

# The Effect of Lower Transaction Costs on SSDI Application Rates and Participation

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## Abstract

We analyze how Social Security Disability Insurance (SSDI) application behavior was affected by iClaim, a 2009 innovation that streamlined the online application process and lowered costs to apply and appeal. We compare application rates before and after 2009 between counties with differential changes in application costs due to high speed internet access. While higher exposure to the online application led to a small increase in applications and more appeals, but lower award rates. These results suggest that in counties with higher internet access, iClaim may have increased the share of marginal SSDI applicants or affect the quality of initial applications.

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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 ineligible individuals receiving benefits, and other truly eligible 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 DI-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. In addition to the volume of information required in order 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 Social Security Disability Insurance (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. Additionally, in a 2011 survey of retired applicants who used iClaim, 99% of respondents reported their experience with the system to be excellent, very good, or good (Lipowicz 2011).

We take advantage of this significant improvement in the online application process to examine how a change in transaction costs affects application and participation in SSDI. Using county-level data from the Social Security Administration (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.

We find that counties with internet access one standard deviation above the mean experienced an increase in applications of approximately 2 percent after the introduction of iClaim. We find larger changes in patterns of appeals and acceptances: following the introduction of the online application, we observe that a 1 standard-deviation increase in internet access is associated with a 5 percent increase in the number of appeals and a 6 percent decline in the number of awards. Taken together, we find that the share of accepted awards dropped by 8 percent following a one standard deviation increase in internet access. We explore heterogeneity in these patterns by broad age categories and find the largest changes occurred among applicants over 55. Together, these results suggest that while the decrease in transaction costs increased the volume of applications, it also affected the composition of the applicant pool, and also potentially the quality

of applications that were filed. 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. However, the reduction in the award rate suggests that ultimately, many of these appeals were not successful.

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. 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 and discusses next steps for the project.

## **2 Transaction Costs and Takeup of Public Programs**

There is a substantial literature on takeup of public programs and the associated transaction costs. Nichols and Zeckhauser (1982) argue that ordeals such as administrative burden and qualification processes impose larger costs on ineligible applicants than on intended recipients, and serve as an effective mechanism for sorting out “impostors”. For example, Parsons (1991) examines whether an increase in initial denial rates of SSDI applications can serve as an ordeal to successfully screen out ineligible applicants. If an applicant is truly able to work, foregoing work for a longer application and potential appeals process poses a larger cost, and could discourage able individuals from applying. Using a sharp increase in denial rates in 1977 as a natural experiment, Parsons (1991) finds that the increase in denial rates reduces subsequent applications. Theoretically, the gains in targeting efficiency could outweigh the welfare losses associated with the increased costs for eligible applicants. However, any mechanism to improve targeting efficiency likely could result in ineligible individuals receiving benefits and vice versa.

Akerlof (1978) highlights that similar to an ordeal mechanism, a categorical requirement, or tag, can improve targeting efficiency. However, measuring the categorical require-

ment is not always straightforward. 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 literature concludes that the optimal design of a public benefits program should include some degree of complexity, so long as the welfare gains of more efficient screening will exceed the associated costs (Kleven and Kopczuk, 2011; Diamond and Sheshinski, 1995).

A related literature examines how technology and high-speed internet change individuals' participation in public programs and the labor force. Ebenstein and Stange (2010) exploit cross-state variation in changes that increased the convenience of applying for unemployment insurance (UI), including the introduction of online and telephone-based application processes. The authors do not find significant changes in UI take-up, nor do they find any changes in the composition of UI applicants. This suggests that factors beyond transaction costs may be barriers to take-up of UI. Kopczuk and Pop Eleches (2007), on the other hand, use time variation in the roll-out of electronic filing for state income taxes and find that the increased availability of electronic tax filing had a significant impact on participation in the Earned Income Tax Credit (EITC). Other work has found that high-speed internet access increases college preparation and application activity for high-SES high school students, (Dettling et al. 2015) and increases labor supply among married women (Dettling 2016).

The role of technology and internet could play a more important role in the disability application process given the physical and mental challenges faced by this population. On one hand, the transaction costs of traveling to an in-person field office could be particularly high, meaning that the increased convenience of applying from home could be particularly important for this population.<sup>1</sup> On the other hand, this group may face

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<sup>1</sup>In ongoing work, Deshpande and Li (2016) exploit geographic variation to examine the effect of Social Security field office closures on SSDI applicants and recipients. They find that disability applications fall by

disproportionate challenges in accessing or using technology, meaning that the gains from the convenience of applying online could be small. Our identification strategy exploits variation in potential internet access, and we examine variation in application and recipient behavior by different age groups in order to understand whether the introduction of the online application had heterogeneous impacts on the disability population.

Additionally, 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 2012). These third-party preparers could be more likely to 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. We examine changes in applications, appeals and awards to examine potential effects of this change at all stages of the process.

### **3 Data**

Using publicly available sources as well as restricted-use data from the Social Security Administration (SSA), we construct a panel dataset comprising all US counties between 1995 and 2011.

