Security Statement nearly doubles SSDI applications among older adults with existing health concerns (Armour, 2018). The challenges of transaction costs are not specific to SSDI, as demonstrated by a large body of empirical literature across many public programs (e.g., Currie, 2006; Aizer, 2007; Bettinger et al., 2012; Bhagrava and Manoli, 2015; Chetty et al., 2013).

Improving access to technology and high-speed internet has been explored as one relatively low-cost mechanism for increasing individuals' participation in public programs. While the introduction of online and telephone-based application processes for Unemployment Insurance (UI) has not been shown to significantly affect UI takeup or change the composition of UI applicants (Ebenstein and Stange, 2010), the increased availability of electronic tax filing increases participation in the Earned Income Tax Credit (EITC) (Kopczuk and Pop Eleches, 2007). Other work has found that high-speed internet access increases college preparation and application activity for high-SES high school students (Dettling et al., 2018), and increases labor supply among married women (Dettling, 2016).

SSDI program participation has grown substantially over the last few decades, now providing over $11 billion in benefits to over 10 million beneficiaries (Office of Research, Evaluation and Statistics, 2017). A combination of demographic changes, more generous eligibility requirements, and business cycle effects can account for the majority of this growth (Autor and Duggan, 2003, 2006; Liebman, 2015; Duggan and Imberman, 2009). Despite the large increase in the number of people receiving benefits, the average SSDI application has a 4-month review process for initial decisions. The wait time for hearings and appeals can be 1-2 years (Social Security Advisory Board, 2017). Longer application times can negatively impact future employment prospects of claimants who are ultimately rejected (Autor et al., 2015). Furthermore, disability is particularly challenging to observe and verify: Benitez-Silva et al. (2006) estimate that approximately 20 percent of awarded applicants are not disabled, and sixty percent of denied applicants were in fact disabled, suggesting that many intended applicants may be missed by the current screening mechanism.

Given these trends in SSDI participation, it is important to understand factors that facilitate applications, and factors that pose as barriers to the right groups of people being able to apply. The role of technology and the internet could play a unique role in this process. SSDI applicants and beneficiaries are a heterogeneous group with a variety of impairments. While some beneficiaries and applicants face significant limitations, others retain some degree of work capacity (e.g., Bound, 1989; Chen and van der Klaauw, 2008; Von Wachter et al., 2011; Maestas et al., 2013; French and Song, 2014). As a result of this heterogeneity, applicants likely face a variety of challenges in the application process as well. The transaction costs of traveling to an in-person field office could be particularly high for applicants with mobility problems, meaning that the increased convenience of applying from home could be particularly important. On the other hand, older applicants, or applicants with mental or psychological impairments may face disproportionate challenges in accessing or using technology, meaning that the gains from the convenience of applying online could be small for these groups.

2.2 The iClaim Process

Applicants can apply for disability and retirement benefits online via iClaim. Retirees have been able to apply for benefits online since a pilot program began in 2000, and the option to apply online for disability benefits began in 2002. However, the initial system was cumbersome and rarely used. As a result, in December 2008, SSA introduced iClaim, an improved, streamlined online application system for both disability and retirement benefits. According to SSA representatives, the main benefits of iClaim were reduced completion time, the ability for submission by third parties, dynamic pathing through the application process, and an increased ability to confirm submission and view the status of an application.[1] Importantly, disability lawyers could also file appeals online, meaning the online application could lower costs on individuals *and* other entities assisting in the application process.

The move to the online application was introduced as part of a broader effort to address the increased workload anticipated at field offices as the baby boomer generation reaches retirement. SSA has been steadily expanding e-Services available to the public, including the ability to check the status of Social Security benefits online. Most of the additional innovations are not targeted towards disability benefits directly: the only other innovation that occurred around the time of the iClaim roll out was the introduction of a retirement estimator tool (Office of the Inspector General, 2008). We do not expect significant spillovers from the estimator tool

[1] Based on correspondence with SSA staff in the Office of Electronic Services, September 2014.

onto disability applications, as the retirement estimator does not provide any information about disability benefits. Based on conversations with SSA representatives, there was no pilot, staggered roll-out or coordinated outreach campaign with the introduction of iClaim, although some independent news articles covered the change in January 2009 (Bismarck Tribune, 2009)

To file for SSDI via iClaim, an applicant accesses the application via an online portal and can first review a published checklist of all the required information for the application. Applicants can save ongoing applications and return to complete them at a later time. Once the application has been submitted, applicants must complete two additional forms and mail them to SSA: the adult disability report (containing details on medical and work history), and an authorization form allowing their information to be disclosed to SSA (Office of the Inspector General, 2011b). A recent survey found that over 90 percent of online disability applicants had a good, very good, or excellent experience with iClaim (Office of the Inspector General, 2011a).

Once filed, online applications are sent to the closest field office, where an SSA employee reviews the application for errors and contacts the applicant for additional information if necessary. An audit study by the Office of the Inspector General found that most online applications required SSA employees to follow up with the applicant for some reason, most commonly to obtain one or both of the forms that must be submitted by mail.[2] While applicants often need to be contacted to submit additional information, an audit of claims submitted over the internet found an accuracy rate near 99 percent. Furthermore, even with this follow up, a survey of SSA employees found that on average, iClaim applications were faster to process than in person or telephone applications (Office of the Inspector General, 2011b). As described by

[2] The need for follow up isn't specific to disability applications: OIG found similar rates of follow up among SSA retirement applications that were submitted online, but for different reasons (Office of the Inspector General, 2011c).

one employee in the audit report, "iClaim is far from perfect, but it is a time saver" (Office of the Inspector General, 2011d). After the initial review at the field office, online applications are forwarded to the state Disability Determination offices in the same way as in person and telephone applications. For those awarded, SSDI benefits are a function of prior wages, but do not vary with disability severity.

Thus, the main benefits to an applicant of applying online are the ability to start the application at any time without having to schedule and wait for an appointment, the ability to view the necessary information in advance, to resume applications at a later time, and to avoid the time and cost of travel to a field office. SSA has had the option to apply by phone via its 800-number since the late 1980s, which also eliminates the travel costs and appointment wait time (Government Accountability Office, 1991). But, the online application provides additional flexibility in gathering information, reviewing and completing the application. Furthermore, recent focus groups of potential applicants found that only 2 percent of applicants indicated that they would apply by phone, while 80 percent said that they would prefer to apply online (Office of the Inspector General, 2011a). While decisions are made in the same way for all types of applications, the overall process is faster for online applications due to a faster experience for both the applicant (by eliminating the initial wait time for an appointment and providing information more accessibly), and SSA (through faster initial processing times).

2.3 Conceptual Framework

Given this background, it is helpful to think about the decision to apply for disability insurance with the following framework. First, consider two types of workers, H and L, who have high and low probabilities of receiving disability insurance conditional on applying ($P_i, i \in H, L$). The cost of applying likely varies between H and L if the severity of an individual's disability affects his or her ability to apply. In both cases, a worker applies if

$$P_i * Award > Cost_i, \forall \text{ i} \in H, L$$

where *Award* is the net present value of the future stream of disability payments. In words, the above expression states that if the expected value of applying is greater than the cost of applying, the worker will apply. If the decrease in application costs induces more people to apply for disability, we should expect applications to increase. Additionally, if the costs decrease by more for the low-type workers, who may not ultimately qualify for SSDI, we would expect applications to increase by more than awards. If the converse is true, then we would expect awards to increase more than applications. However, if similar shares of each type are induced into applying as previously existed, then applications and awards should increase by similar amounts.

To put this discussion in context, we compiled statistics on internet use by SSDI applicants before and after the policy change in Table A1. We calculate these statistics with data from the Survey of Income and Program Participation (SIPP), which asks respondents whether they have applied for disability insurance and asks about their internet use. Respondents are asked these questions in one wave of the SIPP per panel, providing information about internet use in 2005 (Wave 5 for 2004 SIPP), approximately four years before the policy change, and in 2010 (Wave 6 for 2008 SIPP), one year after the change.

In 2005, about 37 percent of SSDI applicants in the SIPP reported using the internet, while about 61 percent of the rest of the population reported using the internet. There are significant increases in internet use among both SSDI applicants and non-applicants by 2010, a year closer to the time of the iClaim implementation. Part of the discrepancy in internet use between applicants and non-applicants is due to the fact that the SSDI population is older than the overall population, but SSDI applicants within each age group are also less likely to use the internet than their non-applicant peers. Still, a substantial share of SSDI applicants reported using the internet before the policy is implemented, which suggests that the iClaim policy could have affected their costs for applying to disability insurance. We note that while these statistics provide data on internet use among the applicants themselves, internet use is presumably higher among third party preparers.

We believe iClaim could reduce the application ordeal through a combination of reduced information and transaction costs. As a result, the marginal applicant could be influenced to apply through one of two main channels (or both): (1) the increased flexibility and clarity of information available in the online application; or (2) the reduced time and travel costs associated with the online application. Each of these channels could influence a different set of applications.

Those influenced to apply by the reduced information costs are likely either younger, better educated (enabling them to collect and process the information provided online themselves), or have access to third party preparers who themselves are now able to better gather the application information available online. Applicants are relying on third-party preparers in increasing numbers, particularly at the appeal stage. In 2011, approximately 14 percent of applicants relied on third party preparers at the initial application stage, and the involvement of outside parties increases throughout each stage of the process. In recent years, between 80 and 90 percent of cases at the hearing level rely on representation by an attorney or non-attorney representative (Social Security Advisory Board, 2017). In addition to the benefits of increased information available online, third-party preparers could also benefit from the reduced transaction costs from the online application, potentially filing paperwork more quickly or filing appeals in cases where it would not have been worth the effort prior to the online application.

