Labour Economics 103 (2026) 102960



Contents lists available at ScienceDirect

Labour Economics

journal homepage: www.elsevier.com/locate/labeco



Ethnic networks and disability insurance take-up over the business cycle

Delia Furtado [a,*], Kerry L. Papps [b], Nikolaos Theodoropoulos [c]

[a] Department of Economics, University of Connecticut, Storrs, CT 06269, USA
[b] University of Bradford School of Management, University of Bradford, Bradford, BD7 1DP, United Kingdom
[c] Department of Economics, University of Cyprus, P.O. Box 20537, CY-1678, Nicosia, Cyprus

ARTICLE INFO

Keywords:
Ethnic networks
Disability insurance
Unemployment
Immigrants

ABSTRACT

We examine the role of ethnic networks in determining Social Security Disability Insurance (SSDI) take-up rates among immigrants in the United States. We show that immigrants in ethnic networks—as defined by their country of origin and state of residence—with high take-up rates are more likely than those from low take-up networks to go on disability when jobs become scarce, a result potentially explained by better information sharing or less stigma against take-up within high take-up groups. We provide evidence suggesting that these results are not likely driven by differences in work norms, occupational sensitivities to business cycles, or eligibility for the SSDI program. The effect is concentrated among those people with fair—rather than excellent or poor—levels of self-reported health, suggesting that ethnic networks play a role in driving those with marginal disabilities to apply for SSDI benefits during economic downturns.

1. Introduction

The Social Security Disability Insurance (SSDI) program was established in 1956 to provide benefits to American workers and their families in the event of disability. Demographic changes imply that the Social Security Administration's current system of funding retirement and disability benefits is not sustainable. In fact, the 2024 Trustees Report predicts that the combined Old-Age and Survivors Insurance (OASI) and Disability Insurance (DI) Trust Funds (collectively referred to as the OASDI fund) will only be able to make scheduled payments until the year 2035 (Social Security Administration, 2024). As policymakers consider changes to the system, it is important to understand the factors, beyond mere disability status, that drive SSDI participation. This paper examines the role of ethnic networks in determining whether people with marginal disabilities apply for and ultimately receive benefits from SSDI.

There is strong causal evidence that people are more likely to receive disability benefits if their parents received benefits (Dahl et al., 2014), a result suggestive of family welfare cultures. However, a growing body of work shows that a range of important health and work choices are affected by the behaviors of people within local communities—not just within families.[1] Furtado and Theodoropoulos (2013, 2016) show that immigrants who live in communities with more co-ethnics are especially likely to take up disability benefits if they are from high take-up ethnic groups. While this finding is certainly consistent with ethnic networks driving SSDI take-up, it could also be driven by selective migration of immigrants to different local areas in the United States; immigrants in high SSDI take-up groups may be more likely to live in ethnic enclaves if they are on SSDI themselves. In this paper, we provide evidence of the role of ethnic networks that is not driven by this type of very local selective migration. In particular, we examine whether immigrants in high SSDI groups—i.e., groups with more information about the SSDI program and surely less stigma against take-up—are especially likely to go on disability in response to economic downturns.

The possibility that take-up decisions exhibit spillovers within communities is potentially a major challenge for policymakers given the evidence that entries to SSDI increase during recessions but never fall back when the economy recovers (Maestas et al., 2021). If disability take-up rates are transmitted within social groups, this problem will be exacerbated since an individual's decision to take up disability insurance in response to economic conditions may lead others to exit (and never re-enter) the labor market, potentially resulting in a ripple effect

* Corresponding author.
E-mail addresses: Delia.Furtado@uconn.edu (D. Furtado), k.l.papps@bradford.ac.uk (K.L. Papps), theodoropoulos.nikos@ucy.ac.cy (N. Theodoropoulos).

[1] For example, there is evidence of local spillover effects in the consumption of alcohol (Eisenberg et al., 2014; Kremer and Levy, 2008), cigarettes (Cutler and Glaeser, 2010; Fletcher, 2010; Powell et al., 2005), and most recently, opioids (Cutler and Donahoe, 2025). Duflo and Saez (2003) show that retirement plan enrollment is also sensitive to spillover effects within communities, while Bertrand et al. (2000) provide evidence of ethnic networks in welfare take-up.

https://doi.org/10.1016/j.labeco.2026.102960
Received 14 August 2024; Received in revised form 20 August 2026; Accepted 31 August 2026
Available online 1 September 2026
0927-5371/© 2026 Elsevier B.V. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

of disability take-up throughout a community.

If everyone with a work-preventing disability applied for and ultimately received benefits, and no one who was capable of working received such benefits, there would be little scope for social networks to play a role in determining SSDI take-up. However, if applying for SSDI is complex due to paperwork or eligibility ambiguity, information sharing within social circles may help ensure that insured individuals who are genuinely incapable of working receive benefits. Conversely, if many SSDI recipients are indeed able to work, stigma within social networks may discourage work-capable individuals from pursuing SSDI. Information sharing and stigma may work together if, for example, people in low-stigma social groups share information with each other about which lawyers are likely to win SSDI cases of applicants who are capable of working. By exploring the role of social networks in determining take-up, we gain insight on whether SSDI benefits are generally awarded fairly and efficiently.

Any analysis of this type faces two main difficulties. The first challenge is how to measure the role of social networks without data on friendship circles. Following a large literature (e.g., Bertrand et al., 2000; Gee and Giuntella, 2011; Furtado and Theodoropoulos 2013, 2016; Furtado et al., 2022), we address this challenge by focusing our analysis on immigrants in the U.S. and assume that other immigrants from their country of origin are overrepresented in their social networks. To get a sense for the amount and quality of information regarding the SSDI program within groups as well as the likely stigma against unjustified SSDI take-up, we construct average SSDI take-up rates by country of origin and state of residence, measured prior to our sample period. Immigrants in groups with historically higher SSDI take-up are presumed to have greater access to program-related information and to face less stigma associated with SSDI receipt within their ethnic networks.