#### **3.1 Outcomes: SSDI Applications**

Our main outcomes are compiled from the Disability Research File, and include county-level counts of applications, appeals, and allowances by gender and broad age groups. These counts are reported in the initial year an application was filed, rather than the year in

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approximately 11 percent in zip codes that experienced a closing, and that allowances fall by 10 percent.

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 on application counts.

To maintain the confidentiality of SSDI applicants, SSA suppressed cells in the county-level aggregation of the data if the count was less than 10. In order to allow us to observe aggregate counts, however, the data had counts suppressed for all subgroups if at least one subgroup had a count of less than 10, but reported the aggregate number.<sup>2</sup>

Missing data 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, 31-44). Approximately half (47 percent) of counties had non-missing data in all years.

These missing data do not reflect inconsistencies in the data, but are rather the results of small numbers of applications. Our preferred specification drops these missing observations; however, we explore other strategies, such as treating these counties as having zero applications, and find very similar results.<sup>3</sup>

### **3.2 Measures of Connectivity**

In order to measure local internet connectivity, we use reports from the Federal Communications Commission (FCC) on the number of high-speed internet providers by zip code. While it is an indirect measure of internet connectivity, the count of internet providers

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<sup>2</sup>For example, if in county X in year YYYY there were 5 males under 30 years old who applied and 15 females, the cell for males under 30 and the cell for females under 30 would be suppressed. However, the cell for total applications under 30 would show a value of 20. This ensures that there is not complementary disclosure.

<sup>3</sup>We also explored imputing the missing data with randomly chosen numbers between 0 and 9, with similar results.

captures the extent of variation in the supply side of high-speed internet access, the main constraint on access during the time frame of our analysis. Other research has also demonstrated the count of internet providers as an effective measure of internet access (Dettling et al., 2015; Iyengar and Westwood, 2015). The FCC publishes zip-code level records of the number of filers of Form 477, which covers high-speed internet service providers with over 250 high-speed lines. To protect confidentiality, the data are suppressed if there were fewer than four providers in a zip code. We count these zip codes as having one provider in the data. As noted by Dettling et al. (2015), there is not a strong correspondence between zip-code level counts of high-speed internet service providers and population. Instead, we adapt the strategy in Dettling et al. (2015) and construct measures of connectivity scaled by county population size.

We aggregate zip code level counts of internet providers to the county level in two ways, both of which are described with the equation below.

$$PROV_{ct} = \frac{\sum_{j \in c} f(N_{jt}) \times a_{jc} \times P_{jt}}{\sum_{j \in c} a_{jc} \times P_{jt}} \quad (1)$$

In equation 1,  $N_{jt}$  is a count of the internet providers from FCC data in zipcode  $j$  and year  $t$ , and  $a_{jc}$  is the allocation factor of a zipcode  $j$  to county  $c$ .<sup>4</sup>  $P_{jt}$  is the population of zipcode  $j$  in year  $t$ . The construct  $PROV_{ct}$  is thus essentially a weighted average of per-capita connectivity at the zip code level.

We construct two measures of internet connectivity by using different functions for  $f(N_{jt})$ . We choose  $f(N_{jt})$  such that  $f(1) > 1$ , and  $\frac{\partial f(N_{jt})}{\partial N} > 0$ . This simply means that a higher number of providers means that households experience better connectivity.

Our first measure (PROV1) specifies a logarithmic function  $f(N_{jt}) = \log(f(N_{jt}) + 1)$ . Thus, PROV1 incorporates the idea that the connectivity of households is likely increasing in the number of providers, but at a decreasing rate. PROV1 is our preferred measure

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<sup>4</sup>The allocation factor is the share of the zip code population in 2000 that resides in county  $c$ . We use Census data to determine these factors.

of connectivity, because it is likely that there are diminishing gains from the entry of additional internet providers in terms of the connectivity of an area. However, we also consider a second measure (which we call PROV2), which specifies a linear function, such that  $f(N_{jt}) = N_{jt}$ . Both measures yield similar results.

In our main specifications, we fix the internet exposure at 2008 levels, which is the first year of data and also the year prior to the introduction of iClaim. Fixing the internet exposure in 2008 abstracts from endogenous internet connectivity growth across areas.<sup>5</sup>

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.<sup>6</sup>

### 3.3 Other Data

We supplement these main sources of data with additional information on county demographics. 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.

### 3.4 Summary Statistics

The first two columns of Table 1 displays summary statistics in the year before the policy change (2008) and two years afterwards (2011). In an average county there were 527

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<sup>5</sup>Our results are very similar if we allow it to vary by year.

<sup>6</sup>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.

SSDI beneficiaries, accounting for 0.7 percent of the working age population. In 2008 approximately five adults applied to SSDI per 1,000 working-age residents. This number grew by 11 percent to 5.4 applicants per 1000 working-age residents by 2011. The number of appeals did not increase. On average, there was approximately one SSDI award per 1,000 working-age residents, with an award rate of 15.5 percent. The award rate grew by 1.4 percentage points between 2008 and 2011.