On the other hand, individuals who are influenced to apply due to the reduced travel and time costs associated with the online application could be more likely to be mobility limited, older, or live farther from a field office. While our data does not provide information on disability type or representation status, we perform heterogeneity analyses to analyze these potential mechanisms. We analyze application, appeal and award patterns separately by age groups and whether applicants live in urban and rural areas. Additionally, our ability to separately analyze appeals could shed light on the information channel, given the high use of third party preparers in the appeals process. We elaborate on each of these analyses in our discussion of results in section 5.

3. Data

Using publicly available sources as well as restricted-use data from SSA, we construct a panel dataset comprising all US counties between 2004 and 2011.

3.1 SSDI Data

Our main outcomes are compiled from the SSA Disability Research File, and include county-level counts of applications, appeals, and allowances for all ages and separately by broad age groups. These counts are reported in the initial year an application was filed, rather than the year in which the decision was reached. The counts include technical denials and exclude pending cases. This last point is important, because it mechanically under-counts applications in later years, which could bias downward our estimates of the effect of iClaim.

Figure 2 shows the distribution of SSDI applications per 1,000 adults by county in 2008, the last year before the policy went into place. The graph shows there is substantial variation in application rates within and across states and regions. As has been documented in prior work (Strand, 2002; Rupp, 2012; Gettens et al., 2016), the highest concentration of applications occur in the Southeastern states, the Rust Belt, and rural regions of Western States.

To maintain confidentiality, the SSA suppressed cells in the county-level age-group counts if the count was less than 10. They also perform complementary suppression on the county-level totals if only one age-group is suppressed.[3] This suppression leads us to have a number of missing cells.

Missing data due to cell suppression are relatively common. In the study period, between 350 and 800 counties had missing totals each year, or between 10 and 25 percent of all counties. For the age breakouts, the number of missing observations is greater. For the older age groups (45-54, 55 and over) approximately a third of counties were not reported, while in some years half of counties were not reported for the younger age groups (under 30, 30-44). Approximately half (47 percent) of counties had non-missing data in all years. Missing cells tend to occur in lower population areas with lower baseline internet connectivity levels, but trends in internet connectivity, labor market indicators, and population are similar between counties with missing data and those without. If a cell has missing counts in it, we impute the values in the following way. If an age group (or total county) has a non-missing value, we use the total as given. If an age group value is missing, we assign it a random value between 0 and 9. To calculate the corresponding total, we sum the actual reported values for age groups with the imputed values

[3] For example, if in county X in year YYYY there were 5 applicants under 30 years old who applied and 15 applicants ages 30-44, the cell for applicants under 30 and the total cell would be suppressed. However, the cell for applicants ages 30-44 would show a value of 15. This ensures that there is not complementary disclosure.}

for missing age groups. As discussed in section 5.3 our results are robust to various other methods of imputing or dropping these missing values.[4]

3.2 Measures of Connectivity

We use reports from the FCC on the count of high-speed internet providers by zip code to measure local internet connectivity. The count of internet providers captures the extent of variation in the supply of high-speed internet access, which was the main constraint on access during the time frame of our analysis.[5] Other research has also demonstrated the count of internet providers as an effective measure of internet access (Dettling et al., 2018; Iyengar and Westwood, 2015). The FCC Form 477 collects records of the number of high-speed internet service providers with over 250 high-speed residential lines at the zip code or county level, depending on the year. In 2008, the FCC changed reporting requirements, meaning that there is no consistent series at the zip code or county level throughout our entire time series. As a result, we benchmark all our internet measures to 2008, the year prior to the policy change and the only year in which both data series are collected. To protect confidentiality of the companies, the data are suppressed if there were fewer than four providers in a zip code; however, true zeros are reported. We count these zip codes (or counties) with suppressed data as having one provider. As internet prevalence has increased, the suppression rates have declined: by 2008, only 9.6 percent of zip codes had zero providers. As noted by Dettling et al. (2018), there is not a strong correspondence between zip-code level counts of high-speed internet service providers and population, and therefore we adapt the strategy in Dettling et al. (2018) and construct measures

[4] We have dropped the missing cells altogether, imputed them as zeroes, ones, and nines, all with little effect on the main results

[5] These counts are available at the FCC website, https://www.fcc.gov/internet-access-services-reports

of connectivity scaled by county population size. Furthermore, our data on SSDI application is at the county level, thus requiring consistent data at the county level for estimation.

We aggregate zip code level counts of internet providers to the county level to estimate the number of internet providers available to the average household in a county. One complication is that zip codes regularly cross county lines. To measure the number of internet providers in a county, we population-weight the providers count by the population of a zip code that resides in a given county, and then sum across all zip codes which are a part of the county. Formally, we calculate the internet providers as below:

$$PROV_{ct} = \frac{\sum_{j \in C} f(N_{jt}) * a_{jc} * P_{jt}}{\sum_{j \in C} * a_{jc} * P_{jt}} \qquad (1)$$

In equation 1, N_{jt} is a count of the internet providers from FCC data in zip code *j* and year *t* and P_{jt} is the population of zip code *j* in year *t.* Because zip codes can span multiple counties, a_{jc} is the share of zip code *j*'s population that resides in county *c*, typically called an allocation factor.[6] We multiply the number of providers in the zip code by the zip code population and the estimated allocation factor, and sum over all zip codes *j* that overlap with county *c.* Then, we divide by the total estimated county population (the sum of all zip code population shares allocated to the county) to obtain $PROV_{ct}$, a population-weighted estimate of internet connectivity at the county level. Thus, equation 1 measures the average number of internet providers to which a resident has access in the county.[7]

We consider two versions of this access estimate (PROV1 and PROV2) with different functional forms in $f(N)_{jt}$ such that $f(1) \geq 1$, and $\frac{\partial f(N_{jt})}{\partial N}$>0. Both versions reflect the fact that a

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[6] We use allocation factors provided by MABLE/GeoCorr version 14 from the Missouri Census Data Center. These allocation factors are provided for the cross walk from zip codes to counties.

[7] In a simple example, imagine that there are 4 zip codes which are part of the county that all have equal population, two of which have 2 internet providers, and the other two have 4 internet providers. On average, a resident of the county will have access to 3 internet providers.

higher number of providers leads to households having more access to internet. Our first measure (PROV1) specifies a logarithmic function $f\left(N_{jt}\right) = \log\left(N_{jt} + 1\right)$. Thus, PROV1 incorporates the idea that the connectivity of households is likely increasing in the number of providers, but at a decreasing rate. Due to the logarithmic specification, a change in this measure can be interpreted as the percentage change in the county-aggregated measure of internet providers. PROV1 is our preferred measure of connectivity, because the relationship between residential internet connectivity and internet provider count is likely concave. We also consider a second measure, PROV2, which specifies a linear function, $f\left(N_{jt}\right) = N(jt)$. As shown in our results tables, both measures yield similar results.

Figure 3 shows the distribution of PROV1 across counties in 2008, the last year prior to the policy change. Again, there is substantial variation within and across states in internet connectivity, with the highest number of providers occurring in urban areas. Notably, the areas with the highest internet connectivity do not entirely coincide with areas with the highest SSDI application rates.

As additional verification in our main measure of internet access, we compare our linear county-level measure PROV2 to the revised series from the FCC in 2008 (the only year in which the two series overlap), and the correlation is 0.45, which suggests that our measure is a good approximation of county-level residential internet connectivity. Additionally, to ensure that our measure was accurately representing the exposure of individuals to high-speed internet access, we compared PROV1 and PROV2 to a measure constructed at the state level from data in the Current Population Survey Internet Use Supplement from October 2007. We calculate the share of the population reporting an internet connection from the Supplement for each state, and find that our measure and the population share from the CPS are highly correlated.[8]

3.3 Other Data

We supplement these main sources of data with additional information on county demographics and labor market conditions to construct the controls included in our baseline specification. We use age, gender, and racial composition information from the Surveillance, Epidemiology, and End Results (SEER) program of the National Cancer Institute. We also use the SEER data to calculate the size of the working age population (ages 16-65). Additionally, we use the Local Area Unemployment Statistics (LAUS) from the BLS in order to measure the size of the labor force and the unemployment rate in the county.

We also collected data on additional time-varying county level characteristics, which we include in further robustness checks. We aggregated total annual county expenditures on other public programs including SNAP, Medicaid and Medicare from the U.S. Bureau of Economic Analysis.[9] To obtain a measure of overall county health, we collected measures on diabetes and obesity prevalence at the county-year level from the Centers for Disease Control.[10] All of these data sources are available for all years and counties included in our panel.

3.4 Summary Statistics

Table 1 displays summary statistics over all counties and years, and shows statistics separately for high and low connectivity counties, averaged over the years before and after the

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[8] The coefficient on a regression of PROV1 on the share of the population with an internet connection in the October 2007 CPS was 0.26, with a T-statistic above 3. In a robustness exercise we used these measures of internet access from the CPS in a state-level version of our main analysis, which is at the county level. We find qualitatively similar results with larger standard errors.

[9] U.S. Bureau of Economic Analysis, "Table 35. Personal Current Transfer Receipts," (accessed March 1, 2018).

[10] Data available at https://www.cdc.gov/diabetes/atlas/countydata/atlas.html and https://www.cdc.gov/obesity/data/databases.html.

policy change. In an average county, approximately 10 adults applied to SSDI per 1,000 working-age residents. Prior to the iClaim policy, there were approximately 13.4 applicants per 1000 working-age adults in low connectivity counties, compared to 9 applicants per 1000 in high connectivity counties. This number grew by approximately 1.5 applicant per 1000 working-age residents in both the low and high connectivity counties to 15.1 and 10.5, respectively. Appeal rates are also higher in low internet counties prior to the policy change, with approximately 2.6 and 1.7 appeals per 1000 working-age adults in high and low internet counties, respectively. On average, there was only a slight increase in appeals for high connectivity counties, by 0.1 appeal per 1000 working-age residents. Awards grew from 2.9 before 2009 to 3.5 afterwards in low connectivity areas, and from 2.7 to 3.2 in high connectivity areas.