The second challenge is to identify the individuals for whom networks are likely to matter: those with a disability severe enough to be awarded benefits but not so severe as to make work impossible.[2] Those without a documentable disability are unlikely to be awarded benefits regardless of whether they apply, and so information sharing and stigma within ethnic networks are unlikely to drive SSDI take-up. At the other extreme, information sharing within networks is less useful for those with severe disabilities due to clear SSDI eligibility and a more straightforward application process. Additionally, there is surely little stigma against receiving benefits for those unable to work at all, regardless of social network.

Following Furtado et al. (2022), which builds on a growing literature showing that applicants induced into the SSDI program during the Great Recession were more likely to have only marginal disabilities (Maestas et al., 2021), we address this challenge by focusing on the role of networks in people's decisions to go on disability in response to poor labor market conditions. Since these individuals are ultimately awarded benefits, they must have a severe enough disability to convince SSDI examiners that they are incapable of work. However, since they were induced to apply for SSDI only by a job loss, they are presumably capable of working, at least under certain conditions.

Using data from the 2001–2019 American Community Surveys (ACS), our first main finding is that immigrants from high SSDI take-up country of origin groups are more sensitive to economic downturns than immigrants in low SSDI take-up origins, a result consistent with ethnic networks driving the decisions of marginal applicants. A potential concern with this interpretation is that same-origin country SSDI participation rates are correlated with other factors influencing take-up rates across the business cycle. For example, immigrants in high SSDI groups may tend to work in industries that are more sensitive to business fluctuations or may be less likely to qualify for SSDI based on their work histories and documentation status. We address these concerns in the paper with a series of robustness and heterogeneity tests along with three placebo tests, considering changes in wages and flows out of the labor force for reasons unrelated to SSDI.

Turning next to data from the Current Population Surveys (CPS), our second main finding is that our results are driven by people with intermediate self-reported health levels. This makes sense in that information about eligibility for the program and how to prove that a disability makes work impossible is more important for those with moderate levels of disability than those with severe disabilities. Moreover, any stigma against receiving benefits is likely important only for those who have a disability that makes it difficult, but not impossible, to work.

This paper extends a closely related paper, Furtado et al. (2022), which shows that immigrants from countries with strong work norms—as measured by home country survey responses—are less likely to take up disability insurance in response to economic downturns than immigrants from countries with weaker work norms. We show that there are spillovers within immigrant groups that cannot be fully explained by differences in work norms alone. Crucially, there is little reason to believe that work norms in the country of origin respond to immigrant SSDI take-up in the United States, making such norms unlikely to generate multiplier effects. In contrast, increases in co-ethnic SSDI take-up within the United States—regardless of its source—may facilitate information sharing and reduce stigma, thereby inducing additional SSDI participation.

The remainder of the paper proceeds as follows. Section 2 provides background on the SSDI program as well as the literature on ethnic networks in general and, in particular, how they relate to SSDI take-up. Section 3 presents our two complementary data sources and provides graphical evidence of some of our findings. Section 4 outlines the empirical strategy and presents the main results as well as results from tests for heterogeneity and placebo tests. Section 5 explores heterogeneity by self-reported health. Section 6 concludes and offers policy implications.

2. Background

2.1. The Social Security Disability Insurance program

Social Security Disability Insurance is a U.S. federal program designed to provide income to people who are unable to work because of a physical or mental disability. To qualify, applicants must satisfy two requirements. First, applicants must generally have worked at least five of the past ten years and ten years in their working lives, although the actual rules depend on the applicant's age and are complicated. Second, applicants must be out of work or earning less than a prescribed amount for five months after their determined "disability onset" date before receiving benefits.[3]

[2] The SSDI application process requires individuals to submit a wealth of information including clinical test results, clinical diagnoses, and physician recommendations, but there are strong indications that many of those who ultimately receive benefits are indeed capable of working (Autor and Duggan, 2003; Black et al., 2002; Charles et al., 2018; Liebman, 2015). In fact, Deshpande and Lockwood (2022) conclude that about half of the value of the U. S. disability system comes from its providing insurance against *non-health* risks. At the other end of the spectrum, the success of the appeals process suggests that initial SSDI denials are made to individuals who might indeed be incapable of working. According to data collected between 1995 and 2009, only one-third of applicants were successful in the initial determination, but almost two-thirds of applicants were ultimately awarded benefits within six years of their initial determination (Maestas et al., 2013). We do not have access to all the data collected by the Social Security Administration to make disability determinations, but even if we did, this literature suggests that it would not be enough to determine whether applicants are able to work.

[3] The maximum earnings limits vary by disability type and year and can be found here: https://www.ssa.gov/oact/cola/sga.html (accessed 13 August 2025).

In addition to these rather technical requirements, medical evidence of a work-preventing disability is provided by doctors and examined at Disability Determination Offices. Examiners evaluate whether the impairment is severe and expected to last more than a year, and whether the claimant can perform 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 from a person who is unable to perform physically demanding work may be denied if that person has the education and experience to work in an office job but approved if they do not.

In general, only about a third of applicants are awarded benefits at the first determination (Maestas et al., 2013). Sixty-five percent of denied applicants appeal, and most of those who appeal eventually have a hearing before an 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 et al., 2013). Around 40 percent of Great Recession-induced applications were ultimately awarded (Maestas et al., 2021), even though applicants were far more likely to have only marginal disabilities.

