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ABSTRACT

Who Goes on Disability When Times Are Tough? The Role of Social Costs of Take-Up Among Immigrants*

Social Security Disability Insurance (SSDI) take-up tends to increase during recessions. We exploit variation across immigrant groups in the non-pecuniary costs of participating in SSDI to examine the role that costs play in applicant decisions across the business cycle. We show that immigrants from country-of-origin groups that have lower participation costs are more sensitive to economic conditions than immigrants from high cost groups. These results do not seem to be driven by variation across groups in sensitivity to business cycles or eligibility for SSDI. Instead, they appear to be primarily driven by differences in work norms across origin countries.

JEL Classification: E32, J61, H55, I18

Keywords: disability insurance, immigrants, unemployment rates, ethnic networks

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1 Introduction

The Social Security Disability Insurance (SSDI) program was established in 1956 to insure U.S workers against the risk of being unable to work due to a disability. Assuming that the timing of onset of work-preventing disabilities is relatively random, we should not expect more SSDI enrollments during bad economic times. Several studies have shown, however, that SSDI take-up rates increase, often quite dramatically, in response to decreases in the availability of well-paying jobs (Black, Daniel and Sanders 2002; Autor and Duggan 2003; Autor, Dorn and Hanson 2013; Charles, Li and Stephens 2018). In this paper, we examine whether this responsiveness to economic conditions is especially strong for people with lower costs of applying by exploiting differences across immigrant groups in the non-pecuniary costs of applying.

SSDI applications and awards tend to increase during economic downturns and then fall shortly after the unemployment rate peaks (Maestas, Mullen and Strand 2015; Maestas, Mullen and Strand 2018; Mueller, Rothstein and von Wachter 2016). Although this general relationship has become weaker in recent years (von Wachter 2010), awards did increase during the Great Recession (Maestas et al. 2018; Mueller et al. 2016). This is problematic because after people enter the SSDI program, they rarely rejoin the labor force—even after the economy recovers—creating efficiency losses for the economy as a whole and income losses for individuals who might have earned higher incomes by working in the labor market (Maestas et al. 2018).

There are several potential explanations for the positive relationship between the unemployment rate and SSDI take-up (Mueller et al. 2016). First, SSDI screeners may take the economy into account when making award decisions. Second, employers may be less likely to make workplace accommodations for the disabled when business is slow. Third, people with only marginal disabilities may be more likely to apply for SSDI, and ultimately be awarded benefits, during bad economic times.

In this paper, we explore the factors that drive workers to take-up SSDI when economic conditions worsen by examining the behavior of immigrants in the US. We exploit the fact that the non-pecuniary costs of receiving SSDI benefits vary by country of origin. As a result, certain immigrant groups may be more sensitive to business cycles than others living in the same states in the same years and thus exposed to similar employers and disability determination offices and courts. Our main assumption is that immigrants in groups with lower costs of SSDI take-up will be more sensitive to business cycles if—as shown by Maestas et al. (2015), Maestas et al. (2018), and Lindner, Burdick and Meseguer (2017)—applicants with marginal disabilities are the main drivers of SSDI business cycle patterns. If in contrast, employers and disability determination officers and judges are the main drivers of the patterns, and they do not give preferential treatment toward immigrants in low take-up cost groups, then the relationship between the unemployment rate and immigrant SSDI take-up should not depend on the immigrant's ethnic background.

We start our analysis with a very simple conceptual model describing the potential relationships between the costs of applying for SSDI and take-up rates. Not surprisingly, our framework predicts that lower costs of application and increased benefits (generated from the anticipation of worse future labor markets) both increase SSDI take-up rates. More interestingly, our conceptual model shows that under certain assumptions, an increase in the costs of SSDI take-up results in weaker responses to an increase in the unemployment rate. For our main purposes, any relationship between application costs and SSDI take-up rates might be viewed as evidence that applicants, as opposed to employers or SSA examiners, are a driving force behind the cyclicality of SSDI take-up. However, our theoretical model allows us to better understand why different people may have different responses to the same changes in the availability of jobs.

We begin by measuring SSDI take-up costs by the average SSDI take-up within a person's ethnic group. As shown in Furtado and Theodoropoulos (2016), there is evidence that ethnic networks play a rather strong role in determining SSDI take-up rates of immigrants in the United States—immigrants who live around others from the same country of origin are especially likely to go on disability if they are from a group with high SSDI take-up rates. While Furtado and Theodoropoulos (2016) are not able to perfectly distinguish whether this is because information is shared more efficiently within ethnic communities or because ethnic communities sustain norms regarding the value of work, for the purposes of this paper, the exact mechanism does not matter. What matters is that people within communities with high SSDI take-up rates have lower costs to take-up. Using this measure of cost of take-up, we can test our model's predictions concerning how take-up cost mediates the relationship between unemployment rates and SSDI take-up.

For our empirical analysis, we start with data from the American Community Survey (ACS) for the years 2001-2016. We show that immigrants in high SSDI take-up groups are more likely to go on disability in response to increases in unemployment rates than immigrants in low take-up groups. This result is certainly consistent with our theoretical model, but there are other potential explanations for this baseline result. One possibility is that variation across origin countries in SSDI take-up is generated from differences in eligibility for the program. Another possibility is that immigrants in groups with high average SSDI rates are more negatively impacted by economic downturns than immigrants in low SSDI groups. Both of these alternative explanations still point to applicants, as opposed to employers or Social Security personnel, driving the cyclicality of SSDI take-up rates, but to determine whether social interactions play a role, we conduct several additional empirical analyses. For example, instead of calculating the unemployment rate at the state-year level, we calculate it at the state-year-country of origin level and state-year-education level. We also run a placebo regression examining impacts of our interaction term of interest on the likelihood of retiring for individuals above retirement age. All of our results suggest that variation in eligibility for the program and experienced severity of the recession are not the driving forces behind our baseline results.

We then examine the likely mechanisms through which ethnic networks operate. Specifically, to provide evidence of the role of social norms, we collect data from the World Values Survey (WVS) and the European Values Survey (EVS) on home country attitudes regarding the importance of work, such as whether a person believes work is a duty to society. We show that during bad economic times, immigrants belonging to ethnic groups with weaker importance of work norms are more likely to take-up SSDI. This suggests that social pressure may be an important consideration for people when deciding whether to apply for government assistance during periods of economic hardship.

For further analyses, we then turn to the Current Population Survey (CPS) for its better measure of SSDI participation, information on general health, and information on parents' country of birth. With these data, using a technique described in Borjas (2017), we can also make predictions about whether a foreign born individual is likely to be undocumented and thus ineligible for SSDI. Our baseline findings are robust to the use of CPS data despite its significantly smaller sample sizes. They are also robust to controlling for a measure of immigrants' self-perceived health status. To evaluate whether our baseline results are likely to be driven by variation across country of origin in the share of undocumented immigrants (who are ineligible for SSDI), we start by confirming that people who are likely to be undocumented have practically zero SSDI take-up rates. Not surprisingly, the relationship between state unemployment rates and take-up rates among this group is not sensitive to average SSDI take-up in their origin groups either. However, when we consider just a sample of immigrants who are likely to be documented, our estimate of the coefficient of interest increases slightly in magnitude, suggesting that variation in documented status across origin countries is not a main driver of our results.

To explore whether our main findings are likely to be generalizable to the general population, we examine SSDI take-up patterns of second-generation immigrants. This population is more likely to be eligible for SSDI given their legal status in the U.S., and because they were born and most likely raised in the country, they are also more likely to satisfy the work history requirements for the program. Not surprisingly, given their higher average SSDI take-up rates, average SSDI take-up rates in their origin groups (constructed from average take-up rates of the foreign-born only) have a larger influence on the relationship between state unemployment rates and SSDI take-up decisions. We view these results as suggestive that our examination of the role of social networks in determining immigrant SSDI take-up rates is relevant to the native population as well.

The remainder of the paper proceeds as follows. Section 2 provides some background on the Social Security Disability Insurance program and discusses how our analysis contributes to the existing literature on SSDI take-up. Section 3 outlines our theoretical background, and section 4 presents our empirical strategy. Section 5 presents the data and outlines the results. Section 6 examines possible mechanisms through which networks operate. Section 7 presents data from the Current Population Survey (CPS) and provides complementary results. Section 8 concludes.

2 Background

2.1 The Social Security Disability Insurance Program

Social Security Disability Insurance is a federal program in the U.S. designed to provide income to people who are unable to work as a result of a physical or mental disability. The largest disability program in the U.S., it paid 142.8 billion dollars to disabled workers in the year 2016 (Annual Statistical Supplement to the Social Security Bulletin, 2017). International evidence across comparable harmonized data sets suggests that the U.S. has the fourth highest disability income receipt across seventeen OECD countries (Börsch-Supan, Bucher-Koenen and Hanemann, 2018).

To be eligible, an applicant must satisfy work history requirements ("technical requirements") and provide sufficient evidence of disability ("medical requirements"). In terms of work history, applicants must generally have worked at least five of the past ten years and ten years in their working lives, but the actual rules depend on the applicant's age and are fairly complicated.[1] Because the Social Security Administration defines disability as the inability to perform substantial gainful activity (SGA), applicants must be out of work for five months before they are eligible—although technically they are allowed to work as long as they do not earn more than the amount determined as SGA—in 2017, this was $1,170 per month. About a quarter of denied claims are denied for technical reasons (Deshpande and Li 2018)—evidence of the potential difficulty applicants face in determining whether they qualify.

While local offices confirm that applicants satisfy the technical requirements and collect the medical evidence provided by medical doctors, the medical evidence is examined at Disability Determination Offices. Examiners first evaluate whether the impairment is severe and whether it is expected to last more than a year (or likely to end in death before that), but even if they determine it is, the claim will not be allowed if the claimant is able to perform his or her past work or any work in the U.S. economy. This determination is based not only on the person's disability level but also his or her age, past work experience, and education. An application of a person who is unable to perform physically demanding work may be

[1] For further details about the work history requirements, see the Social Security Administration website at https://www.ssa.gov/planners/credits.html#&a0=2.

denied for a person who has the education and experience to work in an office job, but approved for a person who would not qualify for such a job.

Only about a third of applicants are awarded benefits at the first determination (Maestas, Mulligan, and Strand 2013). Denied applications can be and often are appealed. Thirty-five percent of denied applicants appeal and most of those who appeal eventually have a hearing before the Administrative Law Judge (Liebman 2015). There are several different levels of appeals starting with a simple reconsideration determination and ending with a trial in a U.S. district court. The appeals process can be long, difficult, and expensive, but appeals are often eventually successful. In general, two thirds of all initial applications are eventually awarded (Maestas, Mullen and Strand 2013). Around 40 percent of Great Recession-induced applications were eventually awarded (Maestas et al. 2018) despite the fact that applicants were far more likely to have only marginal disabilities.