Table 1 also shows fairly similar trends in unemployment rates and demographic characteristics between high and low connectivity counties, before and after 2009. The unemployment rate is higher in low internet counties in both the pre- and post- period. Both high and low internet counties experience an increase in the unemployment rate of approximately 4 percentage points in the post-period, reflecting the impacts of the Great Recession. High connectivity areas did experience a larger increase of layoffs after 2009 relative to low connectivity areas, likely due to the fact that higher connectivity areas tend to be more urban areas. This highlights the importance of controlling for layoffs and population composition in our estimation. Low internet counties also tend to have slightly older populations on average, although the trends are similar over time. In the second part of Section 5, we formally test that these variables are not differentially changing with the policy, and do not find any evidence to that effect.

Finally, Table 1 shows summary statistics on our two measures of internet connectivity, PROV1 and PROV2, based on data from 2008. There were an average of 16 and 11 providers in high and low internet counties in 2008, respectively. As we discussed above, we do not have consistent data for years after 2008, and so we only report the pre-treatment averages.

4. METHODOLOGY

To identify the effect that the iClaim policy had on application behavior, we use a difference-in-difference research design, which compares counties with varying degrees of internet access, before and after the policy was implemented. As explained in Section 2, iClaim likely lowered the application costs either through reduced information or transaction costs for those willing and able to use the technology. In an extreme example, an individual who cannot access the internet anywhere in their county would be unaffected by the iClaim innovation. On the other hand, perfect internet connectivity will not affect everyone in the county if there are other barriers to internet use. As a result, we interact our measure of internet connectivity with the time period after the introduction of iClaim to identify the impact of the online application on SSDI participation with the following equation:

$$y_{ct} = \beta * iClaim_t * PROV_{c,2008} + \theta X_{ct} + \gamma_c + \eta_t + \zeta_c * t + e_{ct} \quad (2)$$

where y_{ct} is one of our outcome variables: log applications, log appeals, or log awards. $iClaim_t$ is an indicator that is 1 from 2009 onwards, once the iClaim policy is in effect, while $PROV_{c,2008}$ is one of the two measures of internet connectivity described by equation 1, fixed at the 2008 level of internet connectivity. We also include a number of other time-varying controls at the county level in X_{ct}: the size of the labor force, the unemployment rate, the count of mass layoffs, and the age distribution of the county, since these all affect the potential pool of disability applicants. We include county and year fixed-effects, county-specific trends, and e_{ct} is the error term. We weight all of our regressions by county population, and we cluster standard errors at the state level (Bertrand et al., 2004; Cameron and Miller, 2015). Our coefficient of interest is β, which shows the differential effect of the iClaim policy in counties with more internet access compared with less connected counties.

The main identifying assumption is that counties with different internet access levels would have experienced similar trends in SSDI applications after 2009 in the absence of the introduction of iClaim. We first show that trends in internet access do not seem to have differentially changed as a result of the policy for counties with different levels of internet access. As mentioned previously, there is no consistent source of data on county-level internet throughout the time period, Figure 4 shows trends in both time series on the same chart, with one overlapping year in 2008. The lines from 2000 to 2008 plot the average of PROV2, our aggregated county measure, for counties above and below the median internet connectivity in 2008. The series from 2008 to 2012 show the raw count of residential internet providers for counties above and below median internet connectivity in 2008 based on the FCC county measure.[11] The figure shows that there were parallel trends in internet access for high- and low-internet counties before and after the policy change and despite the change in reporting.[12]

We show further evidence of parallel trends by examining the outcome variables between counties with different levels of internet access. We estimate a regression of our outcome variables on year dummies, interacted with 2008 internet levels as measured by PROV1. We plot these coefficients in Figure 5, omitting the year 2008, so all the coefficients are measured relative to the year before the policy. As our figures show, there is no clear pre-trend in the

[11] It does not matter whether we categorize the median according to the PROV2 measure or the raw counts- the results are almost identical

[12] We also show evidence of parallel trends in internet access by quartiles of 2008 internet access, in Figure A1.

outcomes before 2009. The coefficients imply that there were higher applications and appeals in high-internet counties in 2004, a year with high application rates overall. However, there is no evidence of differential trends for the 2005-2008 period. The slight decline in appeals in 2011 could again reflect the fact that data are measured in the year of initial application and some appeals may not be processed by the time of our data collection at the end of 2014. Overall, these graphs do not show any strong differential pre-trends between high and low internet counties.

There are other assumptions for the validity of the design. We assume that potential applicants do not delay their application in anticipation of the policy change, which would induce positive bias in our estimate. We also assume that pre-existing internet access levels in a county are not correlated with disability applications. In our time period, this does not seem to be an issue, for a few reasons. A number of papers have shown that internet access expanded during this time period, implying the presence of internet service providers had more to do with supply-side constraints than increases in demand.[13] Table 1 shows that at baseline, application rates are comparable for areas with internet connectivity levels above and below the median.

Another important consideration for our methodology is that the introduction of iClaim occurs at the end of the Great Recession. SSDI application rates have been shown to be sensitive to business cycles due to "conditional applicants" who have health impairments, but wait until they lose a job to apply for SSDI (Autor and Duggan, 2003). Maestas et al. (2015) estimates that rising unemployment rates during the Great Recession increased SSDI applications by 6.7 percent, accounting for approximately 28 percent of the overall increase in applications between 2007 and 2010. This result confirms the earlier findings that SSDI participation is sensitive to business cycle conditions, but the link between the newly unemployed and SSDI participation is

[13] For a discussion of this assumption, see Dettling et al. (2018); also see Faulhaber (2002); Greenstein and Prince (2006); and Grubesic and Murray (2002)

less clear. Some individuals who lost their jobs during the Great Recession first collect unemployment insurance (UI), and may wait to apply for SSDI until their UI has been exhausted. However, Mueller et al. (2016) use variation in UI extensions during the Great Recession to examine the interaction between UI and SSDI, and do not find a strong relationship between UI exhaustion and SSDI application during the Great Recession. They further note that there is very little overlap in the population of UI and SSDI beneficiaries. They estimate that only 28 percent of SSDI awardees had any labor attachment in the prior year. Similarly, Linder (2016) analyzes the interaction between UI benefit generosity and SSDI applications prior to the Great Recession, and does not find a significant relationship between the two. Thus, while the Great Recession accounts for part of the increase in applications over this time frame, a significant share of the increase remains unexplained.

We carefully consider the impact of the Great Recession in our analysis. First, we include measures of the county-year unemployment rate, the size of the labor force, and the number of mass layoffs in our baseline specification. In addition to county and year fixed effects, we include a county-specific trend in our baseline specification as well, to account for counties that may have experienced faster or slower recoveries. We explore sensitivity to inclusion of these measures and, as we discuss in Section 5.2, find that our results are robust to inclusion or exclusion of these controls. We examine the results separately for urban and rural counties, who may have been influenced differently by the Great Recession. Finally, as a placebo test we consider how a public assistance program (Medicaid) that does not have internet applications but is similarly responsive to the business cycle changes concurrently with the policy for high and low internet counties; we find a null result. The results of these specifications are discussed in Section 5.2.

5. RESULTS

5.1 Main Results

Table 2 shows estimates from Equation 2 for our main outcomes, log applications, log appeals and log awards. The first panel shows results using the provider estimate PROV1, while the second panel shows results using the measure PROV2. A clear pattern emerges from these results. First, overall applications increase following the change in policy. The coefficient of 0.0501 means that a 1-percent increase in the number of providers increases applications after 2009 by approximately 0.05 percent. To understand the effect of a more meaningful change in access to internet, the standard deviation of PROV1 from Table 1 represents a change of about 0.31. Scaling by this magnitude, the effect of the policy for a county with a 1 standard-deviation higher access to internet is an increase in applications of approximately 1.6 percent. As Table 2 shows, we find very similar results using PROV2, although the scaling is different. To put our results in context, the average number of providers in a county in 2008 (in logs) was 3.48 and the average county increase in disability applications from 2008 to 2011 was 14.2 percent. Our coefficient of 0.05 translates into a 2.2 percent increase in applications for the average county, which implies that the decrease in application costs via iClaim can explain approximately 15.5 percent of the average increase in applications during this time period.[14] This magnitude is smaller than Deshpande and Li's (2017) finding that SSDI applications decline by 16 percent in areas near field office closures after 2011, but nonetheless suggests that increased online access could offset some of the impacts of these closures. The impact of iClaim is also smaller than Armour (2018), which finds that SSDI applications nearly double among health-impaired older

[14] Application counts can be found at https://www.ssa.gov/oact/STATS/dibStat.html

adults who receive a Social Security Statement. It is not surprising that the impact of iClaim has a smaller impact on SSDI applications in the overall population, given that our estimates are not restricted to those with severe health impairments or specifically to counties directly affected by a major policy change.

The iClaim policy also considerably lowered the costs of appeals, because all of the paperwork could be filed online, even by third-parties. Consistent with a decline in the cost of appealing, we find that the policy leads to a higher number of appeals being filed in counties that have better high-speed internet access. The coefficient of 0.0891 implies that a 1 standard deviation increase in internet connectivity leads to a 2.8 percent increase in appeals.[15] In response to an increase in applications and appeals, the policy also led to an increase in awards. In column 3 of Table 2, the coefficient of 0.0635 scales to a 2 percent increase in the number of applications ultimately accepted for a 1 standard deviation increase in internet connectivity, and is statistically indistinguishable from the application effect. However, when estimating the award rate directly, we find a small positive and significant result, suggesting that iClaim induced applicants who were more likely to ultimately receive an award: a 1 percent increase in internet providers leads to an approximate 0.01 percent increase in the award rate.