Documented immigrants, regardless of whether they are citizens, are eligible for SSDI. Undocumented immigrants do not qualify for the program. The arduous and rather opaque application process makes SSDI take-up ripe for the influence of social networks. About a quarter of denied claims are denied for nonmedical reasons (Deshpande and Li, 2019)—evidence of the potential difficulty applicants face in determining whether they qualify and pointing to a potential role for ethnic networks. Potential applicants with only marginal disabilities may learn from acquaintances that applicants with certain difficult to diagnose conditions, like back pain, may eventually qualify for benefits despite work capacity. Information on how to fill out the forms and regarding the most effective lawyers can also be shared within networks.

Norms established and reinforced within ethnic communities may also play a role. For example, it is possible that deception in court feels more morally comfortable for people whose friends and acquaintances have done the same thing. Moreover, going on disability requires the applicant to stop working, or earn below the prescribed threshold, for five months before benefits begin. For most people, it also means not working throughout the application process, since it is hard to demonstrate an inability to work while working. The psychological costs of leaving the labor force—in terms of a lost sense of identity and purpose—are likely easier to bear for people within communities where many people do not work. The results in Furtado et al. (2022) suggest that immigrants from countries with strong work norms are less likely than those from weak work norm countries to go on disability in response to job loss.

2.2. SSDI applications during economic downturns

Research leveraging local labor demand shocks has shown that worse labor market conditions lead to higher SSDI application rates. In coal-producing counties, disability claims rise when energy prices fall and decline when prices rise (Black et al., 2002). Similarly, Charles et al. (2018) find increased SSDI claims in response to downturns in the oil and gas sectors. According to Autor et al. (2013), greater exposure to Chinese import competition also drives up SSDI participation.

In terms of research focusing on business cycle fluctuations, Duggan and Imberman (2009) show that almost a quarter of the increase in male SSDI participation during the late 20th century was linked to recessions. More recent work has identified significant increases in SSDI awards during and after the Great Recession (Maestas et al., 2021; Mueller et al., 2016).[4] These studies suggest that while some individuals apply for SSDI regardless of economic conditions, there is a group whose take-up of disability benefits is influenced by poor labor market conditions.

Using disability data on SSDI applications, Maestas et al. (2021) show that recession-induced entrants are generally less disabled than other entrants. Using detailed information on medical spending and mortality, Carey et al. (2022) show that when unemployment rates are higher at the time of application, future medical spending and mortality among entrants is lower. They show that the impact of worsening economic conditions is equivalent to the impact of decreasing SSDI eligibility criteria (Carey et al., 2022).

Several papers find that when the (non-pecuniary) costs of take-up decrease, the impact of worsening labor market conditions increases. Kearney et al. (2021) show that in local areas with plausibly exogenous longer SSDI appeals processing times—an added inconvenience to an already rather arduous application process—enrollments did not increase as much in response to economic downturns. Moreover, in places with the largest baseline SSDI enrollment rates, those with longer processing times experienced faster employment recovery rates following Great Recession shocks. Again, in a paper most closely related to ours, Furtado et al. (2022) show that immigrants from countries with weaker work norms (i.e., smaller utility costs to leaving the labor force) are more sensitive to economic conditions than immigrants from countries where work is considered a duty to society. We contribute to this finding by considering the impact of the role of ethnic networks more broadly.

2.3. Ethnic networks and immigrant SSDI participation

There is a large literature examining the role of ethnic networks in determining program participation using data on immigrants. In a seminal paper, Bertrand et al. (2000) show that immigrants residing amidst many 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 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 Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) participation during pregnancy (Figlio et al., 2015), to name a few examples. Battisti et al. (2022) show that immigrants living in areas with larger co-ethnic networks are more likely to be employed soon after arriving in Germany suggesting the importance of ethnic networks for finding jobs, but this advantage disappears after a few years, presumably because those with smaller ethnic networks invest more heavily in host country specific skills.

In terms of SSDI participation, Furtado and Theodoropoulos (2016) show that immigrants residing amidst many co-ethnics within rather small local areas are especially likely to receive disability payments when their ethnic groups have higher take-up rates. Furtado and Theodoropoulos (2013) further show that while immigrants in local networks with high Supplemental Security Income (SSI) for disability participation are more likely to apply for SSI for a disability, conditional on applying, they are in fact less likely to be awarded benefits. This suggests that high take-up ethnic networks induce people with marginal disabilities to apply for benefits, but applications of people with

[4] Interestingly, SSDI applications did not increase in response to the 2020 recession induced by COVID-19 (Maestas and Mullen, 2024). This may have been due to the prolonged closures of SSA field offices or more generous unemployment insurance benefits during this time.

marginal disabilities are often denied.[5]

A main identification problem with this literature is that immigrants choose where to live, and those who are most similar to their ethnic groups in terms of SSDI take-up might be especially likely to choose to live in ethnic enclaves. Thus, what appears as the impact of ethnic networks may simply reflect geographic sorting within states. For this reason, we do not rely on variation across small geographic areas for identification of the role of ethnic networks. As in that literature, we exploit variation in ethnic-group SSDI take-up rates, which we measure at the state–country of origin level. However, rather than interacting group-specific take-up with the size of the ethnic group at a very local level (Furtado and Theodoropoulos, 2013; Bertrand et al., 2000), we interact these rates with state unemployment conditions each year. This specification allows us to include (state-specific) country of origin fixed effects as well as state-year fixed effects, and our identification does not rely on local residential choices.

Our paper links the literature on the role of ethnic networks in program participation with the literature on the cyclicality of SSDI take-up. As discussed previously, SSDI benefits are intended for people who are no longer able to work because of physical or mental disability; the SSDI program is not structured to provide unemployment insurance. By considering how ethnic networks affect recession-induced take-up decisions, we can identify impacts specifically on individuals who would prefer to and are able to work despite having a disability severe enough to be awarded benefits.