While the complicated rules about eligibility and rather arduous appeals process may make it difficult for anyone to navigate the system, they are likely to be especially difficult for immigrants who are often unfamiliar with U.S. programs and may not be proficient in English. Information shared within social circles may substantially lower the costs of ultimately receiving SSDI benefits for immigrants. Immigrant networks may also be especially knowledgeable about issues specific to immigrants, such as whether or not they qualify based on their immigrant status and which types of jobs are covered under the Social Security system.[2]

2.2 Economic Conditions and SSDI Applications

Exploiting plausibly exogenous local labor demand shocks, several papers have shown that worse labor market conditions result in higher SSDI take-up rates. In a seminal article, Black et al. (2002) find that disability claims increase in coal-producing counties when energy prices drop and decrease when prices

[2] Documented immigrants, regardless of whether they are citizens, qualify for SSDI as long as they have the necessary work experience in formal sector jobs. In contrast, non-citizens generally do not qualify for Supplementary Security Income (SSI), the other major income-support program for people with disabilities, even if they are legal permanent residents. Undocumented immigrants do not qualify for either program.

increase. Building on this research, a recent paper conducts a similar analysis focusing on the oil and gas industries (Charles et al. 2018). Despite the different populations being studied and different time periods, both papers estimate very similar elasticities of benefit payments to income (Black et al. 2002; Charles et al. 2018). Using an even more general source of variation in local labor demand conditions, Autor et al. (2013) uncover large increases in disability program take-up in labor markets that are more intensely exposed to Chinese import competition.

In terms of the impact of recessions on SSDI, Duggan and Imberman (2009) found that nearly 25 percent of the increase in male SSDI participation in the late 20th century was due to recessions. While this cyclicality has decreased in more recent years (von Wachter 2010), there were rather large increases in SSDI awards during and shortly after the Great Recession (Maestas et al. 2018, Mueller et al. 2016). One potential explanation for these patterns is that displaced workers turn to the SSDI program for income when their unemployment insurance (UI) payments run out (Mueller et al. 2016). Exploiting plausibly exogenous variation in the duration of UI benefits during the Great Recession, Mueller et al. (2016) fail to find any evidence of this and conclude that the relationship between recessions and SSDI is most likely driven either by changes in the Social Security Administration's judgment of people's potential to work or changes in the relative attraction of SSDI benefits for marginally disabled workers with worse labor market prospects. Using data from before the Great Recession, Lindner (2016) finds an economically, but not always statistically significant substitution effect between UI and SSDI.

We contribute to this literature by examining differences in take-up rates among people residing in the same states in the same years, but with different (non-monetary) costs to participating in and navigating through the SSDI application process.

2.3 Costs of SSDI Take-Up

There is reason to believe that even relatively small changes in the convenience of applying for SSDI can lead to fairly large changes in the number as well as composition of SSDI applicants and recipients. Exploiting plausibly exogenous variation in closings of SSA field offices, Deshpande and Li (2018) show that increased congestion in field offices result in large decreases in the number of SSDI participants. Results are driven by people with moderately severe disabilities, low levels of education, and low pre-application earnings. Considering the impacts of a 2009 innovation to SSDI's online application process which made applying online significantly more convenient, Foote, Grosz, and Rennane (2018) show that post-2009 SSDI applications increased more in counties with better access to high-speed internet, a result pointing to the importance of transactions costs in determining SSDI take-up rates.

Children whose parents received disability payments may face lower (utility) costs of participation in the program. Exploiting variation arising from the random assignment of judges to disability insurance applicants whose cases are initially denied, Dahl, Kostøl, and Mogstad (2014) show adult children whose parents were allowed disability insurance at the appeal stage are more likely to participate in disability themselves. Answering the same question but instead exploiting a policy reform which tightened disability insurance (DI) criteria for existing recipients, Dahl and Gielen (2018) show that the children of those who were pushed out of DI or had their benefits reduced as a result of the policy change were less likely to participate in DI themselves as adults.[3] Our paper contributes to this literature by considering not only the vertical transmission of disability program participation from parents to children, but also horizontal transmission within wider communities. To be able to identify these wider communities in the data, we focus on the immigrant population.

2.4 Immigrant SSDI Participation and the Role of Ethnic Networks

There is a large literature examining the role of ethnic networks in determining program participation using data on immigrants. In a seminal paper, Bertrand, Luttmer, and Mullainathan et al. (2000) show that immigrants residing amidst a large number of co-ethnics are especially likely to receive welfare payments if they belong to high welfare-using language groups. As the authors explain, social networks can affect

[3] Given the nature of the policy change, the impacts are unlikely to be driven by information transmission or even stigma about the disability program itself. Instead, the authors attribute the change to beliefs about the reliability of government provided safety net programs and parent-provided information about the formal labor market.

welfare participation via information sharing about the program and/or via changing stigma associated with welfare participation. Using similar identification strategies, other researchers have uncovered ethnic network effects in health care utilization (Deri 2005; Devillanova 2008), Medicaid take-up (Gee and Giuntella 2011), and WIC participation during pregnancy (Figlio, Hammersma, and Roth 2011).

A separate but related literature provides evidence of the role of norms and culture in determining economic decisions by looking at the relationship between home country behaviors and immigrant behaviors. Fernandez and Fogli (2009) show that higher country of origin fertility and female labor force participation rates are associated with higher employment and fertility rates among second generation immigrants in US. Using similar approaches, other researchers have uncovered a role of culture in determining divorce decisions (Furtado et al. 2013), living arrangements (Giuliano, 2007), participation in the stock market (Osili and Paulson 2008), and the decision to take out a large mortgage (Rodrigues-Planes 2018).

In terms of SSDI participation, Furtado and Theodoropoulos (2016) show that immigrants residing amidst a large number of co-ethnics are especially likely to receive disability payments when their ethnic groups have higher take-up rates. In a separate analysis, they show that while immigrants in networks with high Supplemental Security Income (SSI) for disability participation are especially likely to apply for SSI for a disability, conditional on applying, they are in fact less likely to be awarded benefits (Furtado and Theodoropoulos 2013), a result suggesting that high take-up ethnic networks induce people with marginal disabilities to apply for benefits, but applications of people with marginal disabilities are often denied. Consistent with this general idea, Borjas and Slusky (2018) show that the relationship between medical conditions and self-reported disability status is stronger for the foreign born with legal status than for those who are likely to be undocumented. They interpret this finding as evidence that workers who are eligible for SSDI exaggerate their disabilities in order to receive benefits.

Our analysis uses SSDI participation within a person's ethnic community (defined as the share of co-ethnics receiving SSDI payments) as a measure of the informal costs potential applicants face to ultimately receiving benefits, particularly applicants with only marginal disabilities. As discussed previously, information sharing about SSDI within ethnic networks may help applicants learn whether or not they qualify and how best to navigate the application and appeals process. In addition, taboos against leaving the workplace despite having only a marginal disability are likely to be weaker in high take-up communities – again, decreasing the cost to applying despite potentially being able to work. Furtado and Theodoropoulos (2016) show that immigrants from countries with strong taboos against cheating the government as well as strong importance of work norms are less responsive to exposure to DI take-up within their ethnic communities suggesting that norms within ethnic communities influence DI participation decisions.

3 Theoretical Background

While the SSDI program is intended only for people who are unable to work due to a disability, because disability is very difficult to observe and costly to verify, a major determinant of who ends up on disability is who decides to apply for benefits (Deshpande and Li 2018). In this section, we lay out a framework for thinking about how individuals make decisions about whether to apply for SSDI focusing on how differential costs of participation impact how a change in the unemployment rate might translate into take-up rates.

We assume that an individual who qualifies for the program (i.e. legally in the U.S. with the necessary work experience and some documentable disability) applies if the expected benefits of participation exceed the costs of take-up. We can conceptualize the benefits of participation as the net utility a person would obtain from leaving the labor force but receiving monthly SSDI payments. We can think about these benefits as equal to the difference between the monthly income benefits provided by SSDI, D, and the expected income from working. We let the expected income from working be equal to the person's wage income, w, weighted by the expected probability of having a job. We assume that this expected probability of having a job is equal to 1 minus the unemployment rate, U. Thus, benefits can be written, $D-(1-U)w$.

It is also reasonable to assume that the wage a person can receive in the labor market is a decreasing function of the person's disability severity, *S.* This can be because the disability makes the person less productive while on the job or because the disability requires workplace accommodations and the cost of these accommodations are borne by the worker in the form of lower wages. We assume that S varies between 0 and 1, and takes the value 0 for those who are not at all disabled and 1 for those that are completely disabled. For simplicity, we assume that wage income is a linear function of disability severity, $w = a - bS$ and that both a and b are positive. In order to ensure that wage income is never negative, we assume that a is greater than b. Benefits from SSDI take-up can thus be written as,

$$Benefits = D-(1-U)w=D-(1-U)(a-bS).$$

Note that because a > b, the benefits of SSDI take-up will always increase when the unemployment rate increases. For simplicity, we assume that the costs of SSDI take-up are equal to C,

$$Costs = C$$

To make the problem interesting, we assume without loss of generality that C < D since if C > D, then even someone with zero wages would not apply for SSDI.

Individuals will apply for SSDI if the benefits of SSDI exceed the costs. If the benefits of SSDI participation are increasing in disability severity and the costs are constant, then there exists a disability severity, S*, such that people with a disability level less than S* choose not to apply for benefits and people with more severe disabilities do apply.[4] In our model, S* can written,

$$S^* = \frac{a(1-U)-(D-C)}{b(1-U)}$$

and so we can derive the following comparative statics,

[4] We assume that costs are not a function of disability for simplicity. It is certainly possible, however, that applying for SSDI (and asking doctors to fill out paperwork documenting the disability) comes at higher costs for people with less severe disabilities given the knowledge that the SSDI program is meant for people who are unable to work. Moreover, paying expensive lawyers is likely to be more important for people with relatively minor disabilities. Making costs a decreasing function of severity would complicate our model slightly but would not change the model's predictions, and so we assume that disability severity only affects the benefits of SSDI for ease of exposition. A more problematic possibility is that application costs are increasing in disability, as would be the case if people with more severe disabilities find it especially difficult to fill out an application (Deshpande and Li 2018). Even in this case, we can solve for S* as long as disability severity has a larger impact on the benefits of SSDI than on the costs of application. In any of these cases, the basic intuition provided in this section remains relevant.

$$\frac{\partial S^*}{\partial U} = \frac{C - D}{b(1-U)^2} \qquad (1)$$

$$\frac{\partial S^*}{\partial C} = \frac{1}{b(1-U)} \qquad (2)$$

Because we assumed C < D, equation (1) implies that an increase in the unemployment rate will result in a decrease in S*. This prediction is consistent with the empirical findings of Maestas, Mullen, and Strand (2016) who show that, during the Great Recession, DI applicants tended to have less severe disabilities. As can be seen by equation (2), the severity threshold also increases with the cost of SSDI take-up. If the costs of take-up are high enough, only those with very severe disabilities will take advantage of the program. This has also been supported by papers using different measures of increased costs (Deshpande and Li, 2018; Foote et al. 2018).