To explore which portion of the population is driving these effects, we look at two specific margins: response by age group and response by geography. Table 3 shows the effect for applications, appeals and awards by age group, using only PROV1.[16] To do so, we re-estimate equation 2 but change the dependent variable y_{ct} to reflect applications, appeals, or awards for one of the following age groups: applicants under 30, applicants 30-44, applicants 45-54, and

[15] This effect may be a lower bound, because our data do not capture all appeals that occur for applications originally filed in 2011, because our data were pulled because all of those applications were finalized.
[16] Results using PROV2 are available upon request.

applicants 55 or older. Each coefficient in Table 3 reflects the coefficient on $iClaim_t * PROV_{c,2008}$ from a separate regression for the relevant age group listed in the row, and the relevant outcome (applications, appeals, awards, or the award rate) listed at the column head.

We find that there is some heterogeneity in the responses by age. The results show that the increase in applications due to the iClaim policy is driven by applicants aged above 55; the point estimate for this group is 4 times larger than any other age group. The only significant effect for appeals is for those aged under 30; similarly, the coefficient on appeals for those under 30 is also an order of magnitude larger than the coefficients for the other age groups. The age-specific award results are more noisy: the point estimates suggest that awards increased for all groups, but with the exception of ages 30-44, there are no statistically significant changes. Finally, the award rate increases the most for applicants under age 30 and ages 30-44. These results suggest that the changes in the costs of applications and appeals affected different segments of the age distribution.

We also examine how the pattern of results varies for individuals in urban and rural areas. To do this, we estimate equation 2 separately for the counties that are or are not in a core-based statistical area (CBSA) as of 2010. These results are in Table 4 and show that the effect on applications is much larger for non-CBSA counties, where the decrease in application costs is likely higher because field offices are typically less accessible. However, the CBSA counties account for almost the entirety of the increase in appeals and awards, while these results are insignificant for non-CBSA counties. This suggests that the information channel may play a more important role for appeals, perhaps because third-party preparers are more readily available in urban areas.[17] This finding is also consistent with Deshpande and Li (2017), who find evidence that applications fall in zip codes experiencing a field office closure, likely due in part to the associated increase in travel costs.

5.2 Sensitivity and Robustness

One threat to our research design is that there is some coincident shock that differentially affects counties by internet access. This concern is particularly salient given that the Great Recession occurred at the same time as the iClaim policy and may have disproportionately affected less or more connected counties. We address this concern in two ways. First, we perform a series of falsification tests, in which we estimate equation 2 with our key time-varying control variables as the outcomes. These results are in Table 5 and show that the unemployment rate did not increase more in counties with more internet access. Similarly, there is no systematic change in county population shares with respect to internet access. While there are significant results on the share of the population under 30 and the share aged 40-55 when using PROV2, the point estimates are very small.

Another way to test how the Great Recession differentially affected high or low internet counties is by measuring how other social safety net programs changed. We test these differences using Medicaid spending at the county level, because it is a similar population of people who are on DI, while the vast majority of states at the time did not have online enrollment or application portals at the time.[18] We estimate equation 2, using the log of county Medicaid

[17] While beyond the scope of this paper, one interesting avenue of research would be to examine how this law changed the industry of disability insurance lawyers. In the short-run, a decrease in costs implies higher profits, but presumably firm entry or expansion should bid down the “price" of these services.
[18] The Affordable Care Act, enacted in 2010, required states to set up online enrollment systems for Medicaid by 2014. Other safety net programs already had these systems in place, and the Supplemental Nutrition Assistance Program started implementation in 2004.

spending as the outcome and the results are in the last row of Table 5. We find no difference in Medicaid spending by internet access after the introduction of the iClaim policy.

We perform a number of other robustness checks. We first test if our estimates are sensitive to removing or including more controls, especially ones related to the labor market. We estimate equation 2 without the labor market controls that are included in our baseline specification. The results, shown in Table 6 row 2, are very similar to our baseline results. We then add a number of additional time-varying controls in row 3. These include SNAP enrollment, Medicaid spending, Medicare spending, and rates of diabetes and obesity. Our results do not change with the addition of these controls. To control for state-level policies that may be changing over this time period, we include state-year fixed effects in row 4, and our results do not change significantly either. If we only include larger counties, defined as the top 75 percent of counties by population, our results are also unchanged. Finally, in row 6, even if we eliminate the county-level linear time trends, our results are larger but not qualitatively different.[19]

5.3 Effects of Imputation

For confidentiality reasons, our data on SSDI applications, appeals, and awards are suppressed for counties with fewer than 10 cases. As mentioned earlier, our primary method to address this is to randomly impute a number between zero and nine for these observations. To explore the sensitivity of our results to this imputation, Appendix Tables A7-A9 estimate our main specification on subsamples of the data, based on imputation status. The first column in each of the tables shows our main results. In the second column we drop any observation that was imputed, and in the third column we limit the sample to a balanced panel of counties that always had a non-missing value for that variable. The final column estimates equation 2 with an

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[19] We also show all of the age-specific results from each of these robustness checks in Tables A2-A6; they are consistent with our main results.

imputation dummy as the outcome.

Overall, our main results are robust to these different samples, particularly in the top row for the totals. For the age group results, the results are slightly more sensitive, and for the small sample of counties that do not have imputed appeals for age under 30, we find no effect on applications. The final column of the tables show that it is in general more likely for a value to be suppressed for high internet counties after the policy was implemented, which should bias our estimates toward zero because the counts are noisier for higher internet counties.

6. DISCUSSION

We provide evidence that lowering the transaction costs associated with applying for SSDI has a significant impact on the application process. To put our results in context, the average number of providers in a county in 2008 was 3.48 and the average county increase in disability applications from 2008 to 2011 was 14.2 percent. Our coefficient of 0.05 translates into a 2.2 percent increase in applications for the average county, which implies that the decrease in application costs via iClaim can explain approximately 15.5 percent of the average increase in applications during this time period. This result is qualitatively consistent with related estimates on the impact changes in transaction costs (Deshpande and Li, 2017; Armour, 2018). These findings imply that the lower ordeal costs associated with applying for SSDI slightly improved the targeting efficiency of the application process. Our results are broadly stable in light of several robustness checks, including consideration of additional time-varying controls, specification modifications, and sample restrictions.

We find differential patterns in the response for urban and rural counties: there is a larger impact on applications among rural residents, and a larger impact on appeals and awards among urban residents. These findings indicate that rural residents may have benefited more from the reduced travel costs associated with applying online, while urban residents may have had better access to attorneys or third-party preparers who could assist in the appeal and hearing process. These results also demonstrate that different groups of applicants may respond to the reduction in transaction costs through different channels. While rural applicants may have benefited more from the reduced transaction costs associated with the logistics of applying, urban residents and their preparers may have been better equipped to take advantage of the increased information available in the online application.

We find suggestive evidence of different patterns in these results by age group. While we find a significant increase in applications for all age groups, we find the largest effects on applications for older workers. However, we do not find a corresponding increase in awards for the oldest workers, which implies that some of the increase in applications come from marginal applicants who ultimately are not eligible for SSDI. Conversely, we find slightly smaller application effects for the youngest workers but larger appeal effects, and find the largest award effects for applicants ages 30-44. However, these results are noisy due to data limitations, and should be verified in future research.

These results suggest that the online application likely did reduce the complexity of the SSDI application, and individuals of all ages responded to the reduced application complexity. While a formal welfare analysis is beyond the scope of our analysis, a model of disability application from Low and Pistaferri (2015) provides some intuition. Their model analyzes the welfare implications of various changes to the SSDI application process, taking into account the impact on expanding access to worthy applicants who otherwise would not access the program, and accounting for the increased costs on false applications. Their results imply that reducing the stringency of the online application is overall welfare improving, as the gains to the worthy applicants who are newly awarded benefits exceed the costs of extending access to some false applicants who make it through the system. By reducing the ordeal of the application process, the online application reduces application screening, which is in effect a reduction in stringency. Under the assumptions of the Low and Pistaferri (2015) model, our finding of an increase in awards would suggest that the online application was welfare improving on net.

In addition to these considerations, the increase in applications due to iClaim could have important effects on field office congestion and application processing times. These results are particularly relevant given the field office closures that began in 2011. Deshpande and Li (2017) find a decline in applications in zip codes experiencing a closing, and find evidence of congestion effects in remaining field offices. These effects could have been even larger in the absence of an online application. However, any potential increase in congestion could reduce the welfare gains associated with lowering the application ordeal.

Another interesting outcome to explore would be the market responses to this policy change. Because individuals who decide to appeal often make use of third-party preparers or attorney services, the gains of the online process may have accrued to those who already have other support in facilitating their application, or specifically to third-party preparers. In fact, given that disability attorneys are paid by contingency, this large increase in appeals may be a strategic response by attorneys in light of the lower costs associated with filing an appeal. Depending on the shape of the cost function for law firms, this could increase or decrease the average size of disability law firms, and also increase or decrease competition in this market. We leave this as an avenue for future research.