3. Data and descriptive statistics

Initially, we use data from the 2001 to 2019 samples of the American Community Survey (ACS), as reported by the Integrated Public Use Microdata Series (IPUMS, Ruggles et al., 2025).[6] These data do not allow us to observe the same individuals over time; instead, these are repeated cross sections of the U.S. population. Our baseline ACS sample consists of immigrants (naturalized citizens and noncitizens) between the ages of 25 and 61 who have been in the U.S. for at least five years and do not reside in group quarters. We exclude immigrants who have been in the U.S. less than five years because to be eligible for SSDI, people must generally have worked (in the U.S.) for at least five years. To clearly link people to their country of origin communities, we drop individuals without a clear country of birth listed in the ACS (for example, they may be listed as "Central Africa, ns"). Finally, we drop widows and widowers from the sample because our measure of SSDI receipt is less informative for this population.

The ACS does not directly ask about SSDI income. Instead, the survey asks individual respondents about their Social Security income more broadly, but our sample limitations help to identify SSDI beneficiaries.[7] We also supplement our analysis with data from the Annual Social and Economic Supplement (ASEC) to the March CPS from the years 2001 to 2019 (IPUMS, Flood et al., 2020). Compared to the ACS, the CPS dataset has a substantially smaller sample size but provides a more accurate measure of SSDI income. The dependent variable in the CPS sample is defined as whether a person received Social Security income *for a disability* in the previous year. The CPS also contains better health measures than the ACS.

We construct SSDI take-up within a person's origin group using the share of people born in the same country and living in the same state who report receiving SSDI payments in the 5 percent sample of the 2000 U.S. Census (Ruggles et al., 2025). This provides a measure of average SSDI take-up within an immigrant's network. Since 2000 is before our sample period, this variable is less likely to suffer from Manski's (1993) reflection problem. We gather data on annual state unemployment rates from the Local Area Unemployment Statistics program within the Bureau of Labor Statistics (BLS).

Table 1 shows descriptive statistics of the variables used in the analysis. Our final ACS sample consists of 3,085,321 observations. On average, 1.4 percent of the immigrants in our sample receive SSDI, a number very close to the average state-origin group SSDI rate in the year 2000 (1.6 percent). Our measure of average SSDI in state-country of origin cells is constructed from the 2000 Census 5% sample using data from 126 countries across 51 states.[8] The average unemployment rate in our sample is just over six percent. The average immigrant in our sample is 42 years old. About fifty percent are males, fifty-one percent are Hispanic and fifteen percent are white. Sixty-four percent have children, and sixty-four percent are married (with spouse present). Twenty-six percent are high school graduates, about twenty percent have some college, and twenty-eight percent have a college or higher educational qualification. Those with cognitive, vision/hearing, or independent living difficulties each account for around two percent of the sample. Around three percent have an ambulatory difficulty and one percent a self-care difficulty.

We next graphically explore the relationship between unemployment rates and SSDI take-up separately for immigrants from groups with high and low SSDI receipt. Fig. 1 shows, unsurprisingly, that immigrants from country-states in the top quartile of historical SSDI receipt (triangles) are substantially more likely to receive benefits than those in the bottom quartile (dots). More importantly, this difference widens as the unemployment rate increases, pointing to the possibility that when jobs are scarce, ethnic networks play a stronger role in determining take-up. This may be because marginally disabled individuals, capable of working, are incentivized to pursue SSDI payments upon job loss, but only those with access to information about the program and little stigma to

[5] Consistent with this general idea, Borjas and Slusky (2022) 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.

[6] We restrict the sample to ACS data through 2019 to avoid confounding effects associated with the COVID-19 pandemic. COVID-19 disrupted survey data collection and may have affected data quality in 2020, a period that also coincided with unusually high unemployment rates. In addition, pandemic-related disruptions to the SSDI application process generated substantial backlogs, implying that individuals observed receiving SSDI benefits in more recent ACS waves may have applied several years earlier when exposed to very different business cycle conditions. Given these data and timing concerns, we limit the analysis to the pre-pandemic period.

[7] The ACS includes a general question about Social Security income. Social Security income can come from four sources: SSDI benefits, public pensions, survivor benefits, and Railroad Retirement insurance. Given that our study focuses on working-age individuals, it is unlikely that Social Security income recipients in our sample are receiving retirement income or Railroad Retirement insurance. Additionally, since we exclude widows and widowers from the sample, survivor benefits are not a likely source of Social Security income. Although most individuals receiving Social Security income in our sample are likely to be beneficiaries of SSDI due to their own disabilities, there are instances where non-disabled spouses and children of disabled workers might also receive SSDI benefits. While the ACS data does not allow us to distinguish whether recipients are obtaining SSDI benefits due to their own disabilities, aggregate statistics indicate that over 80% of SSDI recipients are beneficiaries due to their own impairments (Social Security Administration, 2017).

[8] There is significant variation in average SSDI across countries and states. Table A1 in the Appendix reports SSDI take-up rates for each country of origin, averaged across the states. These range from 0 (for Saudi Arabia) to 0.063 (for Portugal). The country-state level values we use in the regression analysis exhibit even more variation.

Table 1
Summary statistics, ACS sample (2001–2019).