For our purposes, we are most interested in how the responses to increases in the unemployment rate vary with the costs of take-up, namely:

$$\frac{\partial^2 S^*}{\partial U \partial C} = \frac{1}{b(1-U)^2} \qquad (3)$$

which is positive. Taken together, equations (1) and (3) imply that while an increase in the unemployment rate leads to a decrease in the disability severity threshold, the magnitude of this decrease will be smaller for people facing higher costs to SSDI take-up.

Figure 1 provides a graphical illustration of these general relationships. The (dark) blue and (light) green lines depict the benefits from SSDI participation. Both are increasing in disability severity, but the line associated with the higher unemployment rates (blue line) always lies above the line associated with lower unemployment rates (green line). More interestingly, the high unemployment line has a smaller slope, conveying the idea that with higher unemployment rates, the additional benefits from SSDI resulting from a more severe disability are lower.[5] The horizontal lines convey the different costs of SSDI participation.

[5] To take an extreme example, for someone who is so severely disabled that wages are zero, then an increase in the unemployment rate will not affect the benefits of SSDI. On the other hand, for someone who has such a marginal

The red dashed line depicts costs for a person facing low costs to SSDI take-up while the orange solid line depicts costs for a person with higher costs.

As can be seen from the figure, a person with high participation costs facing low unemployment rates will take-up SSDI if his or her disability severity is above S_4*. If the unemployment rate increases, this person's threshold disability will drop to S_3*. The corresponding values for someone with low costs are S_2* and S_1*. From the figure, it can be seen that, conditional on the unemployment rate, disability thresholds are always lower for the people with low costs than for those with high costs. It can also be seen that regardless of whether costs of SSDI are low or high, an increase in the unemployment rate will decrease S*. Most importantly, however, the figure shows that the impact of an increase in the unemployment rate on the threshold values is larger for people with lower costs of take-up.

Unfortunately, it is difficult to empirically test this prediction because people's disability thresholds are generally unobservable. What we can observe in the data is whether a person is actually receiving SSDI benefits. However, if we assume that disability severity is uniformly distributed over a range encompassing S_1* and S_4*, then because the distance between S_1* and S_2* is greater than the distance between S_3* and S_4*, the model generates the prediction that take-up rates of people with high take-up costs are less sensitive to a given increase in the unemployment rate than those of people with lower take-up costs. Another plausible assumption is that the probability density function of disability severity falls between S_1* and S_4*, since very severe disabilities are relatively rare among working age adults.[6] In this case, we would expected

disability that wages are really high, an increase in the unemployment rate will have a very large impact on the benefits of SSDI since a high enough unemployment rate means the person does not have access to those high wages.

[6] Although we do not have data on disability severity, Figure 2 shows the distribution of responses to the question, "Would you say your health in general is excellent, very good, good, fair, or poor?" for working age adults in the Current Population Survey (CPS), a dataset representative of the U.S. population. As can be seen from the graph, the modal response from non-SSDI recipients is "very good" with fewer responding "excellent" or "good" and very few responding "fair" or "poor". Regardless of how disability severity is precisely distributed for the general population, individuals considering applying for SSDI are likely to be on the downward sloping portion, towards the right tail, of this distribution. In fact, as can be seen in Figure 2, indeed 85 percent of SSDI recipients have self-reported health levels to the right of the modal response for non-SSDI recipients.

take-up rates of individuals with lower costs of take-up to be even more sensitive to increases in the unemployment rate than those of individuals with higher costs.[7]

To conclude, our theoretical model provides an illustration of why people with low costs of SSDI participation may be more sensitive to increases in unemployment rates than people with high costs of participation. In the next section, we will empirically examine how reactions to increases in the unemployment rate differ for people with different costs of participation using a particular measure of costs specific to immigrants. We remind readers, however, that the main goal of our analysis is not to test the specific predictions of a model, but rather to show that people subject to the same labor market conditions and disability determination screeners can react differently to an increase in the unemployment rate simply because they have different costs of take-up. If instead, all individuals who were not able to work applied for and received benefits without comparing the costs and benefits of take-up, then there would be no reason to believe that the take-up responses to the unemployment rate are indeed driven by applicant decisions.

4 Empirical Strategy

In our empirical analysis, we begin by using average SSDI take-up within a person's ethnic group to measure the non-pecuniary costs of take-up. Certain immigrants groups may have initially had lower costs to application for a variety of relatively minor idiosyncratic reasons (for example, their ethnic neighborhoods may coincidentally be located close to Social Security field offices or at some point in the past they may have systematically held occupations that tended to result in injuries). Regardless of the explanations for any initial lower costs to participation, immigrants connected to ethnic networks with high SSDI participation are likely to more easily find information about the program, get assistance with filling

[7] Another issue to consider when linking our theoretical concept of disability severity thresholds to the likelihood that people in our samples are receiving SSDI benefits is whether Social Security examiners are likely to deny applications. If individuals with low costs of participation are already receiving benefits when unemployment rates are low, then those with low costs who are induced to apply as a result of an increased unemployment rate may have their applications denied while those with high costs of participation (and therefore higher severity thresholds) will have their applications approved. This would make it more difficult for us to find support for our model in the data. However, we believe that in practice, this is unlikely given the evidence in Maestas et al. (2018) suggesting that practically all of Great Recession-induced new applications were denied at the initial level.

out applications, and even perhaps learn about the most lenient doctors and effective lawyers. They may also be less likely to face social stigma as a result of leaving the labor force to receive SSDI payments, even if they have only marginal disabilities, due to differences in attitudes towards receiving benefits within the immigrant community. For all of these reasons, our theoretical model implies that we can expect the marginal applicant in a high SSDI group to have a lower severe disability threshold, S*, than the marginal applicant in a low SSDI group.

Our empirical strategy relies on examining take-up rates of immigrants living in the same states in the same years but with presumably different non-pecuniary costs of take-up. The main empirical specification we use in the analysis is

$$\mathrm{DI}_{iost} = \beta_1 \mathrm{UR}_{st-1} \times \overline{\mathrm{DI}}_o + \beta_2 X_{iost} + \gamma_o + \delta_{st} + \varepsilon_{iost} \qquad (4)$$

where DI_{iost} takes on the value one if person *i* for country of origin *o*, living in state *s* in year *t* receives any disability insurance income and the value zero otherwise. Our right hand side variable of interest is the interaction between the state unemployment rate, *UR*, in the year prior to the survey and the average SSDI take-up rate among immigrants from the same country of origin, $\overline{\mathrm{DI}}$.[8] Empirically, the β_1 parameter is identified from variation across countries of origin (148 countries) and state-year unemployment rates. A positive estimate of β_1 is most consistent with the theoretical model presented in Section 3. If instead, employers and disability examiners drive the relationship between unemployment rates and SSDI take-up, then we would expect β_1 to be equal to zero.

We control for a series of individual characteristics including gender, race, marital status, the number of children in the household, educational attainment, years in the U.S., several measures of disability, and a full set of age as well as years in the U.S. dummy variables. The state-year fixed effects (δ_{st}) control for all factors affecting all immigrants living in the same state at the same time equally. If employers and SSA examiners treat workers and applicants the same regardless of ethnic origin, these fixed

[8] We use the unemployment rate in the year prior to the survey because it can take several months to even years for ultimately successful SSDI applications to be awarded. In Appendix Table A1, we show the sensitivity of our results to different lag structures.

effects will control for changes in employer and examiner behaviors across the business cycle. The country of origin fixed effects (γ_o) will absorb any unobserved tendencies for immigrants from particular backgrounds to take up SSDI. We use multiway clustering based on state, year, and country of origin (Cameron, Gelbach, and Miller 2011).

5 Data and Baseline Results

5.1 American Community Survey Data

We start our analysis using data from the 2001 to 2016 samples of the American Community Survey (ACS), as reported by the Integrated Public Use Microdata Series (IPUMS, Ruggles et al. 2017).[9] Our baseline ACS sample consists of immigrants between the ages of 25 and 61 who have been in the U.S. for more than 5 years, who were not living abroad in the year prior to the survey, and who do not reside in group quarters. Only naturalized citizens and noncitizens are included in the sample; Puerto Ricans and people from other U.S. territories as well as individuals born abroad of American parents are dropped. We also drop American Indians, Alaskan natives, and Hawaiians from our sample given that they are not likely to identify with their country of origin and also individuals whose countries of origin are not clearly specified in the data. We drop widows from the sample in order to better interpret our measure of SSDI take-up.

The ACS does not directly ask about SSDI income. Instead, the survey asks about Social Security income more broadly. There are four different sources of Social Security income: SSDI benefits, public pensions, survivor benefits, and Railroad Retirement insurance payments. Because our sample consists of working age individuals, the people in our sample will not be receiving retirement income and few will be receiving Railroad Retirement insurance payments. Because we also drop widowed individuals, people in our sample will not be receiving survivor benefits. Thus, most Social Security income recipients in our sample will be receiving SSDI. However, even though most SSDI benefits go to disabled former workers, in some cases, non-disabled spouses and children of the disabled workers also qualify for SSDI benefits.

[9] The 2000 survey is also used to construct state unemployment rates for 2001 respondents.

We are not able to determine in our ACS sample if people are receiving benefits for their own disabilities, but we know from aggregate data that over 80 percent of SSDI beneficiaries receive benefits for their own disabilities (Annual Statistical Supplement to the Social Security Bulletin 2017).

We calculate the state unemployment rate using our ACS data, but results are virtually identical if we use the Bureau of Labor Statistics (BLS) published unemployment rates. We calculate the share of a person's origin country community receiving SSDI payments by dividing the number of immigrants from the same country of origin receiving benefits across the United States by the number of immigrants from the same country of origin again across the entire United States.

Table 1 shows descriptive statistics of the ACS variables used in the analysis. On average, 1.4 percent of the immigrants in our sample receive SSDI.[10] Immigrants in our sample have lived in the United States 20 years on average, making the typical person in our sample very likely to be eligible for SSDI. The average immigrant in our sample is 42 years old. Fifty percent are males, sixty-five percent are married (with the spouse present), and sixty-four percent have children. Twenty-six percent have a high school degree, about twenty percent have some college, and twenty-seven percent have a college or higher educational qualification. Fifty percent are of Hispanic race and seventeen percent of white race. Two percent have a cognitive, vision/hearing, or an independent living difficulty. Around three percent have an ambulatory difficulty and one percent a self-care difficulty. The average lagged unemployment rate in our sample is 6.5 percent.[11] Our final ACS sample consists of 2,559,681 observations.

5.2 Baseline Results

Turning now to our regression analysis, we start by examining the relationship between state unemployment

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[10] As can be seen in Appendix Table A2, these averages are constructed from no fewer than 234 observations. The median number of observations in each origin is 3,904. Dropping the individual person before constructing each of these averages makes no difference to our results (estimates available upon request).