Figure 2 shows the distribution of SSDI applications across the country. As has been documented in prior work (Strand, 2002; Rupp, 2012; Gettens et al., 2016), the South and Midwest have particularly high SSDI application rates, but there is a lot of geographic variation across the rest of the country as well.

Table 1 also shows our different measures of internet connectivity. In 2008 there were 4.5 internet connections for each 10 households, which increased by about one connection per 10 households by 2011. The other measures of connectivity, constructed from the number of high-speed providers, show a similar story. Our preferred measure of internet access (PROV1) suggests no change between 2008 and 2011. However, we do find a steady increase in the measure between 2004 and 2007, from a low of 1.51, and then a flat profile between 2008 and 2011. This suggests that the major gains in internet connectivity by this measure occurred prior to 2008. Despite the fact that there is little change in internet access over time, Figure 3 shows a large amount of geographical heterogeneity in our preferred measure of connectivity, PROV1. Our other measure, PROV2, grows steadily throughout the time period.

The final two columns of Table 1 splits counties by whether they had above or below median connectivity as measured by our PROV1 internet connectivity measure. Counties that had above-median connectivity are disproportionately urban, and the higher populations lead to higher application counts. As a share of the population, above-median counties also tended to have slightly more SSDI beneficiaries and applications as a share of the population. Counties with higher connectivity also had approximately double the

rate of appeals and awards as low-connectivity counties at the baseline. Not surprisingly, high-connectivity counties were different in demographic and economic characteristics than low-connectivity counties: high connectivity counties had slightly lower unemployment rates and a higher proportion of minorities. However, the age distribution of the population is similar in high and low connectivity counties.

## 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 put in place. We use internet access to measure the degree of exposure to the reduction in transaction costs. In an extreme example, an individual who cannot access the internet anywhere in their county would be unaffected by the iClaim innovation. Specifically, we estimate the following equation:

$$y_{ct} = \beta \times iClaim_t \times Prov_{c,2008} + \theta X_{ct} + \gamma_c + \eta_t + \epsilon_{ct} \quad (2)$$

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 put into place, while  $Prov_{c,2008}$  is one of the two measures in equation 1, fixed at the 2008 level of internet connectivity.<sup>7</sup> We also include a number of time-varying controls at the county level,  $X_{ct}$ , such as the size of the labor force, the unemployment rate, and the age distribution of the county, since these all affect the potential pool of disability applicants. We include county and year fixed-effects, and  $\epsilon_{ct}$  is the error term, which we cluster at the state level (Bertrand et al. 2004). Our coefficient of interest is  $\beta$ , which shows the differential effect of the iClaim policy in counties with more internet access compared with less connected counties.

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<sup>7</sup>We also estimated equations where we allowed our measure of internet connectivity to vary over time ( $Prov_{ct}$ ), and got very similar results.

There are two main identifying assumptions. First, we assume potential workers do not delay their application in anticipation of the policy change, which would induce positive bias in our estimate. Second, we assume that pre-existing internet access levels in a county are not correlated with the likelihood of disability applications. Particularly for our time period, this does not seem to be an issue, for a few reasons. A number of papers have shown that during this time period high-speed internet access was expanding, implying the presence of internet service providers had more to do with supply-side constraints than demand.<sup>8</sup> Table 1 shows that at baseline, application rates are comparable for areas with internet connectivity levels above and below the median.

There are three main hypotheses of interest. First, we examine how the change in transaction costs affected the number of applications and appeals for disability insurance. Second, we observe whether the policy changed the award rate for disability insurance applicants. Third, we explore whether certain age groups, who might have different propensities to be disabled or apply for disability insurance, may see different effects.

The first hypothesis is straightforward to test, and just requires regressing application and appeal counts in the equation above. The second requires comparing the relative magnitudes of  $\beta$  from the regressions with applications and awards as the outcomes, to measure how the award rate (*Awards/Applications*) has changed. The change in the award rate can be expressed by the following equation:

$$\% \Delta AwardRate = \% \Delta Awards - \% \Delta Applications$$

We also explicitly use the award rate as an outcome in estimation of equation 2.

The effect of iClaim on award rates is theoretically ambiguous. If the application costs were primarily preventing workers who would have qualified for disability to apply, then the award rate should increase after iClaim reduces the application costs. However, if the

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<sup>8</sup>For a discussion of this assumption, see Dettling et al. (2015); also see Faulhaber (2002); Greenstein and Prince (2006); and Grubestic and Murray (2002).

decrease in costs instead induces individuals with more marginal disability cases to apply, but these individuals ultimately are not awarded benefits, there could be a decrease in the award rate. Finally, because we have data on application and award counts by age group, we can isolate for which age groups the effect is largest.