	Mean	Standard deviation	Minimum	Maximum
Disability Insurance Receipt (SSDI)	0.014	0.119	0	1
Average state-origin group SSDI in 2000	0.016	0.014	0	1
Lagged unemployment in state-year cells	0.064	0.022	0.021	0.137
Age	42.378	9.811	25	61
Male	0.503	0.500	0	1
Hispanic	0.511	0.500	0	1
White, non-Hispanic	0.154	0.362	0	1
Black, non-Hispanic	0.074	0.262	0	1
Asian, non-Hispanic	0.257	0.438	0	1
Other race, non-Hispanic	0.013	0.123	0	1
Have children	0.639	0.480	0	1
Married (spouse present)	0.643	0.479	0	1
Less than high school	0.264	0.441	0	1
High school	0.263	0.440	0	1
Some college	0.196	0.397	0	1
College degree or more	0.277	0.448	0	1
Cognitive difficulty	0.019	0.137	0	1
Ambulatory difficulty	0.031	0.173	0	1
Independent living difficulty	0.019	0.135	0	1
Self-care difficulty	0.010	0.099	0	1
Hearing/vision difficulty	0.021	0.142	0	1
Years in the U.S.	20.560	10.830	5	62
Observations	3,085,321			

Notes. Our sample consists of non-widowed, non-institutionalized immigrants, aged 25–61, who have lived in the United States for at least five years. Only naturalized citizens and non-citizens are included meaning that Puerto Ricans and people from other U.S. territories as well as individuals born abroad of American parents are dropped from the sample. We also exclude 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. The variable, "Average state-origin group SSDI in 2000", is constructed using the 5% sample of the 2000 U.S. Census. The lagged unemployment variable is obtained from BLS's (Bureau of Labor Statistics) Local Area Unemployment Statistics program (https://www.bls.gov/lau/). The variable "Have Children" is a dummy variable taking the value of 1 if the individual has children of any age and marital status including biological, stepchildren or adopted children. Estimates are weighted using the appropriate person-level weights provided by the ACS.

take-up end up receiving benefits.

4. Empirical specification and findings

4.1. Empirical specification

Certain immigrant groups living in particular states may have higher SSDI participation rates for relatively minor idiosyncratic reasons. For example, their ethnic neighborhoods may have coincidentally been located close to Social Security field offices or immigrants from certain groups may have systematically held occupations that tended to result in work-preventing injuries. Regardless of the explanations for the high SSDI participation rates in certain groups in the past, immigrants connected to ethnic networks with high SSDI participation are likely to face lower costs (financial, time, or emotional costs) to participation. For example, immigrants in social circles with higher take-up rates can more easily find information about the program, get assistance with filling out applications, and even learn about the most lenient doctors and effective lawyers. In addition, taboos against leaving the workplace despite having only a marginal disability are likely to be weaker in high take-up groups – again, decreasing the cost of applying despite potentially being able to work. This implies that immigrants in high take-up networks

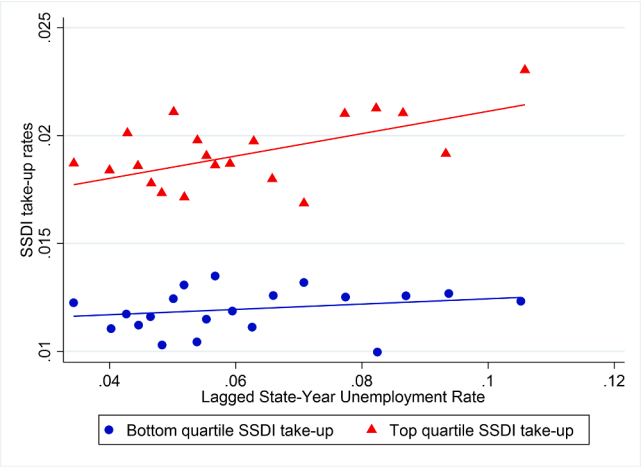


Fig. 1. Average state-origin group SSDI in 2000 and State-Year Unemployment Rate.
Notes. To create the figure, we first regress both SSDI and lagged unemployment rate on a full set of state of residence fixed effects. We then group the residual lagged unemployment rate from this regression into twenty equal-sized bins (triangles or dots) and plot the residual unemployment rate against the corresponding residual SSDI receipt in each bin, separately for each quartile group. The sample mean of each variable is added back to its residuals prior to binning, so that the plotted values remain on the original scale. We overlay a line of best fit estimated on the underlying (non-binned) residualized data.

should respond more strongly to economic downturns than immigrants in low take-up networks.

The main empirical specification used in the analysis to test this is:

$$\text{SSDI}_{iost} = \beta_1 \text{UR}_{st-1} \times \overline{SSDI}_{os}^{2000} + \beta_2' X_{iost} + \gamma_{os} + \delta_{st} + \varepsilon_{iost} \quad (1)$$

where $\text{SSDI}_{\text{iost}}$ is equal to 1 if person i born in country o, living in state s in year t receives any SSDI income, 0 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 SSDI take-up rate among immigrants from the same country of origin living in the same state in the year 2000 (a year prior to the first year in our sample), $\overline{\text{SSDI}}$. Empirically, the β_1 parameter is identified from variation across state-country of origin groups and state-year unemployment rates. By using a measure of average SSDI take-up from before our sample period, we alleviate concerns related to Manski's reflection problem.

The vector $\boldsymbol{X}$ controls for a series of individual characteristics including gender, race, marital status, whether there are children in the household, educational attainment, disability level (measured with broad categories of disability in the ACS analysis and subjective health in the CPS analysis), and a full set of age as well as years in the U.S. dummy variables. The age dummies control for the fact that SSDI take-up rates may increase with age since once people move onto disability, they rarely leave before retirement age. The state-year fixed effects (δ_{st}) control for all factors affecting all immigrants living in the same state in the same year equally. The state–country of origin fixed effects (γ_{os}) absorb any unobserved tendencies for immigrants from particular backgrounds living in particular states to take up SSDI. Since we include state-country of origin fixed effects, we estimate β_1 by comparing changes in take-up rates over time within state-country cells with changes in unemployment rates over the same period.

Table 2
Business cycles and SSDI benefit receipt (ACS 2001–2019).