[11] Appendix Table A3 reports differences in individual characteristics above and below average values of SSDI and the above and below average values of the unemployment rate. Individuals with above average SSDI are more likely to: be older, be white, have a health difficulty, and have more years in the U.S. They are less likely to: be male, and high school dropouts. There are no significant differences in individual characteristics above or below the average unemployment rate.

rates and SSDI take-up. In column 1 of Table 2, we show that, just as predicted by our model, immigrants are more likely to receive SSDI benefits when they reside in states with higher unemployment rates a year prior.[12] In column 2, we test the main prediction of our theoretical model, equation (3). The estimate of the coefficient on the interaction between the lagged unemployment rate and average SSDI take-up is positive, just as predicted by the theoretical model, and statistically significant. In column 3, we replace the lagged unemployment variable with state-year fixed effects and results remain robust. In column 4, we replace the average SSDI variable with country of origin fixed effects, and thereby estimate the empirical model described by equation (4). The estimate of 2.89 suggests that a percentage point increase in the unemployment rate results in a 0.209 percentage point increase in SSDI take-up for Azorean immigrants, the highest SSDI take-up group, since 7.23 percent of Azorean immigrants are on disability, but only a 0.014 percentage point increase for immigrants from Zimbabwe, the lowest SSDI take-up group, since only 0.52 percent of Zimbabweans are on disability (see Appendix Table A2).[13] Most importantly for the purposes of our study, this baseline result suggests that the relationship between unemployment rate and SDDI take-up, at least for the immigrants in our sample,[14] is driven by the decisions of applicants as opposed to those of the employers or Social Security examiners and judges.[15]

[12] The results in Table 2 are robust to using the Bureau of Labor Statistics' (BLS) measure of state unemployment rates (available upon request). We use the ACS-constructed unemployment rates because later in the paper, we will use country of origin (and education, occupation, etc.) specific state unemployment rates that are not available from the BLS.

[13] Appendix Table A2 reveals substantial heterogeneity in SSDI take-up across immigrant countries. Borjas and Trejo (1991, 1993) also report substantial variation in immigrant participation in public assistance programs in the U.S.

[14] We focus on immigrants because they are most likely to have their social circles comprised predominantly of others from the same country of origin, giving us a way to identify probable social networks within data sets spanning entire business cycles. Nevertheless, to explore whether our general results are likely to generalize to the non-foreign born population, we also ran our analysis on the native-born who identify with a particular ancestry. Results reported in the Appendix Table A4 show the relationship between business cycles and SSDI take-up rates is stronger for natives (column 1) who identify with a particular ancestry, than for immigrants (column 2). This is not our preferred specification because of the self-selection issues with the ancestry variable. In Section 7, we explore the generalizability of our results using data on the native-born with foreign born parents since country of birth of parents is a more objective measure of background than self-reported ancestry (see Duncan and Trejo 2017 for a more thorough discussion of the self-selection issues with the ancestry variable).

[15] For further evidence that these results are driven by applicant decisions, we also examine whether they are strongest during economic downturns or recoveries. Downturn years are defined as years in which the current year's unemployment rate is higher than the previous year's unemployment, and recovery years are the opposite. As shown in Appendix Table A5, results are strongest for downturn years, when potential applicants were presumably feeling more negative about their prospects in the labor market, and not statistically significant for recovery years despite the larger sample size in the recovery years.

5.3 Further Support for our Interpretation of Results

Our results are consistent with a story in which all immigrants residing in the same state in the same year experience the same labor market conditions but that immigrants from different countries face different costs of SSDI take-up. There are two main alternative explanations for our baseline results, however. One story is that the variation across origin groups in SSDI take-up arises mainly from variation in eligibility for SSDI, for instance work experience in the formal sector as well as legal status in the United States. Another potential explanation for our results is that immigrants in high SSDI take-up groups are simply more likely to become unemployed during economic downturns. We take several different approaches to exploring these possibilities, noting that, in themselves, these alternative processes do not rule out a role for take-up costs. For example, an origin group with more documented immigrants may initially have slightly higher SSDI take-up rates. These initially higher take-up rates may then generate more information sharing about the program and social acceptance of SSDI participation within the group which may then lead to rather large differences in SSDI take-up rates. Our main motivation for this section is to show that our baseline results are not entirely driven by these issues.

We start by adding several interactions between the lagged unemployment rates and average characteristics of the origin group. In column 1 of Table 3, we add to our model interaction variables between unemployment rates and average years of schooling, average age, and average years in the U.S. in the origin group.[16] As can be seen in the table, the estimated coefficient on the interaction between unemployment rates and average SSDI take-up increases in magnitude and remains statistically significant when the additional interaction terms are added to the model suggesting that country of origin differences in schooling, age, and years in the United States are not driving the different business cycle sensitivities by country of origin.

[16] People with fewer years of schooling are more likely to lose their jobs during economic downturns (Hoynes et al. 2012). Although it is difficult to get accurate data on the informal economy, it would not be surprising that people with lower levels of education are more likely to work under the table. Moreover, foreign born with very low levels of education are more likely to be undocumented immigrants (Borjas 2017). Similarly, younger individuals are also more sensitive to labor markets and are more likely to be undocumented (Hoynes et al. 2012; Borjas 2017). Immigrants with fewer years in the U.S. are less likely to have worked in the U.S. for enough years to qualify for SSDI.

Next, to specifically address concerns about differential job loss responses to changes in state unemployment rates, we construct unemployment rates within more narrowly defined cells. First, we replace the state unemployment rates with immigrants' origin-specific unemployment rate and then interact this variable with average SSDI take-up.[17] This is not our preferred specification because many of these origin-state-year cells are quite small and the sampling error resulting from our construction of unemployment rates from such small samples is likely to attenuate our estimates. Nevertheless, we show these results in column 2 of Table 3. While the estimate is smaller than the estimate in our baseline, it remains positive and statistically significant despite potentially suffering from severe attenuation bias.

Next, since many of the immigrants in our sample have very low levels of education, and low-skill labor markets tend to be more sensitive to business cycles (Hoynes, Miller, and Shaller 2012), we construct unemployment rates within education-state-year cells. As seen in column 3 of Table 3, the estimate of the coefficient on our interaction is positive and significant in this specification as well. In fact, the magnitude of the estimate is even bigger than our baseline, presumably because the skill-specific unemployment rates are more relevant for people making decisions about leaving the labor force. Next, in column 4 of Table 3, we construct unemployment rates within occupation–state–year cells. Again, the estimate of the interaction coefficient between this unemployment rate and average disability take-up within origin group is positive and statistically significant. This is not our preferred specification because so many of the people on disability, even those new to the system, have not worked in many years (Mueller et al. 2016) and so do not list an occupation or industry in the ACS.[18]

Taking yet a different approach to addressing both recession severity and eligibility for SSDI issues at the same time, we conduct a placebo-style analysis. Following Furtado and Theodoropoulos (2016), we

[17] Because there are some countries of origin represented in a state in one year but not the previous year, we are unable to construct lagged unemployment rates for some observations. In order to make clear comparisons across the different specifications in Table 3, we drop observations with missing data on any of the three definitions of unemployment rate used.

[18] Survey respondents who have not worked within the past five years do not list an occupation in the ACS. We assigned all individuals without a listed occupation the average unemployment rate for people from their country of origin living in their state in the same year. We also added a dummy variable to the model to control for whether the person's state-year-occupation unemployment rate was imputed in this manner.

take advantage of the fact that the Social Security Retirement Insurance program is very similar to the disability insurance program. In fact, Social Security is a term often used to refer to the federal Old-Age, Survivors, and Disability Insurance (OASDI) program, which provides benefits to those who are either above retirement or below retirement age but with a disability making it impossible to work. Undocumented immigrants are not allowed to claim Social Security retirement benefits just like they are not allowed to claim SSDI. Also, the work experience necessary to qualify for SSDI is very similar to the work experience necessary to qualify for Social Security Retirement benefits.[19] The monthly benefits from claiming disability are exactly the same as the benefits from claiming retirement at full retirement age (age 65 for the people in our sample). Moreover, just like SSDI applications increase during recessions (Maestas et al. 2015), people are more likely to leave the labor force and collect (retirement-based) Social Security earlier if there is a recession around the time they reach retirement age (Coile and Levine 2011).

The main difference between the two Social Security programs is that anyone with appropriate work experience can claim Social Security retirement benefits starting at age 62 (receiving a portion of their full benefits) and their full retirement benefits starting at age 65. To claim full benefits before age 65, an applicant must provide proof of a disability. To explore whether work experience (in a covered job) is driving our results, we simply rerun our analysis in a sample of immigrants age 62 and above. If all of our results were driven by differences in legal status, work experience, or even labor market conditions by country of origin, we would expect to see especially large increases in Social Security claiming during bad economic times for immigrants in groups with high average SSDI take-up. If, in contrast, our results are driven by information sharing or norms related specifically to proving the existence or exaggerating a disability or leaving the workforce at a young age, then average SSDI take-up will not be associated with

[19] Applicants for Social Security Retirement benefits must have at least 10 years of work experience. The SSA determines eligibility with a system of credits where the number of credits earned per year depends on wage income. A maximum of four credits can be earned for every year worked, and 40 credits of work experience are necessary to qualify for Social Security. In order to qualify for SSDI, the total number of credits necessary depends on the applicant's age with fewer than 40 credits required for younger applicants. Unlike Social Security, there is also a recent work requirement. For all but the youngest applicants, at least 20 credits must be earned in the decade immediately preceding the SSDI application submission.

the impact of business cycles on Social Security retirement claims. As can be seen in Column 5 of Table 3, the latter is more likely. In this sample of age 62 and above immigrants, the estimate of the coefficient on the interaction between unemployment rates and average SSDI take-up is not statistically different from zero, fairly small in magnitude, and even has a negative sign.

As a final approach to determining whether our baseline estimates are likely to be driven by differences in costs of application arising from network effects, we examine whether immigrants that are more tightly connected to their ethnic communities are more likely to take-up SSDI during recessions when they belong to high SSDI ethnic groups. We start by splitting the sample by whether the immigrant is fluent in English. Comparing columns 1 and 2 of Table 4, we can see that our results are driven by immigrants who speak English either "not at all", "speak English but not well" or "speak well". While the estimate of interest is positive for those who speak English "very well" or "only English", it is not statistically significant and much smaller in magnitude than our baseline estimate in column 4 of Table 2.

In the last two columns of Table 4, we compare immigrants who live geographically isolated from other immigrants from the same country of origin to those who live closer to other immigrants born in the same country. The estimate of the interaction coefficient is positive but statistically insignificant and of substantially smaller magnitude (see column 3 of Table 4) when using a sample of isolated immigrants, as defined by whether they live in a state where the share of same-origin inhabitants is less than the median of this variable (.008) in the overall sample. In contrast, for non-isolated immigrants, the estimate of the interaction coefficient is positive, statistically significant, and a bit larger in magnitude (see column 4 of Table 3) compared to our baseline estimate shown in column 4 of Table 2.