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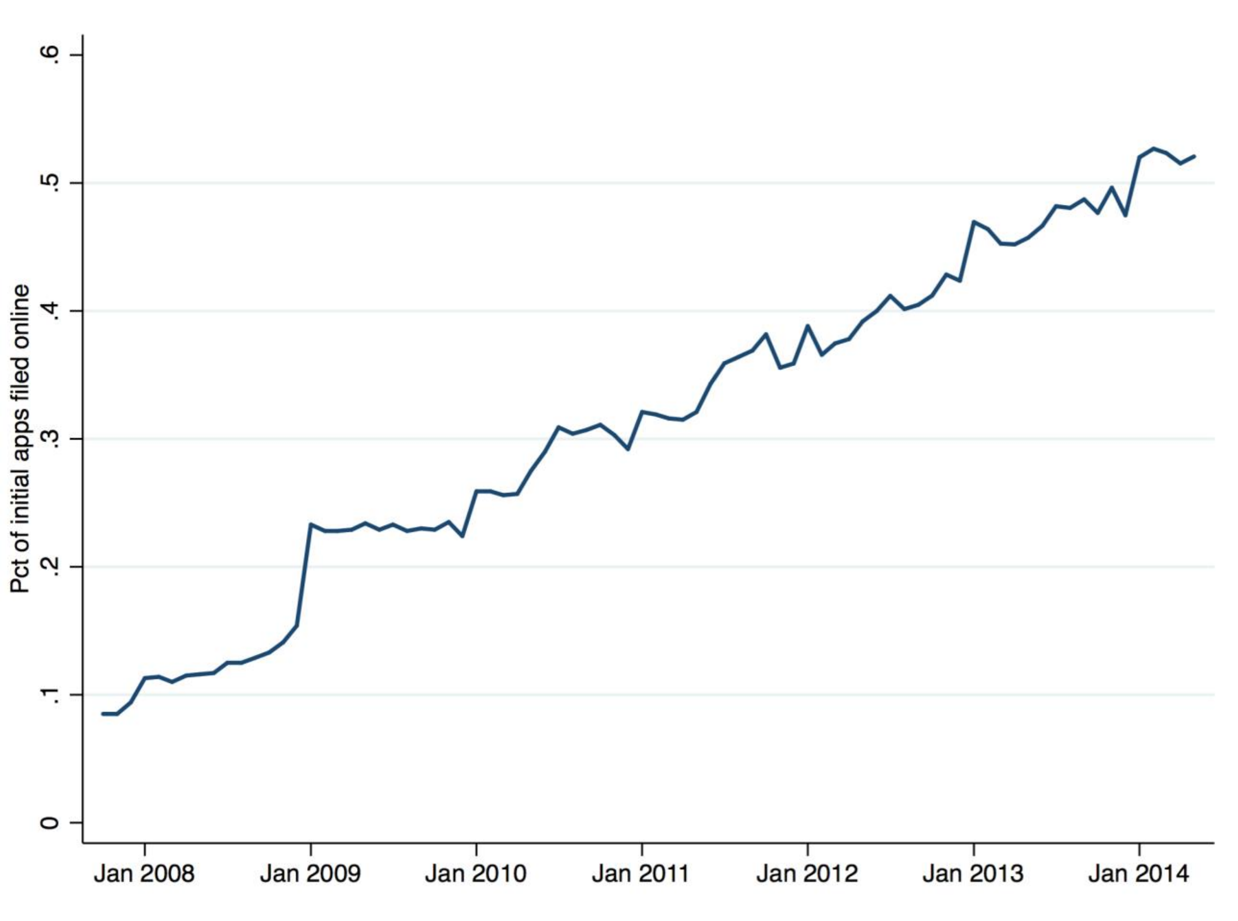
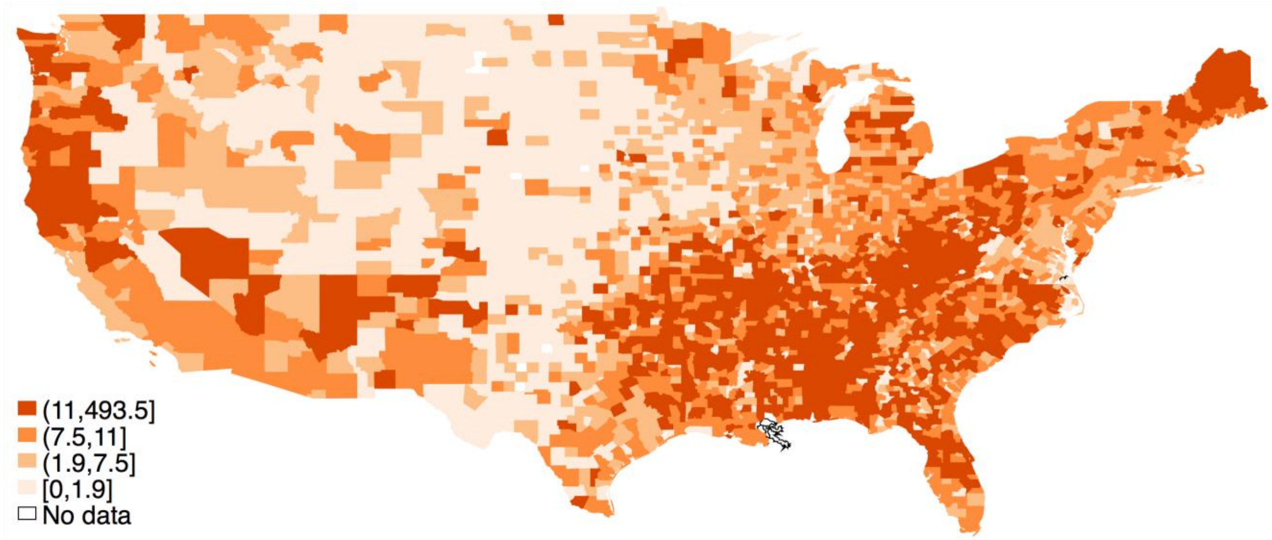
7. FIGURES

Figure 1: Percentage of all SSDI Initial Applications Filed via Internet



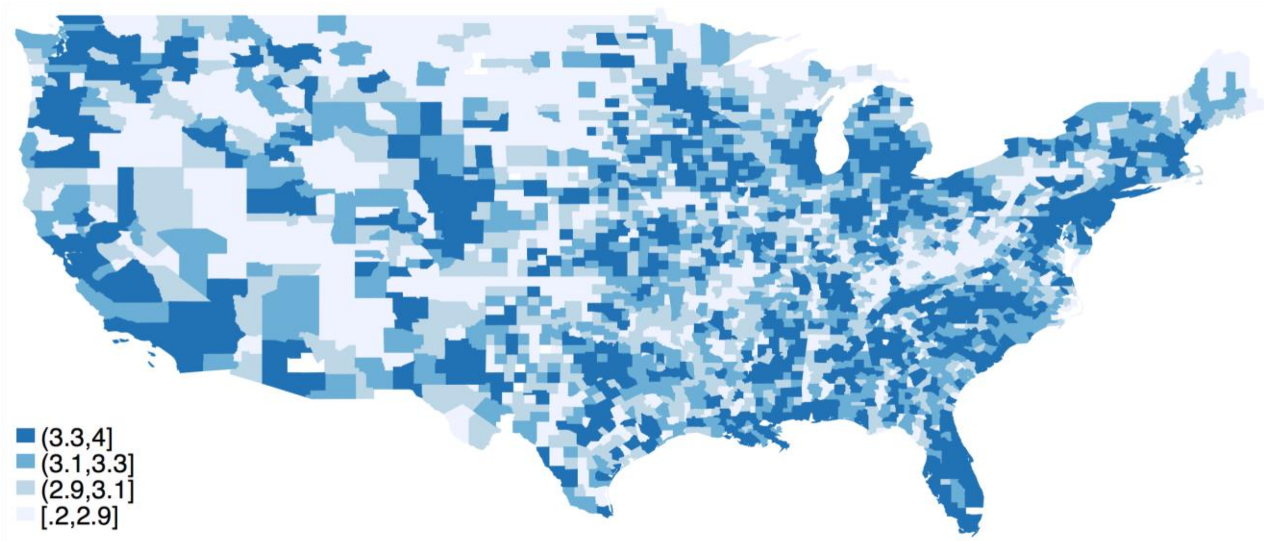
Notes: This figure shows the share of SSDI initial applications filed online, measured nationally at monthly increments. Source: Social Security Administration national-level dataset, www.data.gov.

Figure 2: SSDI Applications per 1000 adults, 2008



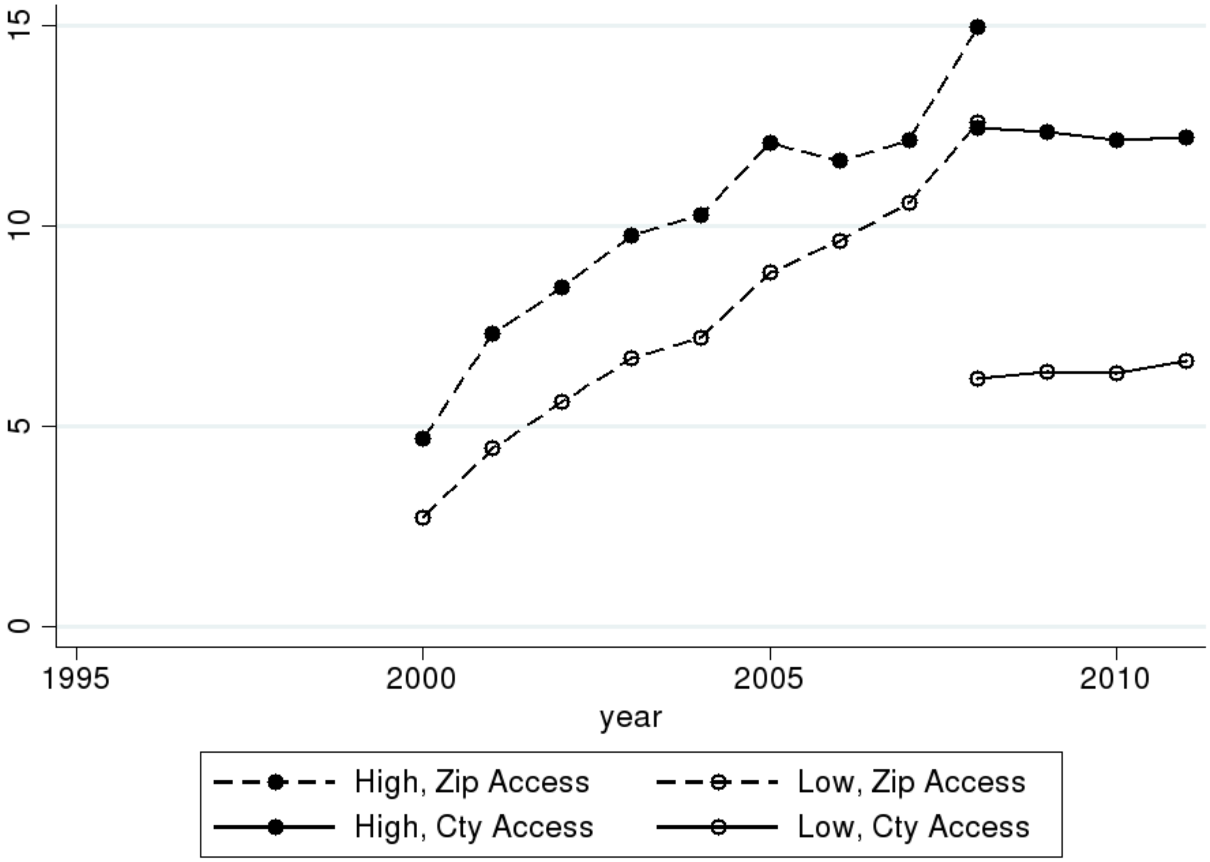
Notes: This map shows the number of SSDI Applications per 1,000 working-age adults in 2008, at the county level. Counties with fewer than 10 overall applicants have suppressed data and appear as missing in the map. Source: Social Security Administration Disability Research File Form 831.