One important consideration for our methodology is that the iClaim policy occurs during the Great Recession, which could affect our results in a few ways. First, individuals who lost their jobs during the Great Recession may be less likely to apply for disability insurance, since they were able to collect unemployment insurance for a longer spell. Second, individuals who did not receive unemployment insurance may apply at a higher rate. We will address concerns about the effect of the Great Recession by controlling for time-varying measures of the employment-population ratio and a measure of mass layoffs. Our assumption is that conditional on these controls, the Great Recession did not have a differential impact on areas with higher or lower levels of internet connectivity. As another way to compare counties within a state with similar labor market conditions, we perform a robustness check including state-year fixed effects.

## 5 Results

Table 2 shows estimates from equation 2 for our main outcomes, applications, appeals and awards. Panel A shows results using the provider estimate PROV1, while Panel B shows results using the internet provision PROV2. A clear pattern emerges from these results. First, overall applications increase following the change in policy. The coefficient of 0.057 means that a 1-percent increase in the number of providers increases applications after 2009 by approximately .05 percent. To understand the effect of a more meaningful change in access to internet, the standard deviation on PROV1 from Table 1 in the post-period represents approximately a 30 percent change in the number of internet providers. 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 2 percent.

We also find that the policy leads to a higher number of appeals being filed in counties that have better high-speed internet access. In addition to allowing initial applications to be filed online, the iClaim policy also encouraged appeal materials to be filed online. Our estimates suggest that areas with a standard-deviation higher level of internet access saw approximately a 5 percent increase in appeals after the introduction of iClaim.

Given the increase in applications and appeals, we may expect awards to increase, although not one-for-one. In fact, we see award counts decrease: our estimates suggest that awards decreased by 3-6 percent for a one standard deviation increase in internet access. Comparing applications and awards, the final column of Table 2 shows that the share of applications that was accepted for SSDI benefits also decreased. A one standard deviation increase in internet connectivity led to an eight percent decrease in the award rate.

A likely reason for the drop in the award rate following the introduction of iClaim is that the policy affected the composition of applicants. In particular, we expect that the share of eligible applications fell while ineligible applications rose by more. On the other hand, it could be that individuals who apply online at home may submit lower quality applications than they would have if they applied in person. For example, a field office representative might better understand how to highlight the most important information for the reviewer, or provide a more sufficient level of detail.

To further explore this hypothesis, and to examine which portions of the population are driving these effects, Table 3 shows the effects for applications, appeals and awards by age group, using only PROV1.<sup>9</sup> Each age group is in a separate panel, and each column is a different outcome. First, we find a significant and positive effect on appeals across every age group. While the confidence intervals overlap between age groups, the point estimate is largest for applicants under 30. For this age group, a one standard-deviation

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<sup>9</sup>Results using PROV2 are available upon request.

increase in internet access led to an increase in appeals by approximately 9 percent. This larger effect for the youngest applicants could reflect the fact that they are most likely to be comfortable using the internet. Second, there is a significant increase in applications for the 30-44 and 55 and over age groups, with the largest effect of a nearly 3 percent increase in applications for those over 55. These results are consistent with the fact that older workers could be most likely to consider applying for SSDI and thus be more responsive to a decline in application costs. While the overall sample shows a significant decline in awards, we do not find a significant effect on awards for the 55 and older subgroup.

The final column of Table 3 shows that the drop in award rate following iClaim is centered on the oldest and youngest groups of SSDI applicants. Applicants under 30 and applicants over 55 both saw large and statistically significant drops in the award rate, of equal magnitude. There are also negative coefficients for applicants between 30 and 54 years old, though these results are smaller and not statistically significant. Because the online application led to the largest increase in applications among individuals over 55, the decline in the award rate could indicate that the new applications filed came from more marginal applicants. Because the results do not show a significant increase in applications for younger applicants, the decline in award rate could result if younger applicants filed a lower quality of initial application online.

The results tell the following story. First, the improved online application led to an increase in the number of initial applications, as well as a substantial increase in the number of appeals. This first result is a response to the lower costs of applying (and appealing) for DI. Despite the increase in applications, we also find that the number of awards and the award rate decreased. This suggests that the decrease in application costs caused individuals to submit less-qualified applications for disability insurance.

We find the largest effect on appeals for the youngest applicants, who could be most comfortable using the internet, and for the oldest applicants, who could be most at risk for applying for SSDI. The large effects on appeals suggest that online applications could have

a larger impact on transaction costs for attorneys or other third party preparers, making it easier to appeal in more marginal cases.

## 5.1 Robustness Checks

The main possible violation of our research design is that areas with high and low internet connectivity had differential trends in the outcome variable before 2008, which would lead us to falsely attribute an effect to the introduction of iClaim. To examine whether there are differential trends in high and low-exposure counties, we estimate the following regression:

$$y_{ct} = \sum_{i=2004}^{2011} \beta_i \mathbb{1}(Year = i) \times Prov_{ct} + \theta X_{ct} + \psi Prov_{ct} + \gamma_c + \eta_t + \epsilon_{ct} \quad (3)$$

This is a similar analysis as in the previous section, but in an event study framework. To normalize our coefficient to the year before the policy was put into place, we omit the coefficient for 2008, so all the coefficients are in relation to 2008 levels. Figures 4 through 6 show the pre-trend graphs for the overall sample.<sup>10</sup> From the results, it does not appear as though there is a strong pre-trend in any of the outcome variables, which is encouraging. The negative effect on appeals during the pre-trend suggests that individuals in counties with better high-speed internet access had lower rates of appeal prior to iClaim, but that trend is reversed by a large increase in appeals following the introduction of iClaim.