6 Social Norms and Values as a Potential Mechanism

Taken together, the evidence provided in the previous section is certainly consistent with a model in which immigrants in high SSDI take-up groups have lower costs to SSDI take-up and so become more likely to go on disability during economic downturns. These lower costs may be a result of information sharing within ethnic networks making it easier to learn about the program, navigate the system, and even hire the most effective lawyers. Another potential source of the lower participation costs is that in high SSDI groups, leaving the workforce potentially by exaggerating a disability may be less taboo than in the groups with much lower SSDI take-up rates.

Although we will not be able to differentiate these mechanisms, in this section we provide some suggestive evidence that social norms may be playing a role by exploiting information provided in the World Values Survey and the European Values Survey. Specifically, we replace the average SSDI take-up by origin group with various measures of norms obtained from the values surveys. In doing so, we will not only be able to provide some suggestive evidence that norms play a role in people's take-up decisions, but we will also gain an insight into the specific values that may be driving these decisions. An additional advantage of this analysis is that the norms variables were created using data on the norms of people still in their home countries. Thus, these specifications are unlikely to suffer from the reflection problem (see Manski 1993), an issue with almost any analysis of network effects.

6.1 Integrated World Values Survey-European Values Survey (WVS-EVS) Data

The World Values Survey (WVS) and the European Values Survey (EVS) are two large-scale, cross-national and longitudinal survey research programs. While the two surveys are processed by different organizations, their questions overlap. For our analysis, we use the Integrated Values Surveys 1981-2014 data file which includes four waves of the EVS conducted between 1981 and 2008 and six waves of the WVS conducted between 1981 and 2014 (Inglehart et al. 2014). In the end, we have data from 113 countries spanning several years.

We use several different questions to measure the (lack of) importance of work norms. Specifically, for each country, we calculate the share of respondents (over all of the years) who "*strongly disagree*" with the following statements: "*Work is a duty towards society*," "*People who do not work turn lazy*," and "*To* *develop talents, you need to have a job*."[20] We then merge these WVS-EVS variables with our ACS data by country of origin. Of the 148 countries in our ACS sample, we have information on the work is a duty question for 79 countries and the other two questions for 78 countries.

6.2 Results

Table 5 shows results from a model similar to that in Equation 4 but with average SSDI take-up replaced with the share of people from a person's home country who agree with several statements regarding the value of work. In column 1, the lagged state unemployment rate is interacted with the share of people from an individual's home country who strongly disagree with the statement that people do not work turn lazy. The estimated coefficient of 1.15 suggests that immigrants from Iceland, the country with the highest proportion of people strongly disagreeing that not working makes people lazy (14.2 percent), are 30 times more likely to take up disability when the unemployment rate increases by one percentage point compared to immigrants from Turkey, the country with the lowest share strongly disagreeing with that statement (0.46 percent). Similar results can be seen in columns 2 through 3 of Table 4 for the other measures of the importance of work in people's home countries. We next use principal components analysis to construct an index of all of the variables related to importance of work norms. Column 4 shows similar results when using this index measure. These results are consistent with previous work on network effects (Furtado and Theodoropoulos 2016) showing that work norms make SSDI network effects stronger. In column 5, we include both our original measure of cost of take-up – average SSDI take-up – and the importance of work norms measure. Interestingly, the importance of work norms seem to be driving the results, since the estimated coefficient on the interaction between the unemployment rate and average SSDI take-up is found to be insignificant while the estimated coefficient on the work norms interaction remains the same.

[20] For these questions, survey respondents could answer with a 1 through 5, 1 corresponding to strongly agree and 5 corresponding to strongly disagree. We note that not all questions are asked in all countries in all years, but by using as many years as possible, we hope to get as much information as we can about work norms from each country.

We conclude from these findings that values and norms appear to be an important factor in determining SSDI take-up rates. We cannot, however, rule out the possibility that information sharing is also driving part of our results.[21] Unfortunately, we do not have data that would allow us to say anything conclusively about information sharing about the SSDI application process.

7 Additional Evidence from the Current Population Survey

We supplement our analysis with data from the Annual Social and Economic Supplement (ASEC) to the CPS (March CPS) from the years 2001 to 2017, provided by the Integrated Public Use Microdata Series (IPUMS, Flood et al. 2017). The CPS is a monthly survey covering approximately 60,000 households. The advantages of the CPS dataset over the ACS dataset are that the CPS dataset provides a more direct measure of SSDI income, it has better health measures, and it can help us to differentiate between documented and undocumented immigrants. Further, in contrast to the ACS data, the CPS data provide information on parental country of birth. This can help us to identify second generation immigrants. The disadvantage of the CPS data compared to the ACS data is the smaller number of observations on immigrants.

We make the same sample restrictions on the CPS data that we used for the ACS sample (i.e. immigrants between the ages of 25 and 61 who have been in the U.S. for more than 5 years, who do not reside in group quarters and are not currently in school). We only include households that have been in the CPS for four months or less, to ensure that the same household does not appear in the sample twice. The dependent variable is now defined as whether a person received Social Security income *for a disability* in the previous year. The average level of SSDI receipt from the ACS is merged in at the country of birth level and the lagged unemployment rate from the ACS is merged in at the state-year level. Appendix Table A6 presents descriptive statistics of the CPS-ASEC variables used in the analysis.

The results of estimating the primary specification using the CPS sample broadly match those from

[21] Armour (2018) shows that in response to being sent the Social Security Statement, a document providing information about current SSDI coverage status and potential SSDI benefits, people previously reporting a work limitation became twice as likely to apply for SSDI, suggesting that information sharing is an important driver of take-up decisions.

the ACS, as seen in the first column of Table 6. Adding controls for a person's health status (in column 2) makes little difference to the results, as does adding the interaction of average years in the U.S., average education and average age with the unemployment rate (in column 3). With the CPS data, we can also determine whether an individual was receiving unemployment insurance income. To allow for the possibility that immigrants switch from SSDI towards unemployment insurance when the unemployment rate rises, the interaction of the average unemployment insurance take-up rate within a person's origin group and the lagged unemployment rate is added as a regressor (in column 4). The estimated coefficient on this term is negative, as expected; however, it is insignificant. Its inclusion in the model does not qualitatively change the estimate of our interaction of interest — a result that may not be surprising given the evidence that the availability of unemployment insurance does not strongly influence people's SSDI take-up decisions (Mueller et al. 2016).

Next, for further support that our results are driven by marginal applicants, we perform the primary regression separately by health status—a variable that is not available in the ACS data. As can be seen in Table 7, a significant coefficient on the average SSDI-unemployment rate interaction term is only found for those with good or fair self-reported health and not for those with the best or worst health. This is consistent with the idea that people in perfect health do not qualify for SSDI, and people with the worst health apply for and are awarded benefits regardless of the state of the economy or average SSDI take-up in their origin groups. These results are consistent with the findings of Maestas et al. (2018) that it is the applicants with marginal disabilities that are most likely to go on disability during bad economic times.

Table 8 examines whether our results are driven by differences across origin groups in the likelihood of being undocumented. We identify likely documented immigrants following the procedure described in Borjas (2017) and used again in Borjas and Slutsky (2018).[22] Since undocumented immigrants are not eligible for SSDI, variation in the number of undocumented immigrants by origin country might explain the pattern of results uncovered so far, because those countries with high numbers of undocumented

[22] Borjas (2017) used a person's receipt of Social Security benefits as one criterion for documented status. We excluded this criterion since SSDI, our outcome of interest, is a type of Social Security benefit.

immigrants will have low baseline levels of SSDI receipt and their take-up rates are unlikely to vary over the business cycle. To address this issue, we separate our sample into a group consisting only of probable undocumented immigrants and a group of probable documented immigrants. In the undocumented sample, it is not surprising that the average SSDI-unemployment rate term does not affect the likelihood of receiving SSDI (column 1), after all, they do not qualify for SSDI. We view this result simply as evidence that our algorithm for identifying undocumented immigrants is working well. More importantly, we find a significant positive coefficient when the sample is restricted to documented immigrants (column 2), a result suggesting that undocumented immigrants are not driving our main findings.

While our study focuses on immigrants, we see no obvious reason to believe that the mechanisms driving the relationship between unemployment rates and SSDI participation to be substantially different for immigrants and natives. If anything, because many of the foreign born in our sample are not eligible for the SSDI program, it is more difficult for us to uncover any impacts in this population. To examine this issue, we turn to a sample of the native-born children of immigrants. For this group, average SSDI receipt is calculated among all first generation immigrants from a person's parent's country of origin. Second generation immigrants are an especially interesting demographic group because, like third and higher generation immigrants, they were born in the U.S. and so most likely qualify for SSDI. However, like first generation immigrants, they may still have strong connections to their ethnic communities (Borjas 1992; Bisin and Verdier 2011; Guiso Sapienza and Vingales 2006). The first and second columns of Table 9 show that average SSDI receipt among those from both a person's mother's and father's country affects the likelihood of receiving SSDI when unemployment rates increase, with a slightly larger coefficient for those from the mother's country. The final column of Table 9 restricts the analysis to those immigrants whose parents came from the same country. The coefficient of interest is similar in magnitude for this group, although it loses statistical significance due to the smaller sample size. We conclude from this analysis that social interactions are likely to play an important role in native-born SSDI take-up decisions.

8 Conclusion

Previous studies have consistently found that Social Security Disability Insurance (SSDI) take-up rates increase during bad economic times. As discussed in Mueller et al. (2016), this may be because when jobs are scarce, SSDI examiners are more lenient or employers are unable to make more workplace accommodations for the disabled. Another possibility is that people with marginal disabilities go on SSDI during bad economic times because expected future wages are lower and therefore relative SSDI benefits are higher.

This paper provides evidence of the latter explanation by examining SSDI take-up responses to changes in state unemployment rates of immigrants from different origin countries. Immigrants within high SSDI take-up ethnic communities are likely to have more access to informal information regarding the SSDI application process and may face weaker taboos against leaving the labor force to go on disability, both of which make it easier to apply for benefits despite marginal disabilities. In contrast, because all immigrants living in the same areas are exposed to the same labor market and apply for SSDI benefits in the same offices, we should generally not expect different sensitivities to the business cycle by origin country if employers and disability offices are the main drivers of the relationship between unemployment rates and SSDI applications.

Using both ACS and CPS data, each with their set of advantages and disadvantages, our evidence suggests that immigrants are more likely to take-up disability insurance in response to high unemployment rates if they are from ethnic communities with high SSDI take-up, a result consistent with the theoretical model we provide in the paper. This result suggests that the relationship between business cycles and SSDI take-up is driven, at least partially, by applicant decisions. Our analysis of data from the World Values Surveys might be interpreted as evidence that strong work norms limit take-up rates among immigrants.

We focus our analysis on immigrants because this allows us to assign people to exogenously determined social networks based on country of birth. Our similar results using data on second-generation immigrants suggest that our findings of the importance of social networks are generalizable to the rest of the U.S. population.