Figure 3: Internet Access (PROV1 Measure), 2008



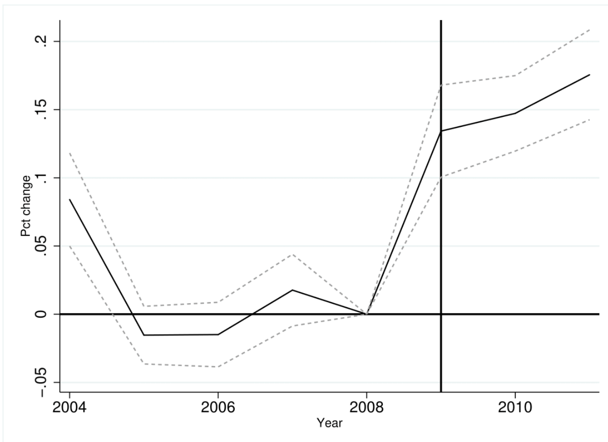
Notes: This map shows the distribution of PROV1, a logged measure of internet connectivity, at the county level. The measure aggregates zip-code level information on the number of high-speed internet providers with respect to population. See text for details on the construction of the measure. Source: Federal Communications Commission Form 477 files.

Figure 4: Internet Connectivity Over Time

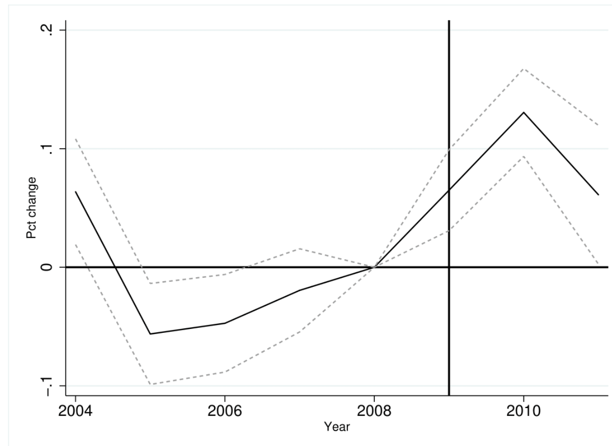


Notes: This graph shows trends in the average number of residential internet providers (PROV2) by county prior to 2008, and the count of residential high-speed internet connections per county from 2008-2011. Trends are shown separately for counties with high and low internet connectivity. Counties with high internet connectivity are identified as those with an above-median number of providers in 2008. Source: Federal Communications Commission Form 477 files.

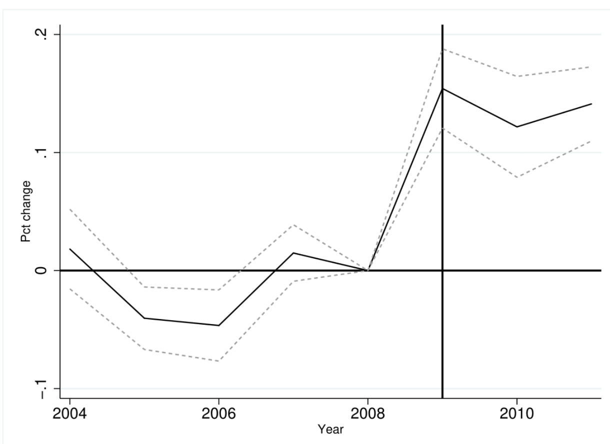
Figure 5: Event Study Estimates of Applications, Appeals and Awards



a) Applications



b) Appeals



c) Awards

Notes: This figure shows coefficients of the interaction terms of PROV1 in 2008 interacted with year dummy variables for each year before and after the introduction of iClaim. Dashed lines indicate 95 percent confidence intervals, and 2008 is normalized to zero. Solid vertical line indicates introduction of iClaim in 2009. The F-statistics and p-values on a test that the pre-2008 coefficients are all zero are 1.84 (0.14) for applications, 3.3 (0.03) for appeals, and 5.9 (0.002) for awards. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files.

8. TABLES

Table 1: Summary Statistics

	All	Pre 2009		Post 2009	
		Low	High	Low	High
SSDI Applications	7466.3	1287.7	7587.6	1623.3	8965.2
	(12380.8)	(3063.8)	(12131.0)	(3874.3)	(13795.5)
SSI Applications/1000 working age adults	9.982	13.37	8.981	15.08	10.46
	(4.869)	(8.822)	(3.233)	(13.34)	(3.553)
SSDI Appeals	1040.8	208.2	1054.1	252.2	1247.9
	(1495.5)	(505.8)	(1415.3)	(623.3)	(1709.7)
SSDI Appeals/1,000 working age adults	1.869	2.616	1.734	2.624	1.877
	(1.248)	(2.313)	(1.003)	(2.659)	(1.006)
SSDI Awards	1855.3	297.5	1901.8	386.6	2207.1
	(2895.9)	(769.5)	(2866.9)	(974.9)	(3165.9)
SSDI Awards/1,000 working age adults	2.887	2.898	2.675	3.477	3.164
	(1.465)	(3.140)	(1.022)	(3.525)	(1.141)
Unemployment Rate	0.0682	0.0616	0.0510	0.103	0.0932
	(0.0283)	(0.0196)	(0.0141)	(0.0304)	(0.0242)
Workers in Mass Layoffs	6119.3	306.3	4689.8	485.0	10024.6
	(18714.7)	(616.7)	(10909.3)	(978.0)	(28143.6)
Population Share Black	0.132	0.120	0.132	0.119	0.135
	(0.128)	(0.168)	(0.123)	(0.165)	(0.123)
Population Share White	0.806	0.842	0.806	0.840	0.796
	(0.140)	(0.179)	(0.135)	(0.177)	(0.135)
Population Share under 30	0.411	0.401	0.415	0.393	0.409
	(0.0456)	(0.0529)	(0.0444)	(0.0547)	(0.0442)
Population Share 30-44	0.205	0.193	0.212	0.183	0.199
	(0.0231)	(0.0182)	(0.0223)	(0.0183)	(0.0216)
Population Share 45-54	0.145	0.144	0.145	0.144	0.145
	(0.0132)	(0.0142)	(0.0128)	(0.0140)	(0.0135)
Population Share over 55	0.239	0.262	0.229	0.281	0.247
	(0.0493)	(0.0517)	(0.0462)	(0.0557)	(0.0479)
PROV1 Internet Measure (logged)	3.48	3.70	3.26		
	(0.31)	(0.12)	(0.28)		
PROV2 Internet Measure	13.94	16.49	11.39		
	(3.21)	(1.89)	(2.02)		
Observations	24445	6061	9223	3631	5530

Notes: All summary statistics reflect county-level means, weighted by county population. Standard deviations are in parentheses. Columns 2-5 split the results by whether counties had above or below median internet connectivity in 2008 (high and low, respectively). Data for the two internet access measures (PROV1 and PROV2) come from 2008 and are not available for years after 2008. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files.