Another concern is that controlling for county unemployment rates and mass layoffs is not sufficient to capture the labor market conditions in an area. To ensure that we are comparing counties with similar economic conditions, we estimate equation 2 and include state-year fixed effects. The inclusion of these fixed effects means that we are comparing counties within the same state that have different internet connectivity levels.

Table 4 show our results using state-year fixed effects. While the coefficient on ap-

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<sup>10</sup>Pre-trend graphs for age-specific regressions are available upon request.

plications decreases in magnitude and becomes statistically insignificant, the remaining coefficients remain unchanged. These results suggest that some of the increase in applications could have been due to local labor market effects, but local labor market conditions do not affect our estimates on appeals or awards in a meaningful way.

## 6 Discussion

The findings in this paper provide evidence that lowering the transaction costs associated with applying for SSDI has a significant impact on the application process. First of all, we find that counties with internet access that is 1 standard deviation higher than the mean experienced approximately a 2 percent increase in applications. This suggests that the online application lowered the ordeal associated with applying for SSDI. A 1 standard deviation increase in high-speed internet access is also associated with approximately a 5 percent increase in appeals, and a 3-6 percent decline in awards. These findings imply that the increase in applications was driven by individuals who are less likely to be determined eligible for benefits by the SSDI screening process either at the initial stage or the appeal stage. As a result, the lower ordeal costs associated with applying for SSDI may have come at the expense of a decline in targeting efficiency of the application process. Indeed, we find a substantial decline in the overall award rate, of eight percent.

Our results suggest that additional applications or appeals may have come from individuals on the margin of being accepted to SSDI, and would likely not have applied if required to file the forms in person. For these individuals, the online application may have been just enough of a reduction in cost to induce applications, and thus changed the overall composition of individuals who decide to apply. We find the effects of the online application are largest among applicants over the age of 55. Since SSDI participation is highest among this age group (Rupp, 2012), our results suggest that these oldest applicants could be more likely to be on the margin of applying for DI, and were induced to apply

by the online application. The decline in awards without a corresponding increase in applications for younger applicants suggests that the increased convenience of applying online could also have affected the quality of initial applications that were filed.

These results suggest that the online application likely did reduce the complexity of the SSDI application, but that this change may not have been targeted towards individuals who face the highest costs. Expansions of government services online might not increase accessibility in predictable ways, since some individuals have low computer literacy or no internet access, and these groups may be particularly in need of disability insurance.

The results also suggest that the online process significantly reduced the costs of filing an appeal. 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 to the lower appeal costs. There is scope for future work to better understand who decides to appeal the initial SSDI decision, and to understand what resources are needed to appeal.

However, the decline in the award rate suggests that, ultimately, many of these applications and appeals were unsuccessful. Additionally, the increase in appeals and associated decline in awards likely indicates that the online application has led to an increased workload and administrative cost on the system. As a result, while the online application process lowers application costs for the applicant, its effects on overall screening and transaction costs are ambiguous. The efficiency gains of the online application could likely be combined with additional efforts to increase in-person assistance or outreach efforts to improve the efficiency of the application process for individuals who were not targeted by this reform.