More generally, our analysis provides further support for the notion that the SSDI program is not being used solely to provide insurance against the possibility of becoming permanently disabled. It seems to also work as insurance against the possibility of job loss. This is problematic because while recession-induced job losses tend to be temporary, people who go on disability tend to stay on disability. Given that the combined Old Age, Survivors and Disability Insurance Program (OASDI) and the SSDI Trust Fund face exhaustion in 2027 (Goss 2010), policy makers may consider changes to the program if it is to survive.

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Figure 1. Costs and Benefits of SSDI Take-Up by Disability Severity

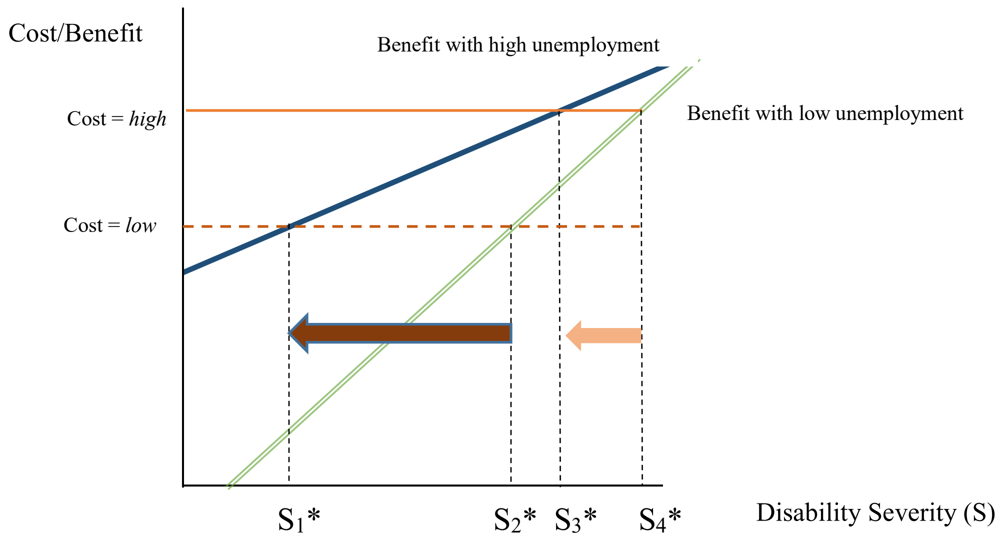
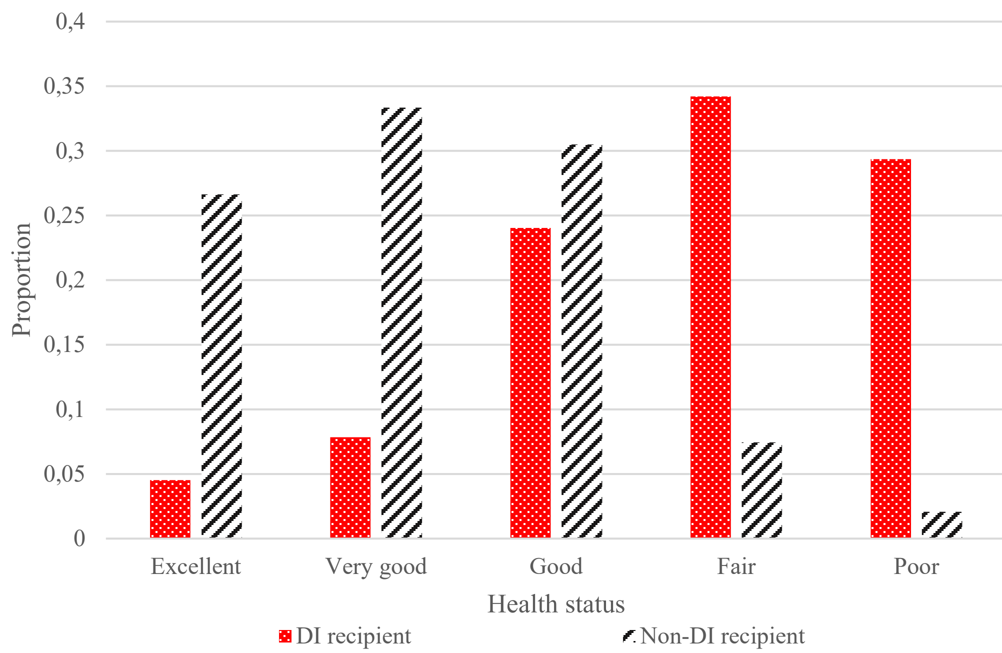


Figure 2. Health by SSDI Status



Note: The same sample restrictions are used as in Table 7.

Table 1. Summary Statistics for the ACS Sample (2001-2016)

Variable	Mean	Standard deviation	Minimum	Maximum
Disability Insurance Receipt (SSDI)	0.014	0.119	0	1
Lagged unemployment in state-year cells	0.065	0.019	0.017	0.132
Age	42.049	9.797	25	61
Male	0.504	0.500	0	1
Hispanic	0.499	0.500	0	1
White non-Hispanic	0.172	0.378	0	1
Black non-Hispanic	0.074	0.262	0	1
Asian non-Hispanic	0.254	0.435	0	1
Other race non-Hispanic	0.014	0.119	0	1
Children	0.640	0.480	0	1
Married (spouse-present)	0.649	0.477	0	1
Less than high school	0.267	0.443	0	1
High school	0.262	0.440	0	1
Some college	0.197	0.397	0	1
College plus	0.274	0.446	0	1
Cognitive difficulty	0.020	0.138	0	1
Ambulatory difficulty	0.033	0.178	0	1
Independent living difficulty	0.020	0.141	0	1
Self-care difficulty	0.010	0.101	0	1
Hearing/vision difficulty	0.020	0.141	0	1
Years in the U.S.	20.055	10.723	5	61
Lagged unemployment rate at education cells	0.076	0.038	0	0.319
Lagged unemployment rate at country cells	0.066	0.048	0	1
Occupational unemployment rate	0.067	0.054	0	1
Average years of schooling at country cells	12.618	2.506	7.305	16.616
Average years in the U.S. at country cells	18.435	3.586	4.608	34.699
Average age at country cells	41.283	2.015	32.679	48.150
Observations	2,559,681			

Notes. Our sample consists of non-widowed, non-institutionalized immigrants, aged 25-61, who were living in the Unites States five years prior to the survey and were not living abroad in the year prior to the survey. Only naturalized citizens and non-citizens are included. We also exclude American Indians, Alaskan natives, and Hawaiians from our sample as well as individuals whose countries of origin are not clearly specified in the data. SSDI is a dummy variable that equals one if the person receives Social Security Income. Estimates are weighted using the appropriate person-level weights provided by the ACS.

Table 2. Business Cycles and SSDI Benefit Receipt				
	(1) SSDI	(2) SSDI	(3) SSDI	(4) SSDI
Average SSDI receipt in origin group × Lagged unemployment in state-year cells		3.31749**	2.84760*	2.88958*
		(1.042)	(0.981)	(1.067)
Lagged unemployment	0.02112**	-0.06719**		
	(0.007)	(0.014)		
Average SSDI receipt in origin group		0.13450	0.16487*	
		(0.080)	(0.075)	
Male	0.00009	0.00015	0.00015	0.00011
	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic	0.00048	-0.00199	-0.00200	0.00031
	(0.001)	(0.002)	(0.002)	(0.002)
White	0.00029	-0.00060	-0.00060	0.00009
	(0.001)	(0.002)	(0.001)	(0.002)
Black	0.00144	-0.00067	-0.00069	0.00137
	(0.001)	(0.002)	(0.002)	(0.002)
Asian	-0.00223*	-0.00053	-0.00054	-0.00231
	(0.001)	(0.001)	(0.001)	(0.002)
Child	-0.00103**	-0.00100+	-0.00101+	-0.00105+
	(0.000)	(0.001)	(0.001)	(0.001)
Married (Spouse present)	-0.00524**	-0.00511**	-0.00511**	-0.00524**
	(0.000)	(0.001)	(0.001)	(0.001)
High school degree	-0.00298**	-0.00271*	-0.00270*	-0.00297*
	(0.000)	(0.001)	(0.001)	(0.001)
Some college	-0.00573**	-0.00532**	-0.00530**	-0.00574**
	(0.000)	(0.001)	(0.001)	(0.001)
College degree or more	-0.00846**	-0.00758**	-0.00757**	-0.00851**
	(0.000)	(0.001)	(0.001)	(0.001)
Cognitive difficulty	0.06545**	0.06535**	0.06533**	0.06529**
	(0.003)	(0.011)	(0.012)	(0.011)
Ambulatory difficulty	0.08024**	0.08046**	0.08041**	0.08031**
	(0.002)	(0.004)	(0.004)	(0.004)
Independent living difficulty	0.06554**	0.06591**	0.06595**	0.06587**
	(0.004)	(0.010)	(0.010)	(0.011)
Self-care difficulty	0.04828**	0.04808**	0.04807**	0.04806**
	(0.004)	(0.007)	(0.007)	(0.007)
Hearing/vision difficulty	0.01410**	0.01396**	0.01397**	0.01402**
	(0.002)	(0.003)	(0.003)	(0.003)
Age fixed effects	Yes	Yes	Yes	Yes
Years in the U.S. fixed effects	Yes	Yes	Yes	Yes
Country of origin fixed effects	Yes	No	No	Yes
Year fixed effects	No	Yes	No	No
State fixed effects	No	Yes	No	No
Year-State fixed effects	No	No	Yes	Yes
Observations	2,559,681	2,559,681	2,559,681	2,559,681
Adjusted R-squared	0.076	0.076	0.076	0.076
Dependent variable (mean)	0.0144	0.0144	0.0144	0.0144

Notes. See Table 1 for information on sample restrictions. Coefficients are estimated using linear probability models. The omitted categories are female, mixed race, no child in the household, not currently married with a spouse present (either married with no spouse present, separated, divorced, never married), high school dropout, and with no (cognitive, ambulatory, independent living, self-care or hearing/vision) difficulties. In column 1 we cluster the standard errors by state-year cells and in columns 2-4 we use multiway clustering based on state, year, and country of origin. Estimates are weighted using the appropriate person-level weights provided by the ACS. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table 3. Robustness Checks					
	Sample: Working Age Individuals				Sample: Individuals Age 62 and Above
Dependent Variable: Receipt of ...	SSDI	SSDI	SSDI	SSDI	Retirement Benefits
	(1)	(2)	(3)	(4)	(5)
Average SSDI receipt in origin group × Lagged unemployment in state-year cells	4.771**				
	(1.552)				
Average SSDI receipt in origin group × Lagged unemployment in state-year-country of birth cells		0.395*			
		(0.182)			
Average SSDI receipt in origin group × Lagged unemployment in state-year-education cells			5.786**		
			(1.208)		
Average SSDI receipt in origin group × Lagged unemployment in state-year-occupation cells				0.469**	
				(0.024)	
Average SSDI receipt in origin group × Lagged unemployment in state-year cells					-0.227
					(0.286)
Additional Interactions Terms	Yes	No	No	No	No
Observations	2,559,681	2,512,574	2,512,574	2,512,574	801,889
Adjusted R-squared	0.076	0.076	0.076	0.089	0.288
Dependent variable (mean)	0.0144	0.0144	0.0144	0.0144	0.659