Dependent variable: SSDI receipt	(1)	(2)	(3)
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells		1.3563**	0.7095*
		(0.344)	(0.349)
Lagged unemployment in state-year cells	0.0232**	−0.0304+	
	(0.009)	(0.016)	
Average state-origin group SSDI in 2000		−0.0237	
		(0.020)	
Male	−0.00001	0.00002	0.00010
	(0.000)	(0.000)	(0.000)
Hispanic	−0.0022*	−0.0018*	0.0004
	(0.001)	(0.001)	(0.001)
White, non-Hispanic	0.0014	0.0013	0.0006
	(0.001)	(0.001)	(0.001)
Black, non-Hispanic	0.0007	0.0002	0.0020+
	(0.001)	(0.001)	(0.001)
Asian, non-Hispanic	−0.0018*	−0.0009	−0.0019*
	(0.001)	(0.001)	(0.001)
Have children	−0.0013**	−0.0012**	−0.0013**
	(0.000)	(0.000)	(0.000)
Married (spouse present)	−0.0050**	−0.0050**	−0.0050**
	(0.000)	(0.000)	(0.000)
High school degree	−0.0021**	−0.0024**	−0.0029**
	(0.000)	(0.000)	(0.000)
Some college	−0.0048**	−0.0050**	−0.0057**
	(0.000)	(0.000)	(0.000)
College degree or more	−0.0075**	−0.0076**	−0.0084**
	(0.000)	(0.000)	(0.000)
Cognitive difficulty	0.0646**	0.0643**	0.0638**
	(0.003)	(0.002)	(0.002)
Ambulatory difficulty	0.0806**	0.0806**	0.0802**
	(0.002)	(0.002)	(0.002)
Independent living difficulty	0.0765**	0.0767**	0.0766**
	(0.004)	(0.003)	(0.003)
Self-care difficulty	0.0424**	0.0422**	0.0422**
	(0.004)	(0.004)	(0.004)
Hearing/vision difficulty	0.0134**	0.0133**	0.0132**
	(0.002)	(0.001)	(0.001)
Age fixed effects	Yes	Yes	Yes
Years in the U.S. fixed effects	Yes	Yes	Yes
Year fixed effects	No	Yes	No
State fixed effects	No	Yes	No
State-year fixed effects	No	No	Yes
State-country of origin fixed effects	No	No	Yes
Observations	3,085,321	3,085,321	3,085,321
Adjusted R-squared	0.076	0.076	0.078
Dependent variable (mean)	0.0143	0.0143	0.0143

Notes. See Table 1 for information on sample restrictions. Coefficients are estimated using linear probability models. In column 1, we cluster the standard errors by state-year cells and in columns 2 and 3, we cluster the standard errors by state, year, and country of origin cells. Estimates are weighted using the appropriate person-level weights provided by the ACS. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

4.2. Main findings (ACS data)

We begin our analysis by confirming that, like the general population, the immigrants in our sample are more likely to go on disability when the unemployment rate increases. Column 1 of Table 2 shows the raw relationship between the state unemployment rate and SSDI take-up among immigrants; indeed the relationship is positive. In column 2, we add the state-specific origin average SSDI take-up in the year 2000 and its interaction with the unemployment rate, along with state and year fixed effects. As expected, the estimate of the coefficient on the interaction term is positive and significant, suggesting that immigrants in groups with higher take-up are especially sensitive to economic conditions. In column 3, we replace the un-interacted unemployment rate with state-year fixed effects and the un-interacted origin-state average SSDI rates with state by country of origin fixed effects, thereby estimating Eq. (1). The coefficient on the interaction term between historical SSDI and lagged unemployment rate drops but remains statistically significant at the 5% level.

The estimate of 0.71 in column 3, our preferred specification, suggests that a percentage point increase in the unemployment rate results in a 0.05 larger percentage point increase in SSDI take-up among the Portuguese (the highest SSDI take-up group in our sample) than among Saudi Arabians (the lowest SSDI take-up group in our sample); Portuguese immigrants are on average exposed to 6.3 percent take-up rate in their ethnic networks while Saudi Arabians are on average exposed to no take-up (see Appendix Table A1). While this difference might initially seem small, it amounts to four percent of the average SSDI take-up rate in our sample (see Table 1). Moreover, it implies that a five percentage point increase in the unemployment rate (akin to the increase during the Great Recession) would result in a 0.25 percentage point difference in take-up between the Portuguese and Saudi Arabians, 18 percent of the SSDI take-up mean.[9] In sum, despite the rather demanding set of controls we use in our regression analysis, the pattern depicted in Fig. 1 persists: Ethnic networks appear especially important during economic downturns when the more marginally disabled are applying for benefits.[10]

Under the interpretation that one person's decision to take up SSDI raises the likelihood that others in the same immigrant group do so, we can follow Bertrand et al. (2000) and calculate a social multiplier. Evaluated at the mean unemployment rate, this multiplier is approximately 1.05 suggesting that a policy that would raise the SSDI take-up rate by one percentage point, absent any network effects, would instead raise it by about 1.05 percentage points because of network effects.[11]

There are several alternative explanations for our baseline results. First, high take-up ethnic groups may systematically come from origin countries with weak work norms. Because leaving the labor force is generally a prerequisite for receiving benefits, immigrants from countries where working plays a major role in people's identities may not apply for SSDI benefits despite eligibility, even during economic downturns. Indeed, Furtado et al. (2022) show that immigrants from countries with weak work norms are more likely to go on disability when unemployment rises. To examine whether our results are driven solely by work norms, we add an interaction between home country work norms and the unemployment rate to our model as a control. In column 1 of Table 3, we start by estimating our baseline specification (Eq. (1)) on a sample of immigrants from countries for which we have information on whether respondents agree with the statement "Work is a duty towards society" in the World Values Survey (WVS) and the European Values Survey (EVS) (Inglehart et al., 2014). Our estimate of interest

[9] See https://www.bls.gov/spotlight/2012/recession/pdf/recession_bls_spotlight.pdf.