Table 2: Effect of iClaim with on Applications, Appeals and Awards with Fixed 2008 Provider Measure

	Ln(Applications)	Ln(Appeals)	Ln(Awards)	Award Rate
Internet Measure PROV1: logged count of providers in 2008				
$iClaim_t$*$PROV1_{c,2008}$	0.0501***	0.0891***	0.0635***	0.00874*
	(0.0159)	(0.0332)	(0.0215)	(0.00492)
Internet Measure PROV2: linear count of providers in 2008				
$iClaim_t PROV2_{c,2008}$	0.00435***	0.00842***	0.00636***	0.00110**
	(0.00142)	(0.00299)	(0.00195)	(0.000503)
Y-Mean	7.715	6.068	6.556	0.323
R-Squared	0.998	0.994	0.996	0.713
N	24412	24412	24412	24412

Notes: Outcome variables are listed at the top of each column. Award Rate is calculated as the share of applications that were awarded benefits. Panel A uses PROV1, the logged count of residential internet providers, while Panel B uses PROV2, a linear count of internet providers. Details on the calculation of PROV1 and PROV2 are described in Section 3. All regressions control for age distribution, race composition, county unemployment rate, total annual county layoffs, as well as year and county fixed-effects and county-specific linear time trends. Regressions are weighted by population. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table 3: Effect of iClaim by Age Group ($Post_t$ x $PROV1_{c,2008}$)

	Ln(Applications)	Ln(Appeals)	Ln(Awards)	Award rate
All Ages	0.0501***	0.0891***	0.0635***	0.00874*
	(0.0159)	(0.0332)	(0.0215)	(0.00492)
Under 30	0.00715	0.251**	0.121	0.0588**
	(0.0274)	(0.116)	(0.0730)	(0.0279)
Ages 30-44	-0.00736	0.0233	0.100**	0.0417*
	(0.0306)	(0.0477)	(0.0467)	(0.0228)
Ages 45-54	0.0144	0.0448	0.0488	0.0251
	(0.0191)	(0.0412)	(0.0411)	(0.0198)
Ages 55+	0.0566**	0.0549	0.0298	-0.0147
	(0.0226)	(0.0492)	(0.0262)	(0.0177)

Notes: Outcome variables are listed at the top of each column. We use PROV1 as our measure of internet connectivity, which is described in Section 3. Each panel corresponds to regression results from a different age group. All regressions control for age distribution, race composition, unemployment rate, total county layoffs, as well as year and county fixed-effects, and county-specific linear time trends. Regressions are weighted by the age-specific population in the local area. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table 4: Metro vs Non-Metro, using PROV1

	Ln(Applications)	Ln(Appeals)	Ln(Awards)	Award Rate
Non-Metro	0.0519***	0.0099	0.0176	0.0091
	(0.0207)	(0.0500)	(0.0359)	(0.0061)
Metro	0.0297*	0.0587*	0.0483**	0.0008
	(0.0161)	(0.0345)	(0.0237)	(0.0154)

Notes: Outcome variables are listed at the top of each column. In the first row, the sample is all non-CBSA counties, and the second row is all counties in a CBSA; metro status is based on 2010 CBSA definitions. PROV1 is the internet measure used; details on the calculation of PROV1 are described in Section 3. All regressions control for age distribution, race composition, county unemployment rate, total annual county layoffs, year and county fixed-effects, and county-specific trends. Regressions are weighted by population. Standard errors are clustered at the state level. The metro regressions have 13,896 observations in each regression, and non-metro regressions have 10,516. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table 5: Falsification Tests

	PROV1	PROV2
Unemp. Rate	0.0478	0.0026
	(0.4008)	(0.0559)
Share Under 30	-0.00083	-0.00015***
	(0.00061)	(0.00005)
Share 30-44	0.00049	0.00005
	(0.00039)	(0.00004)
Share 45-54	0.00035	0.00007**
	(0.00031)	(0.00003)
Share 55+	-0.000003	0.00004
	(0.00072)	(0.00006)
Log Medicaid Spending	-0.0081	-0.00078
	(0.0245)	(0.0028)

Notes: Outcome variables are listed in each row, and the internet measure used is at the head of the column. All regressions control for year and county fixed-effects, as well as county-level trends. Regressions are weighted by population. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

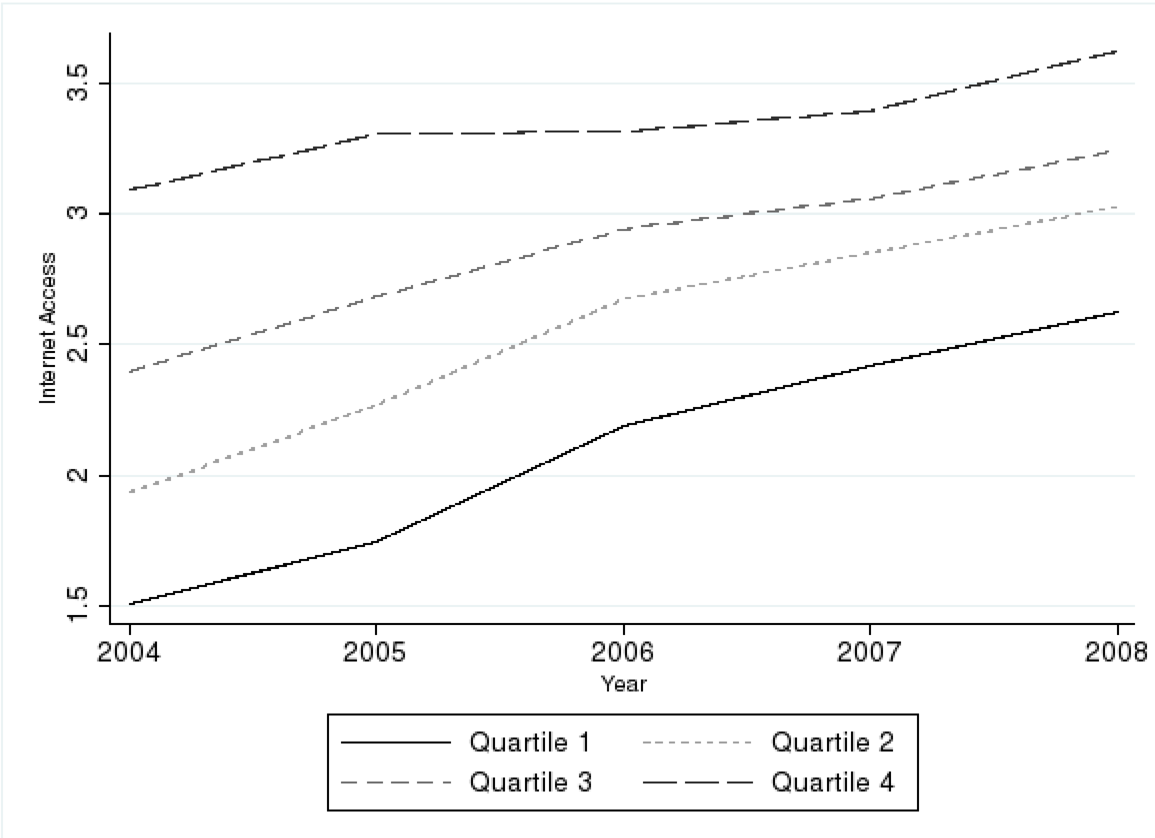
Table 6: Additional Robustness Checks

	Ln(Applications)	Ln(Appeals)	Ln(Awards)	Award rate
Main Result	0.0501***	0.0891***	0.0635***	0.00874*
	(0.0159)	(0.0332)	(0.0215)	(0.00492)
Excluding Labor Market Indicators	0.0501***	0.0937***	0.0635***	0.00886*
	(0.0159)	(0.0333)	(0.0210)	(0.00485)
Time-Varying Controls	0.0599***	0.0810**	0.0678***	0.00697
	(0.0160)	(0.0361)	(0.0239)	(0.00590)
State-year Fixed Effects	0.0603***	0.117***	0.0799***	0.0102**
	(0.0151)	(0.0389)	(0.0152)	(0.00425)
Larger Counties Only	0.0467***	0.0736**	0.0581***	0.00599
	(0.0162)	(0.0334)	(0.0215)	(0.00472)
No Linear Time Trend	0.0697***	0.103***	0.0893***	0.00592
	(0.0196)	(0.0374)	(0.0215)	(0.00653)

Notes: Outcome variables are listed at the top of each column. We use PROV1 as our measure of internet connectivity, which is described in Section 3. Each row shows the main coefficient of interest from a different robustness check, as indicated in the row title. All regressions control for age distribution, race composition, unemployment rate, total county layoffs, as well as year and county fixed-effects, unless otherwise indicated in the robustness check title. Regressions are weighted by the age-specific population in the local area. Standard errors are clustered at the state level. For Row 3, the additional controls are SNAP enrollment, Medicaid and Medicare spending, and rates of obesity and diabetes. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

9 Appendix Figures and Tables

Figure A1: Internet Access Trends, by 2008 Quartile



Notes: This figure shows the average value for PROV1 (described in Section 3) for counties in the first, second, third and fourth quartiles of internet access in 2008. Sources: Federal Communications Commission Form 477 files, Authors' calculations.

Table A1: Summary Statistics from SIPP on DI Applicants

	2005		2010	
	DI Applicant	Rest of Pop	DI Applicant	Pop
Age	45.35	41.48***	44.99	42.18***
Percent Male	43.79%	48.23%**	46.85%	48.61%
Use Internet	37.20	61.37***	42.72	63.98***
Use Internet at Home	31.00	53.89***	36.34	58.21***
Use Internet for Govt. Svcs.	16.11	21.50***	19.84	22.82*
Internet Use by Age				
Age 18-32	55.96%	64.16%	60.02%	67.92%
Age 33-47	39.93%	64.55%	53.08%	66.10%
Age 48-61	28.88%	57.10%	32.42%	59.85%

Notes: Population is 18-65 year olds. Stars in second column indicate whether the values are significantly different between the DI applicant and remaining population. Author's calculations from the 2004 and 2008 panels of the Survey of Income and Program Participation. The 2004 panel asked about internet access in Wave 5 of the panel, which occurred in 2005; the 2008 panel asked about internet access in Wave 6 of the panel. *p<0.10, **p<0.05, ***p<0.01

Table A2: Robustness: excluding labor market indicators, by age

	Ln(Applications)	Ln(Appeals)	Ln(Awards)	Award rate
All Ages	0.0500***	0.0952***	0.0634***	0.00866*
	(0.0158)	(0.0338)	(0.0210)	(0.00484)
Under 30	0.00185	0.255**	0.117	0.0592**
	(0.0288)	(0.116)	(0.0730)	(0.0278)
Ages 30-44	-0.00580	0.0294	0.0989**	0.0416*
	(0.0303)	(0.0473)	(0.0463)	(0.0229)
Ages 45-54	0.0162	0.0505	0.0478	0.0241
	(0.0184)	(0.0413)	(0.0405)	(0.0198)
Ages 55+	0.0577**	0.0642	0.0310	-0.0147
	(0.0231)	(0.0496)	(0.0262)	(0.0175)
N	24412	24412	24412	24412