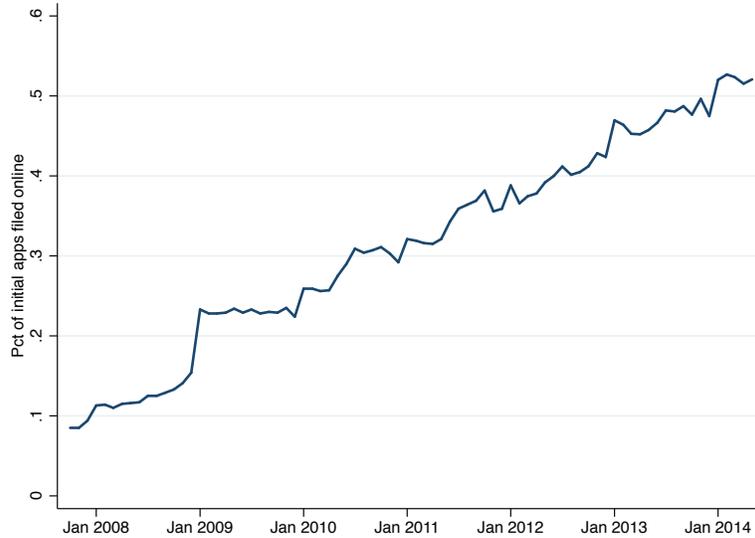
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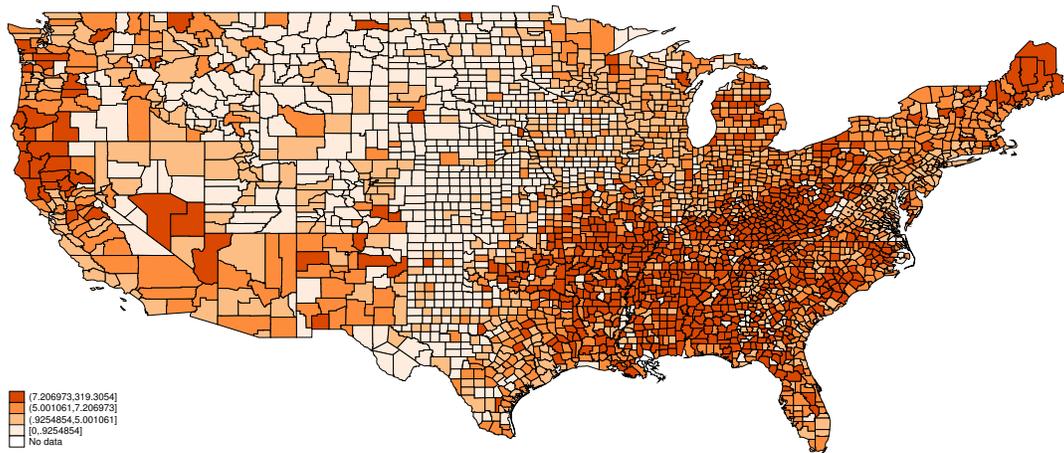
# Figures and Tables

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



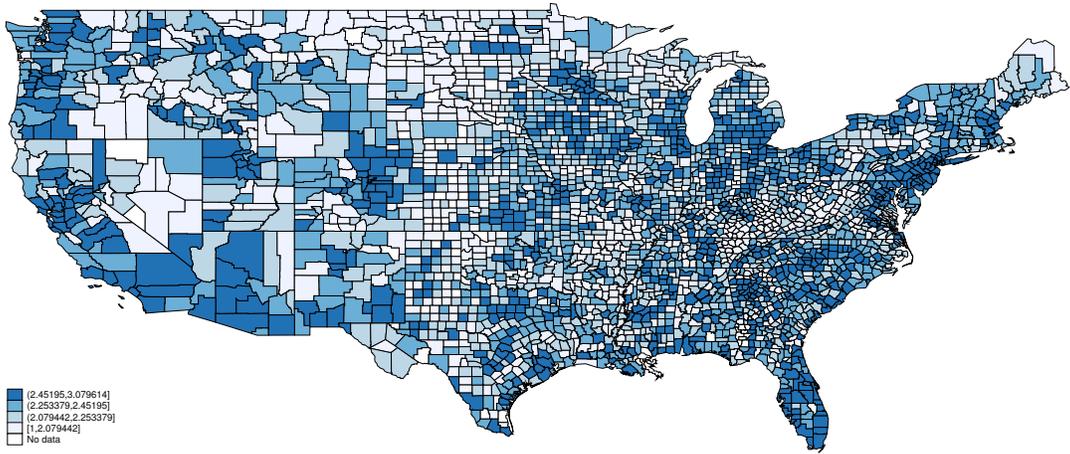
Notes: This figure shows the share of SSDI initial applications filed online, measured nationally at monthly increments. Source: Social Security Administration national-level dataset, [www.data.gov](http://www.data.gov).

Figure 2: SSDI Applications, 2008



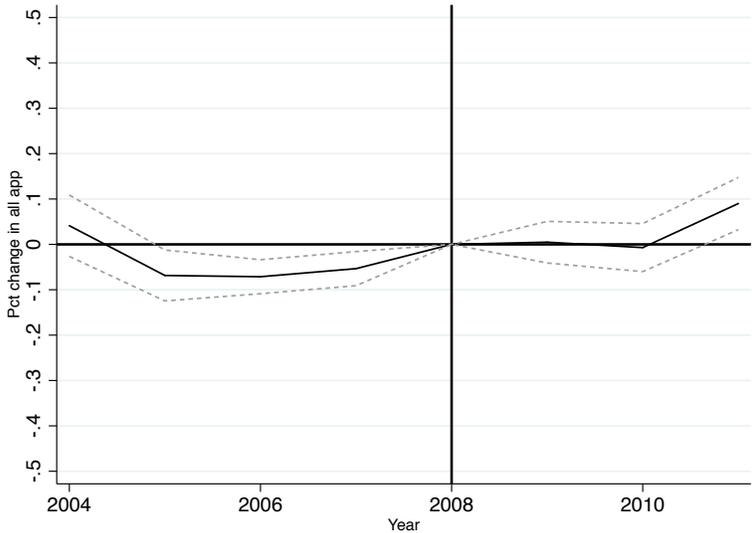
Notes: This map shows the number of SSDI Applications per 1,000 working-age adults in 2008, at the county level. Counties with fewer than 10 overall applicants have suppressed data and appear as missing in the map. Source: Social Security Administration Disability Research File Form 831.