[10] Our results do not appear to be driven by any particular country of origin. In Table A2, we drop in turn the largest country (Mexico, column 1), the country with the highest average take-up (Portugal, column 2), and the country with the lowest average take-up (Saudi Arabia, column 3). The results change little in each case. Nor is there evidence that our results are driven by the concentration of immigrants in specific states or industries. To address this, we calculate values of the Herfindahl index, a common measure of concentration, for each country. As seen in Table A2, dropping the country with the highest value of the Herfindahl index across states (Armenia, column 4) or across industries (Yemen, column 5) makes no difference to our results.

[11] Adapting the Bertrand et al. (2000) formula to our context, the multiplier is equal to $1/(1-\beta_1\overline{UR}_{st-1})$, where $\overline{UR}_{st-1}$ is the average unemployment rate across the full sample. This calculation assumes that the level of SSDI take-up in a person's group directly determines the quality of information available and the degree of stigma within the network, that is, that the estimated effect is endogenous in the sense of Manski (1993). If instead, group take-up is simply a good proxy for information quality and stigma within the group, then an exogenous increase in group SSDI take-up need not itself change the information and stigma facing group members, and there would be no multiplier effect (see Bertrand et al. (2000), footnote 34).

Table 3
Robustness checks.

	(1)	(2)	(3)	(4)	(5)
Dependent variable: SSDI receipt	WVS/EVS sample		Full sample		
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	0.7574+	0.6834+	0.7092*	0.6617+	0.5805+
	(0.388)	(0.392)	(0.354)	(0.347)	(0.350)
Share disagree work duty × Lagged unemployment in state-year cells		0.5827+			
		(0.342)			
Average years of schooling × Lagged unemployment in state-year cells			−0.00001		
			(0.001)		
Average age × Lagged unemployment in state-year cells				0.0034*	
				(0.002)	
Average number of years in the U.S. × Lagged unemployment in state-year cells					0.0028+
					(0.001)
Observations	2,302,760	2,302,760	3,085,321	3,085,321	3,085,321
Adjusted R-squared	0.080	0.080	0.078	0.078	0.078
Dependent variable (mean)	0.0131	0.0131	0.0143	0.0143	0.0143

Notes. Number of observations is smaller in columns 1 and 2 as they are being estimated on a smaller WVS/EVS sample where we have information on whether individuals agree with the statement "Work is a duty towards society." Column 1 estimates our baseline (Eq. (1)) in this smaller sample and column 2 adds an interaction term between the share of respondents who "strongly disagree" that work is a duty towards society and the unemployment rate. For columns 3, 4 and 5 see Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. In columns 3, 4 and 5 interactions between the state-year unemployment rate and average years of schooling, average age, and average number of years in the United States constructed at state-country of origin cells are included as extra controls in the baseline (Eq. (1)) respectively. Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the ACS. We cluster the standard errors by state, year, and country of origin cells. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

increases slightly in magnitude. In column 2, we add an interaction between the unemployment rate and the share of respondents who "strongly disagree" that work is a duty towards society to the model. The estimated coefficient on the average SSDI-unemployment interaction falls in magnitude by about 9.8%, suggesting that work norms do play some role, but it remains positive and statistically significant, albeit at the 10% level.

There are additional alternative explanations for our baseline results. One is that immigrants in high SSDI take-up groups are simply more likely to become unemployed during economic downturns. Another potential explanation is that variation across origin groups in SSDI take-up may arise mainly from variation in eligibility for SSDI, for instance, due to work experience in the formal sector as well as legal status in the United States. It may be then that, regardless of ethnic group, all immigrants who are eligible for SSDI would apply during downturns given the opportunity, but immigrants in high SSDI groups are simply more likely to be eligible. We take several different approaches to exploring these possibilities.

We start by adding several interactions between the lagged unemployment rates and average characteristics, besides average SSDI, of the origin group (living in the person's state), constructed over all the years of data we have for the ACS. First, we include the interaction between the unemployment rate and average years of schooling because people with fewer years of schooling are more likely to lose their jobs during economic downturns (Hoynes et al., 2012) and because the foreign born with very low levels of education are more likely to be undocumented immigrants (Borjas, 2017). By controlling for the education-unemployment rate interaction, we are not allowing the 2000 average SSDI rate interaction coefficient to simply pick up these relationships. Similarly, we add an average age-unemployment rate interaction term to the model because younger individuals are also more sensitive to labor markets (Hoynes et al., 2012) and are more likely to be undocumented (Borjas, 2017). Finally, we include the average years in the U.S.-unemployment rate interaction because 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. As seen in columns 3–5 of Table 3, the estimated coefficient on the interaction between unemployment rates and average SSDI take-up remains statistically significant when the additional interaction terms are included in the model. Although not reported, we find similar results when we sequentially add controls for interactions of the unemployment rate with the share of the group working in each of the 24 major occupational categories. This suggests that country of origin differences in demographic and work characteristics are not driving the different business cycle sensitivities to average origin SSDI take-up.