Notes. See Table 1 for information on sample restrictions and Table 2 for information on the control variables and fixed effects included in all specifications. In column 1, interactions between the state unemployment rate and average years of schooling, average age, and average number of years in the United States are included in the model. Columns 2-4 have a smaller number of observations because lagged unemployment rates were not available for people in certainly narrowly defined cells. For comparison purposes, we restrict the sample to individuals with non-missing information on all three measures of the unemployment rate. Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the ACS. We use multiway clustering based on state, year, and country of origin. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table 4. Immigrants' Connection to Their Ethnic Communities

Dependent variable: SSDI receipt	Sample: Fluent in English	Sample: Not fluent in English	Sample: CA below median	Sample: CA above median
	(1)	(2)	(3)	(4)
Average SSDI receipt in origin group × Lagged unemployment in state-year cells	1.762 (1.746)	4.123** (0.285)	2.063** (0.420)	6.505* (2.830)
Observations	1,293,512	1,266,169	1,325,890	1,233,791
Adjusted R-squared	0.086	0.073	0.076	0.077
Dependent variable (mean)	0.0137	0.0184	0.0147	0.0142

Notes. See Table 1 for information on sample restrictions and Table 2 for information on the control variables and fixed effects included in all specifications. Column 1 is restricted to individuals who speak only English or speak English very well. Column 2 is restricted to individuals who speak English well, speak English but not well, or do not speak English. Column 3 is restricted to individuals who live in states with a contact availability (CA) value below the median (CA< .0079718) and column 4 to those individual living in states where the CA value is above the median (CA> .0079718). CA is calculated by dividing the number of people from a specific country of origin living in the state by the total number of people living in that state. Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the ACS. We use multiway clustering based on state, year, and country of origin. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table 5. Social Norms and SSDI Receipt

Dependent variable: SSDI receipt	(1)	(2)	(3)	(4)	(5)
"Turn lazy" × Lagged unemployment in state-year cells	1.145**				
	(0.217)				
"Talent develop" × Lagged unemployment in state-year cells		0.576+			
		(0.273)			
"Work duty" × Lagged unemployment in state-year cells			1.473**		
			(0.381)		
PCA work norms × Lagged unemployment in state-year cells				0.012**	0.012*
				(0.004)	(0.004)
Average SSDI receipt in origin group × Lagged unemployment in state-year cells					0.043
					(0.968)
Observations	1,863,180	1,863,180	1,885,155	1,863,180	1,863,180
Adjusted R-squared	0.077	0.077	0.077	0.077	0.077
Dependent variable (mean)	0.0134	0.0134	0.0133	0.0134	0.0134

Notes. In column 1, the interaction variable is the product of co-ethnics who "strongly disagree that people who do not work turn lazy" ("Turn lazy") and the lagged unemployment rate in state-year cells. In column 2, the interaction variable is the product of co-ethnics who "strongly disagree that to develop talents you need to have a job" ("Talent develop") and the lagged unemployment rate in state-year cells. In column 3, the interaction variable is the product of co-ethnics who "strongly disagree that work is a duty towards society" ("Work duty") and the lagged unemployment rate in state-year cells. In column 4, the interaction variable is the product of the first principal component of the above three work norm variables and the lagged unemployment rate in state-year cells. Coefficients are estimated using linear probability models. Out of the 148 origin countries in the ACS sample, we are able to match 79 countries in column 3 and 78 countries in columns 1 and 2. This is the reason why the number of observations in this Table is lower than in the previous Tables, as well as why numbers of observations differs between column 3 and the rest of the columns in this Table. See Table 1 for information on sample restrictions and Table 2 for information on the control variables. Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the ACS. We use multiway clustering based on state, year, and country of origin. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table 6. Business Cycles and SSDI Benefit Receipt in the CPS First Generation Sample

Dependent variable: SSDI receipt	(1)	(2)	(3)	(4)
Average SSDI receipt among those from same birth country × lagged unemployment in state	6.687*	7.685**	8.991**	11.697**
	(2.684)	(2.363)	(0.003)	(2.687)
Average years in the U.S. × lagged unemployment in state			0.006	
			(0.017)	
Average age × lagged unemployment in state			-0.024	
			(0.017)	
Average years of education × lagged unemployment in state			0.006	
			(0.017)	
Average UI receipt × lagged unemployment in state				-0.273
				(0.210)
Health status controls	No	Yes	Yes	Yes
Observations	112,015	112,015	112,015	104,189
Adjusted R-squared	0.023	0.064	0.064	0.062
Dependent variable (mean)	0.0114	0.0114	0.0114	0.0111

Notes: All columns include controls for, gender (dummy for male), having a child, married, high school, some college, college, Hispanic, white non-Hispanic, black non-Hispanic, Asian non-Hispanic, age fixed effects, years in the U.S. fixed effects, country of birth fixed effects and state/year fixed effects. The health status controls include health excellent, very good, good, and fair dummies. Sampling weights (normalized to sum to the same value each year) are used. Households that have been in the sample for more than 4 months are dropped. Standard errors are reported in parentheses and use multiway clustering based on state, year, and country of origin. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table 7. Business Cycles and SSDI Benefit Receipt in the CPS First Generation Sample by Health Status

Dependent variable: SSDI receipt	(1) Health excellent	(2) Health very good	(3) Health good	(4) Health fair	(5) Health poor
Average SSDI receipt among those from same birth country × lagged unemployment in state	-1.176	-0.887	11.146**	78.738**	-42.323
	(6.447)	(3.655)	(0.009)	(19.537)	(120.268)
Observations	29,200	37,125	34,298	8,588	2,445
Adjusted R-squared	0.029	0.010	0.031	0.053	0.098
Dependent variable (mean)	0.0020	0.0027	0.0089	0.0496	0.1379

Notes: All columns include controls for, gender (dummy for male), having a child, married, high school, some college, college, Hispanic, white non-Hispanic, black non-Hispanic, Asian non-Hispanic, age fixed effects, years in the U.S. fixed effects, country of birth fixed effects and state/year fixed effects. The health status controls include health excellent, very good, good, and fair dummies. Sampling weights (normalized to sum to the same value each year) are used. Households that have been in the sample for more than 4 months are dropped. Standard errors are reported in parentheses and use multiway clustering based on state, year, and country of origin. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table 8. Business Cycles and SSDI Benefit Receipt in the CPS First Generation Sample by Documented Status

Dependent variable: SSDI receipt	(1) Undocumented	(2) Documented
Average SSDI receipt among those from same birth country × lagged unemployment in state	-0.492 (2.426)	8.640* (3.948)
Observations	40,216	71,784
Adjusted R-squared	0.002	0.075
Dependent variable (mean)	0.0012	0.0170

Notes: All columns include controls for gender (dummy for male), having a child, married, high school, some college, college, Hispanic, white non-Hispanic, black non-Hispanic, Asian non-Hispanic, age fixed effects, years in the U.S. fixed effects, country of birth fixed effects and state/year fixed effects. The health status controls include health excellent, very good, good, and fair dummies. Sampling weights (normalized to sum to the same value each year) are used. Households that have been in the sample for more than 4 months are dropped. Standard errors are reported in parentheses and use multiway clustering based on state, year, and country of origin. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table 9. Business Cycles and SSDI Benefit Receipt in the CPS Second Generation Sample

Dependent variable: SSDI receipt	(1) Father foreign born	(2) Mother foreign born	(3) Father and mother from same country
Average SSDI receipt among those from father's country of birth × lagged unemployment	8.156** (0.168)		
Average SSDI receipt among those from mother's country of birth × lagged unemployment		9.812** (3.033)	
Average SSDI receipt among those from parents' shared country of birth × lagged unemployment			9.406 (6.406)
Observations	32,684	33,511	18,465
Adjusted R-squared	0.125	0.114	0.114
Dependent variable (mean)	0.0210	0.0186	0.0153

Notes: Column (1) and (2) include only those whose fathers and mothers were born outside the U.S., respectively. Column (3) includes those with at least one parent born outside the U.S. All columns include controls for gender (dummy for male), having a child, married, high school, some college, college, Hispanic, white non-Hispanic, black non-Hispanic, Asian non-Hispanic, health excellent, very good, good, fair, age fixed effects, parent's country of birth fixed effects, and state/year fixed effects. Column (3) also includes dummies for whether the person's father and mother were born outside the U.S. Sampling weights (normalized to sum to the same value each year) are used. Households that have been in the sample for more than 4 months are dropped. Standard errors are reported in parentheses and use multiway clustering based on state, year, and parent's country of origin. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Appendix Tables

Table A1. Choosing Unemployment Rate Lag (ACS 2001-2016)

Dependent variable: SSDI receipt	(1) Current UR	(2) UR Lag (-1)	(3) UR Lag (-2)	(4) UR Lag (-3)
Average SSDI receipt in origin country × Current unemployment in state-year cells	2.368*			
	(0.861)			
Average SSDI receipt in origin country × Lagged unemployment in state-year cells		2.890*		
		(1.067)		
Average SSDI receipt in origin country × Lagged unemployment two years ago in state-year cells			2.127	
			(1.553)	
Average SSDI receipt in origin country × Lagged unemployment three years ago in state-year cells				2.042
				(1.231)
Observations	2,577,904	2,559,681	2,503,775	2,451,537
Adjusted R-squared	0.074	0.076	0.077	0.078

Notes. For information on the sample see Table 1. Coefficients are estimated using linear probability models. For reasons of brevity, we only present estimates for the interaction variable. Other controls include those shown in column 3 of Table 2. Standard errors are clustered at state-year-country of origin cells. Estimates are weighted using the appropriate person-level weights provided by the ACS. We use multiway clustering based on state, year, and country of origin. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table A2. SSDI Receipt by Country of Origin Ranked from Highest to Lowest (ACS 2001-2016)