Figure 3: Internet Access (PROV1 Measure), 2008



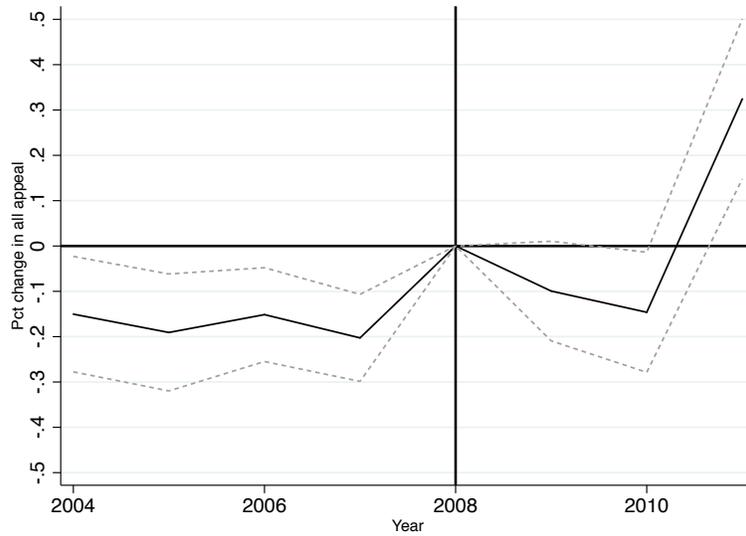
Notes: This map shows the construct PROV1, which measures residential internet connectivity, at the county level. The measure aggregates zip-code level information on the number of high-speed internet providers with respect to population. See text for details on the explicit construction of the measure.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

Figure 4: Effect of iClaim on Application Behavior Over Time



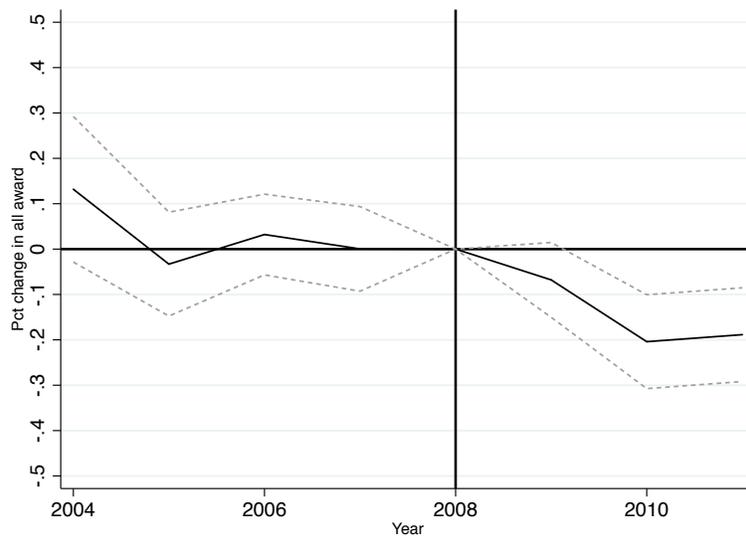
Notes: This graph shows the effect of high-speed internet access, measured by PROV1, on applications over time. The vertical solid line for 2008 indicates the omitted year in the analysis, the year prior to when iClaim went into effect. Source: Federal Communications Commission Form 477 files.

Figure 5: Effect of iClaim on Appeal Behavior Over Time



*Notes:* This graph shows the effect of high-speed internet access, measured by PROV1, on appeals over time. The vertical solid line for 2008 indicates the omitted year in the analysis, the year prior to when iClaim went into effect. Source: Federal Communications Commission Form 477 files.

Figure 6: Effect of iClaim on Awards Over Time



*Notes:* This graph shows the effect of high-speed internet access, measured by PROV1, on awards over time. The vertical solid line for 2008 indicates the omitted year in the analysis, the year prior to when iClaim went into effect. Source: Federal Communications Commission Form 477 files.