Notes: Outcome variables are listed at the top of each column. We use PROV1 as our measure of internet connectivity, which is described in Section 3. Each panel corresponds to regression results from a different age group. All regressions control for age distribution, race composition, unemployment rate, total county layoffs, as well as year and county fixed-effects and county-specific time trends. Regressions are weighted by the age-specific population in the local area. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table A3: Robustness: adding additional time-varying controls, by age

	Ln(Applications)	Ln(Appeals)	Ln(Awards)	Award rate
All Ages	0.0597***	0.0829**	0.0676***	0.00697
	(0.0160)	(0.0370)	(0.0239)	(0.00590)
Under 30	0.0337	0.213**	0.140*	0.0564*
	(0.0280)	(0.0901)	(0.0764)	(0.0294)
Ages 30-44	-0.00109	0.0185	0.106**	0.0422*
	(0.0323)	(0.0510)	(0.0498)	(0.0246)
Ages 45-54	0.0230	0.0473	0.0561	0.0220
	(0.0180)	(0.0375)	(0.0453)	(0.0208)
Ages 55+	0.0670***	0.0627	0.0382	-0.0144
	(0.0236)	(0.0551)	(0.0273)	(0.0178)
N	23936	23936	23936	23936

Notes: Outcome variables are listed at the top of each column. We use PROV1 as our measure of internet connectivity, which is described in Section 3. Each panel corresponds to regression results from a different age group. All regressions control for age distribution, race composition, unemployment rate, total county layoffs, as well as year and county fixed-effects and county-specific time trends. Regressions are weighted by the age-specific population in the local area. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table A4: Robustness: adding state-year fixed effects, by age

	Ln(Applications)	Ln(Appeals)	Ln(Awards)	Award rate
All Ages	0.0603***	0.117***	0.0799***	0.0102**
	(0.0151)	(0.0389)	(0.0152)	(0.00425)
Under 30	0.0104	0.308**	0.184**	0.0694**
	(0.0292)	(0.129)	(0.0729)	(0.0309)
Ages 30-44	-0.000150	0.0656	0.121**	0.0481*
	(0.0335)	(0.0514)	(0.0505)	(0.0267)
Ages 45-54	0.0143	0.0745*	0.0729	0.0293
	(0.0198)	(0.0400)	(0.0484)	(0.0209)
Ages 55+	0.0639***	0.0760	0.0353	-0.00940
	(0.0227)	(0.0478)	(0.0279)	(0.0225)
N	24412	24412	24412	24412

Notes: Outcome variables are listed at the top of each column. We use PROV1 as our measure of internet connectivity, which is described in Section 3. Each panel corresponds to regression results from a different age group. All regressions control for age distribution, race composition, unemployment rate, total county layoffs, as well as year and county fixed-effects and county-specific time trends. Regressions are weighted by the age-specific population in the local area. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table A5: Robustness: Larger counties only, by age

	Ln(Applications)	Ln(Appeals)	Ln(Awards)	Award rate
All Ages	0.0467***	0.0736**	0.0581***	0.00599
	(0.0162)	(0.0334)	(0.0215)	(0.00472)
Under 30	-0.0175	0.234*	0.107	0.0657**
	(0.0314)	(0.122)	(0.0749)	(0.0289)
Ages 30-44	-0.0107	-0.00675	0.0910*	0.0446**
	(0.0322)	(0.0489)	(0.0482)	(0.0202)
Ages 45-54	0.0129	0.0268	0.0256	0.00882
	(0.0214)	(0.0441)	(0.0441)	(0.0155)
Ages 55+	0.0492**	0.0435	-0.00415	-0.0194
	(0.0211)	(0.0544)	(0.0277)	(0.0135)
N	18367	18367	18367	18367

Notes: Outcome variables are listed at the top of each column. We use PROV1 as our measure of internet connectivity, which is described in Section 3. Each panel corresponds to regression results from a different age group. All regressions control for age distribution, race composition, unemployment rate, total county layoffs, as well as year and county fixed-effects and county-specific time trends. Regressions are weighted by the age-specific population in the local area. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table A6: Robustness: excluding county-specific linear time trends, by age

	Ln(Applications)	Ln(Appeals)	Ln(Awards)	Award rate
All Ages	0.0697***	0.103***	0.0893***	0.00592
	(0.0196)	(0.0374)	(0.0215)	(0.00653)
Under 30	0.133***	0.243***	0.138***	0.0465***
	(0.0339)	(0.0449)	(0.0338)	(0.0125)
Ages 30-44	0.0395	0.0719**	0.0468	-0.00146
	(0.0249)	(0.0305)	(0.0319)	(0.00768)
Ages 45-54	0.0593***	0.103***	0.126***	0.0252**
	(0.0191)	(0.0307)	(0.0285)	(0.00949)
Ages 55+	0.119***	0.102**	0.180***	0.00313
	(0.0251)	(0.0413)	(0.0330)	(0.0107)
N	24412	24412	24412	24412

Notes: Outcome variables are listed at the top of each column. We use PROV1 as our measure of internet connectivity, which is described in Section 3. Each panel corresponds to regression results from a different age group. All regressions control for age distribution, race composition, unemployment rate, total county layoffs, as well as year and county fixed-effects. Regressions are weighted by the age-specific population in the local area. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table A7: Sensitivity to Imputation, Applications

	Outcome: Disability Application			Outcome: Suppressed
	Main	No Impute	Bal. Panel	Main
All Ages	0.0501***	0.0501***	0.0495***	0.000103
	(0.0159)	(0.0160)	(0.0159)	(0.000246)
	24412	24359	23842	24412
Under 30	0.00715	0.0446*	0.0218	0.0397***
	(0.0274)	(0.0227)	(0.0247)	(0.0114)
	24412	14656	7112	24412
Ages 30-44	-0.00736	0.0490	0.0390	0.0446***
	(0.0306)	(0.0297)	(0.0294)	(0.0135)
	24412	16368	12536	24412
Ages 45-54	0.0144	0.0583***	0.0520***	0.0325***
	(0.0191)	(0.0176)	(0.0185)	(0.00785)
	24412	17356	12656	24412
Ages 55+	0.0566**	0.0601***	0.0564***	0.0108**
	(0.0226)	(0.0187)	(0.0186)	(0.00501)
	24412	17893	12456	24412

Notes: Column 1 shows the main results. Column 2 excludes observations where the outcome was imputed due to a count under 10. Column 3 creates a balanced panel of counties that had no imputed outcome values across the entire study period. Column 4 has the outcome be that the SSDI outcome was imputed. All regressions control for year and county fixed-effects, as well as county-level trends. Regressions are weighted by population. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table A8: Sensitivity to Imputation, Appeals

	Outcome: Disability Appeal			Outcome: Suppressed
	Main	No Impute	Bal. Panel	Main
All Ages	0.0891***	0.0860**	0.0774**	-0.00130
	(0.0332)	(0.0324)	(0.0320)	(0.00191)
	24412	24105	21262	24412
Under 30	0.251**	0.0770	0.0265	0.0115
	(0.116)	(0.0552)	(0.115)	(0.0255)
	24412	3319	1240	24412
Ages 30-44	0.0233	0.0572	0.0357	0.0705***
	(0.0477)	(0.0516)	(0.0523)	(0.0197)
	24412	8482	5232	24412
Ages 45-54	0.0448	0.0810**	0.0581	0.0493***
	(0.0412)	(0.0373)	(0.0391)	(0.0178)
	24412	10069	5864	24412
Ages 55+	0.0549	0.0255	-0.0194	0.0299*
	(0.0492)	(0.0500)	(0.0548)	(0.0174)
	24412	6192	3096	24412

Notes: Column 1 shows the main results. Column 2 excludes observations where the outcome was imputed due to a count under 10. Column 3 creates a balanced panel of counties that had no imputed outcome values across the entire study period. Column 4 has the outcome be that the SSDI outcome was imputed. All regressions control for year and county fixed-effects, as well as county-level trends. Regressions are weighted by population. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01

Table A9: Sensitivity to Imputation, Awards

	Outcome: Disability Award			Outcome: Suppressed
	Main	No Impute	Bal. Panel	Main
All Ages	0.0635***	0.0632***	0.0609***	0.0000731
	(0.0215)	(0.0215)	(0.0214)	(0.000651)
	24412	24236	22249	24412
Under 30	0.121	0.0328	0.0593	0.00803
	(0.0730)	(0.0425)	(0.0623)	(0.0159)
	24412	4396	1736	24412
Ages 30-44	0.100**	0.0118	-0.00729	0.0259**
	(0.0467)	(0.0473)	(0.0439)	(0.0101)
	24412	5550	3408	24412
Ages 45-54	0.0488	0.0483	0.0429	0.0295**
	(0.0411)	(0.0304)	(0.0314)	(0.0145)
	24412	8506	4736	24412
Ages 55+	0.0298	0.0641**	0.0420*	0.0431***
	(0.0262)	(0.0251)	(0.0246)	(0.0154)
	24412	12638	6728	24412

Notes: Column 1 shows the main results. Column 2 excludes observations where the outcome was imputed due to a count under 10. Column 3 creates a balanced panel of counties that had no imputed outcome values across the entire study period. Column 4 has the outcome be that the SSDI outcome was imputed. All regressions control for year and county fixed-effects, as well as county-level trends. Regressions are weighted by population. Standard errors are clustered at the state level. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files. *p<0.10, **p<0.05, ***p<0.01