Country	Observations	SSDI Receipt
Azores	1,829	0.0723
Portugal	13,936	0.0388
Italy	19,701	0.0375
Greece	8,486	0.0348
Croatia	2,741	0.0340
Yemen Arab Republic (North)	1,908	0.0336
Iceland	311	0.0333
Bhutan	468	0.0332
Cape Verde	2,108	0.0330
Serbia	968	0.0326
Yugoslavia	5,029	0.0321
Czechoslovakia	1,019	0.0302
Macedonia	1,761	0.0294
Cuba	57,295	0.0294
Dominican Republic	48,219	0.0294
Germany	34,356	0.0283
Caribbean, ns	2,017	0.0274
Afghanistan	4,285	0.0263
Iraq	7,241	0.0262
Laos	16,342	0.0257
Gambia	307	0.0248
Dominica	1,866	0.0247
Syria	4,441	0.0240
Marshall Islands	288	0.0240
St. Vincent	1,481	0.0238
Cambodia (Kampuchea)	12,565	0.0238
Egypt/United Arab Rep.	9,383	0.0234
Bahamas	1,952	0.0214
Montenegro	415	0.0213
Austria	2,508	0.0212
Hungary	3,886	0.0208
Somalia	2,747	0.0207
Scotland	3,922	0.0198
United Arab Emirates	234	0.0197
Belgium	2,033	0.0196
Eritrea	1,654	0.0193
Fiji	2,947	0.0191
Haiti	33,123	0.0187
Jordan	4,561	0.0185
Belize/British Honduras	3,123	0.0180
Cyprus	326	0.0179
Saudi Arabia	1,133	0.0179
Bosnia	8,030	0.0179
Panama	7,086	0.0178
Armenia	5,561	0.0175
Lebanon	9,504	0.0175
Canada	55,440	0.0174
Poland	31,606	0.0173
Netherlands	5,490	0.0172
Libya	289	0.0170
Jamaica	42,305	0.0170
Costa Rica	5,354	0.0169
Tonga	1,200	0.0169
Barbados	3,543	0.0168
Guyana/British Guiana	18,535	0.0167
Spain	5,202	0.0165
Romania	11,491	0.0162
Ireland	8,369	0.0161
England	23,791	0.0161

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Country	Observations	SSDI Receipt
Uzbekistan	2,703	0.0160
Trinidad and Tobago	16,381	0.0159
Colombia	41,902	0.0158
Bermuda	468	0.0154
Nicaragua	17,541	0.0152
Paraguay	952	0.0152
Ecuador	23,878	0.0151
Sudan	1,924	0.0148
Liberia	3,513	0.0148
Tanzania	1,263	0.0147
Norway	1,280	0.0146
Czech Republic	1,939	0.0145
Azerbaijan	1,121	0.0142
Iran	24,786	0.0142
Chile	5,970	0.0140
Zaire	395	0.0139
St. Kitts-Nevis	435	0.0139
Vietnam	99,334	0.0139
Philippines	133,573	0.0133
Other USSR/Russia	21,311	0.0132
Israel/Palestine	9,724	0.0132
Latvia	961	0.0131
Mexico	754,543	0.0130
Ethiopia	8,938	0.0129
Thailand	13,889	0.0129
Kazakhstan	1,063	0.0128
Albania	4,029	0.0126
Togo	469	0.0124
Antigua-Barbuda	1,246	0.0123
Algeria	1,223	0.0121
Ukraine	18,635	0.0121
Lithuania	1,838	0.0119
Ghana	7,589	0.0118
Peru	26,048	0.0118
Bulgaria	4,287	0.0114
Argentina	11,716	0.0114
Estonia	250	0.0114
Uganda	1,287	0.0112
France	9,813	0.0112
Burma (Myanmar)	4,603	0.0111
El Salvador	79,339	0.0111
St. Lucia	1,268	0.0111
Byelorussia	3,354	0.0110
Congo	234	0.0109
Japan	20,647	0.0109
Finland	1,218	0.0107
Korea	68,437	0.0107
Uruguay	3,009	0.0106
Sierra Leone	2,017	0.0104
Republic of Georgia	857	0.0104
Grenada	2,207	0.0103
United Kingdom, ns	19,424	0.0103
Moldavia	2,017	0.0103
Bolivia	4,727	0.0102
Switzerland	2,502	0.0101
Hong Kong	21,975	0.0100
Sri Lanka (Ceylon)	3,238	0.0098
Honduras	26,602	0.0098
South Korea	2,904	0.0097

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Country	Observations	SSDI Receipt
New Zealand	2,185	0.0097
Bangladesh	11,020	0.0097
Kuwait	1,780	0.0096
Senegal	1,173	0.0096
Nepal	2,897	0.0094
Australia	5,057	0.0094
Morocco	4,234	0.0093
Cameroon	1,895	0.0093
Turkey	7,175	0.0093
China	99,113	0.0092
Pakistan	21,211	0.0092
Brazil	21,489	0.0091
Sweden	2,996	0.0091
Singapore	1,986	0.0089
Guatemala	46,427	0.0086
Micronesia	963	0.0086
Taiwan	33,776	0.0082
South Africa (Union of)	6,823	0.0080
Denmark	1,699	0.0079
Venezuela	11,713	0.0078
Northern Ireland	654	0.0075
Indonesia	6,359	0.0075
Nigeria	13,856	0.0075
Slovakia	1,400	0.0073
India	123,168	0.0072
Kenya	4,938	0.0071
Malaysia	4,984	0.0068
Guinea	598	0.0056
Zambia	347	0.0053
Zimbabwe	1,258	0.0052

Notes. ACS 2001-2016. Means are weighted using the appropriate person-level weights provided by the ACS.

Table A3. Summary Statistics by Average SSDI and Average Unemployment Rate (ACS 2001-2016)

Variable	Below average SSDI		Above average SSDI		Below average Unemployment		Above average Unemployment	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Disability Insurance Receipt (SSDI)	0.012	0.108	0.022	0.146	0.014	0.118	0.015	0.121
Lagged unemployment in state-year cells	0.066	0.019	0.066	0.019	0.053	0.008	0.085	0.015
Age	41.277	9.675	44.216	9.811	41.807	9.769	42.419	9.827
Male	0.514	0.500	0.476	0.499	0.507	0.500	0.500	0.500
Hispanic	0.573	0.495	0.290	0.454	0.491	0.500	0.511	0.500
White non-Hispanic	0.089	0.285	0.406	0.491	0.176	0.381	0.166	0.372
Black non-Hispanic	0.029	0.168	0.201	0.401	0.079	0.270	0.066	0.249
Asian non-Hispanic	0.308	0.462	0.103	0.303	0.252	0.434	0.257	0.437
Other race non-Hispanic	0.011	0.104	0.024	0.152	0.014	0.116	0.015	0.122
Children	0.661	0.473	0.582	0.493	0.641	0.480	0.639	0.480
Married (spouse-present)	0.661	0.473	0.615	0.487	0.658	0.474	0.635	0.481
Less than high school	0.318	0.466	0.125	0.330	0.267	0.443	0.267	0.442
High school	0.247	0.431	0.304	0.460	0.264	0.441	0.258	0.438
Some college	0.170	0.375	0.272	0.445	0.194	0.395	0.201	0.401
College plus	0.266	0.442	0.299	0.458	0.275	0.446	0.274	0.446
Cognitive difficulty	0.017	0.127	0.028	0.165	0.020	0.141	0.019	0.135
Ambulatory difficulty	0.029	0.167	0.044	0.206	0.036	0.185	0.029	0.167
Independent living difficulty	0.018	0.133	0.027	0.162	0.022	0.148	0.017	0.130
Self-care difficulty	0.009	0.093	0.015	0.120	0.010	0.102	0.010	0.099
Hearing/vision difficulty	0.019	0.138	0.023	0.149	0.020	0.139	0.021	0.144
Years in the U.S.	19.133	9.952	22.646	12.273	19.694	10.672	20.607	10.775

Notes. For information on the sample look at Table 1. Estimates are weighted using the appropriate person-level weights provided by the ACS.

Table A4. Effects of "Networks" on DI Receipt by Ancestry (ACS 2001-2016)		
Dependent variable: SSDI	(1)	(2)
	Natives-Ancestry	Immigrants-Ancestry
Average SSDI receipt in origin country ×	2.352**	1.713*
Lagged unemployment in state-year cells	(0.601)	(0.802)
Observations	13,541,180	2,410,433
Adjusted R-squared	0.167	0.081
Dependent variable (mean)	0.0365	0.0154

Notes. We use the first self-reported ancestry, variable "ancestr1" in the ACS samples. For information on the sample see Table 1. Coefficients are estimated using linear probability models. For reasons of brevity, we only present estimates for the interaction variable. Other controls include those shown in column 3 of Table 2. Estimates are weighted using the appropriate person-level weights provided by the ACS. We use multiway clustering based on state, year, and ancestry. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table A5. Recovery Years versus Downturn Years (ACS 2001-2016)		
Dependent variable: SSDI	(1)	(2)
	Recovery years	Downturn years
Average SSDI receipt in origin country ×	2.134	3.291**
Lagged unemployment in state-year cells	(1.413)	(0.001)
Observations	1,740,029	819,652
Adjusted R-squared	0.078	0.074
Dependent variable (mean)	0.0161	0.0159

Notes. Recovery years are defined as years in which the current year's unemployment rate is lower than the previous year's unemployment, and downturn years are the opposite. For information on the sample see Table 1. Coefficients are estimated using linear probability models. For reasons of brevity, we only present estimates for the interaction variable. Other controls include those shown in column 3 of Table 2. Estimates are weighted using the appropriate person-level weights provided by the ACS. We use multiway clustering based on state, year, and country of origin. Levels of significance: ** p<0.01, * p<0.05, + p<0.1.

Table A6. Summary Statistics for the CPS Samples

Variable	Mean	Standard deviation	Minimum	Maximum
Panel A. First generation				
Disability Insurance receipt (SSDI)	0.011	0.106	0	1
Lagged unemployment	0.066	0.019	0.017	0.132
Age	41.973	9.783	25	61
Male	0.506	0.500	0	1
Hispanic	0.520	0.500	0	1
White non-Hispanic	0.166	0.372	0	1
Black non-Hispanic	0.068	0.252	0	1
Asian non-Hispanic	0.246	0.431	0	1
Other race non-Hispanic	0.00003	0.006	0	1
Child	0.649	0.477	0	1
Married	0.674	0.469	0	1
Less than high school	0.271	0.445	0	1
High school	0.252	0.434	0	1
Some college	0.168	0.374	0	1
College	0.283	0.450	0	1
Health excellent	0.264	0.441	0	1
Health very good	0.330	0.470	0	1
Health good	0.304	0.460	0	1
Health fair	0.078	0.268	0	1
Health poor	0.024	0.153	0	1
Years in the U.S.	19.325	10.021	5	61
Observations	112,015			
Panel B. Second generation				
Disability Insurance receipt (SSDI)	0.022	0.146	0	1
Lagged unemployment	0.065	0.019	0.017	0.132
Age	39.781	10.742	25	61
Male	0.507	0.500	0	1
Hispanic	0.350	0.477	0	1
White non-Hispanic	0.479	0.500	0	1
Black non-Hispanic	0.044	0.206	0	1
Asian non-Hispanic	0.126	0.332	0	1
Other race non-Hispanic	0.0002	0.015	0	1
Child	0.476	0.499	0	1
Married	0.545	0.498	0	1
Less than high school	0.060	0.237	0	1
High school	0.240	0.427	0	1
Some college	0.296	0.456	0	1
College	0.391	0.488	0	1
Health excellent	0.329	0.470	0	1
Health very good	0.343	0.475	0	1
Health good	0.238	0.426	0	1
Health fair	0.067	0.249	0	1
Health poor	0.023	0.149	0	1
Observations	49,700			

Notes. SSDI is a dummy variable that equals one if the person receives social security income and said that a reason for doing so was because of a disability.