Table 1: Summary Statistics, 2008 and 2011

	2008	2011	Connectivity, 2008	
			Low	High
SSDI Measures				
Beneficiaries	527.5 (1647.2)	606.5 (1851.4)	125.9 (195.5)	898.0 (2212.8)
Beneficiaries/1,000 working age adults	7.268 (10.48)	8.165 (12.91)	6.665 (14.18)	7.833 (4.891)
Applications	670.8 (2074.4)	761.8 (2344.8)	154.2 (248.5)	1147.3 (2782.8)
Applications/1,000 working age adults	4.829 (6.781)	5.367 (8.428)	4.496 (9.152)	5.146 (3.132)
Appeals	97.78 (298.4)	97.46 (316.5)	15.13 (42.25)	174.0 (396.9)
Appeals/1,000 working age adults	0.581 (1.207)	0.497 (1.289)	0.374 (1.479)	0.778 (0.824)
Awards	165.6 (521.3)	187.8 (568.6)	23.85 (61.40)	296.4 (695.2)
Awards/1,000 working age adults	0.840 (1.831)	0.992 (1.875)	0.539 (2.414)	1.127 (0.909)
Award Rate	0.155 (0.129)	0.169 (0.124)	0.0919 (0.109)	0.199 (0.123)
Employment & Population				
Unemployment Rate	5.681 (2.291)	8.436 (3.352)	5.822 (2.313)	5.552 (2.264)
Population (1,000s)	95.45 (307.7)	97.77 (315.9)	20.73 (22.75)	164.4 (414.3)
Population Share Black	0.0930 (0.146)	0.0952 (0.145)	0.0786 (0.150)	0.106 (0.141)
Population Share White	0.875 (0.157)	0.871 (0.156)	0.889 (0.167)	0.861 (0.147)
Population Share under 30	0.384 (0.0536)	0.378 (0.0540)	0.369 (0.0513)	0.399 (0.0517)
Population Share 30-44	0.183 (0.0237)	0.177 (0.0229)	0.178 (0.0233)	0.189 (0.0228)
Population Share 45-54	0.151 (0.0152)	0.146 (0.0144)	0.153 (0.0147)	0.149 (0.0154)
Population Share over 55	0.281 (0.0574)	0.299 (0.0597)	0.300 (0.0555)	0.264 (0.0534)
Internet Connectivity				
Internet Connections per Household	0.450 (0.166)	0.546 (0.150)	0.388 (0.147)	0.508 (0.163)
Residential Providers	7.679 (3.088)	7.662 (3.001)	6.334 (2.476)	8.961 (3.068)
PROV1 (logs)	2.257 (0.295)	2.248 (0.831)	2.027 (0.187)	2.488 (0.180)
PROV2 (levels)	10.13 (3.072)	13.52 (9.747)	7.776 (1.362)	12.48 (2.439)
Observations	3147	3147	1510	1637

*Notes:* All summary statistics reflect county-level means, weighted by county population. Standard deviations are in parentheses. 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

	Applications	Appeals	Awards	Award Rate
<i>Internet Measure PROV1: logged count of providers in 2008</i>				
$Post_t \times PROV1_t$	0.0577** (0.0263)	0.169*** (0.0449)	-0.181*** (0.0604)	-0.020** (0.0084)
<i>Internet Measure PROV2: linear count of providers in 2008</i>				
$Post_t \times PROV2_t$	0.00757** (0.00300)	0.0149*** (0.00445)	-0.00623 (0.00540)	-0.0013 (0.0008)
Y-Mean	7.46	5.569	6.056	0.264
N	23913	23913	23913	23913

*Notes:* Outcome variables are listed at the top of each column, and are log counts of corresponding outcomes. Award Rate is calculated as the share of applications that were awarded benefits. Panel A uses PROV1, while Panel B uses PROV2 as the measure of internet connectivity; both are described in Section 3. All regressions control for age distribution, race composition, as well as year and county fixed-effects. 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.

Table 3: Effect of iClaim by Age Group ( $Post_t \times PROV1_{ct}$ )

	Applications	Appeals	Awards	Award Rate
All Ages	0.0577** (0.0263)	0.169*** (0.0449)	-0.181*** (0.0604)	-0.020** (0.0084)
Under 30	-0.00421 (0.0410)	0.310*** (0.0760)	0.0720 (0.0687)	-0.037*** (0.0092)
Ages 30-44	0.0660** (0.0311)	0.184*** (0.0571)	0.0827 (0.0646)	-0.012 (0.0064)
Ages 45-54	0.0439 (0.0270)	0.114** (0.0466)	0.00259 (0.0729)	-0.010 (0.0091)
Ages 55+	0.0925*** (0.0259)	0.199*** (0.0536)	-0.0753 (0.0544)	-0.034** (0.0134)

*Notes:* Outcome variables are listed at the top of each column, and are log counts of corresponding outcomes. Award Rate is calculated as the share of applications that were awarded benefits. 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, 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.

Table 4: Effect of iClaim, with State-year fixed effects

	Applications	Appeals	Awards	Award Rate
PROV1	0.0161 (0.0257)	0.165*** (0.0406)	-0.243*** (0.0607)	-0.0261*** (0.00444)
PROV2	0.00280 (0.00295)	0.0121** (0.00463)	-0.0073 (0.00538)	-0.0011*** (0.000367)
Y-Mean	7.46	5.569	6.056	0.264
N	23913	23913	23913	23913

*Notes:* Outcome variables are listed at the top of each column, and are log counts of corresponding outcomes. Panel A uses PROV1, while Panel B uses PROV2 as the measure of internet connectivity; both are described in Section 3. All regressions control for age distribution, race composition, as well as year and county fixed-effects. Standard errors are clustered at the state level. Regressions are weighted by population. Sources: Social Security Administration Disability Research File, Bureau of Labor Statistics Local Area Unemployment Statistics, SEER, and Federal Communications Commission Form 477 files.