To further address concerns about differential job loss responses to changes in state unemployment rates, we start by constructing unemployment rates within more narrowly defined cells.[12] To do this, we construct the unemployment rates ourselves from the ACS data because the BLS does not produce unemployment rates within the narrowly defined cells. In column 1 of Table 4, we show that our main estimate is slightly smaller if we use these ACS-constructed state unemployment rates compared to our baseline estimates using the BLS state unemployment rates (column 3 of Table 2), but it remains significant at the 10% level. Next, we replace the state unemployment rates with immigrants' country of origin-specific state unemployment rate and then

[12] An alternative potential test of this is to estimate Eq. (1) using a dummy for whether a person is unemployed as the dependent variable. If our baseline results are driven by immigrants in high-SSDI groups working in jobs with more layoffs during downturns, we may expect more unemployment in these groups when the state unemployment rate rises. As reported in column 1 of Table A3, the estimated coefficient on the interaction term is indeed positive and statistically significant. This result is difficult to interpret, however, because alternative explanations are equally consistent with our network story. Importantly, we observe unemployment status at the time of the survey, not job loss itself. Individuals who lose a job and eventually go on SSDI may report being unemployed at any point along the way: while weighing whether to apply, while learning about the program from others, or while an application is pending. If immigrants in high SSDI groups are more likely to go on disability after a job loss, they may also be more likely to report being unemployed at the time of the survey, before benefits are awarded. In addition, stigma against being out of the labor force—one of the mechanisms underlying our network interpretation—may lengthen unemployment spells following a layoff among high-SSDI groups. The positive coefficient might then reflect stigma about not working in high SSDI groups rather than differential job loss. Because the ACS is not a panel, we cannot distinguish among these explanations and so do not emphasize this result.

Table 4
Additional specifications.

Dependent variable: SSDI receipt	(1)	(2)	(3)	(4)	(5)
Average state-origin group SSDI in 2000 × ACS Lagged unemployment in state-year cells	0.5394+				
	(0.290)				
Average state-origin group SSDI in 2000 × ACS Lagged unemployment in state-year-country of birth cells		0.2299**			
		(0.059)			
Average state-origin group SSDI in 2000 × ACS Lagged unemployment in state-year-education cells			1.5401**		
			(0.223)		
Average state-origin group SSDI in 2000 × ACS Lagged unemployment in state-year-occupation cells				0.2403+	
				(0.143)	
Average state-origin group SSDI two years prior to the survey × BLS Lagged unemployment in state-year cells					0.6054**
					(0.222)
Average state-origin group SSDI two years prior to the survey					−0.0857**
					(0.014)
Observations	3,085,321	3,069,552	3,069,552	3,069,552	3,012,063
Adjusted R-squared	0.080	0.077	0.078	0.091	0.079
Dependent variable (mean)	0.0143	0.0142	0.0142	0.0142	0.0143

Notes. See Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. Column 1 replicates column 3 of Table 2 but replaces the BLS state-year unemployment rate with the state-year unemployment rate constructed using ACS data. Columns 2–4 are estimated on a smaller number of observations because lagged unemployment rates were not available for some people in narrowly defined cells. For ease of comparison, in columns 2 to 4 we restrict the sample to individuals with non-missing information on all three measures of the unemployment rate. 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 specification to control for whether the person's state-year-occupation unemployment rate was imputed in this manner. Column 5 constructs average state-origin group SSDI from two years prior to the survey (rather than in 2000) using ACS data. This yields a smaller sample because we are restricted to data for 2003 onwards and because some country of origin-state combinations lack matches. Since this lagged SSDI measure is not absorbed into state-year fixed effects, column 5 includes an additional control for average state-origin group SSDI in year t-2. Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the ACS. We cluster the standard errors by state, year, and country of origin cells. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

interact this variable with average SSDI take-up.[13] The results in column 2 of Table 4 show that while the estimate is certainly smaller than the estimate in our baseline, it increases in statistical significance.

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 et al., 2012), we construct unemployment rates within education-state-year cells. As seen in column 3 of Table 4, the estimate of the coefficient on our interaction is positive and statistically significant in this specification as well.

In column 4 of Table 4, 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, statistically significant at the 10% level, but of a lower magnitude than that in our baseline specification. While certainly comforting, this is also 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.[14]

A drawback of using the Census to construct average take-up rates is that the time interval from when we measure group take-up (the year 2000) to when we measure individual take-up varies over the sample period. For individuals observed in the final year of our sample, group take-up is measured almost 20 years earlier, whereas for those observed at the start of our sample period, the interval is only one year. If a group's take-up changes substantially over time, this induces measurement error. An alternative is to use the ACS to construct average take-up, since the ACS is conducted annually. This comes at a cost: the ACS has a much smaller sample size, which likely introduces measurement error of its own into our group averages. Therefore, we prefer the Census measure in our baseline estimates. However, to assess this, in column 5 of Table 4 we construct origin-group take-up rates from two years before the reference period (one year before the point at which we measure the unemployment rate) using the ACS.[15] Compared to our baseline, the coefficient is smaller, consistent with attenuation bias, but remains positive and statistically significant at the 1% level.

We next turn to three placebo tests to address potential concerns. We start by considering impacts on wages. If our baseline results were indeed driven by differential sensitivities to the state unemployment rate (for example, because immigrants in high SSDI groups work in industries with more cyclical demand), then we might expect lower wages in response to increases in the unemployment rate for immigrants in high SSDI groups. To test this, column 1 of Table 5 shows results from running our baseline specification on a sample of immigrants who worked last year (and report positive income from work) but replacing the outcome variable with the log of wages. The estimate of the interaction coefficient is small and statistically insignificant, a result consistent with a network explanation of our baseline estimates.[16]

The wage test speaks to whether immigrants in high-SSDI groups are more exposed to cyclical downturns, but it is imperfect in that we can only observe wages for those who work. People who continue working through a downturn are likely to be strongly attached to the labor force, and to their jobs in particular. They may therefore differ substantially

[13] Because there are some countries of origin represented in a state in one year but not in 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 4, we drop observations with missing data on any of the three constructed measures of the unemployment rate.

[14] 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.

[15] Since the lagged take-up rate varies over time within country-state combinations, it is no longer subsumed by the origin-state fixed effects, and so we include it directly as a control.

[16] We restrict the sample to individuals who worked in the previous year and reported positive income from work to limit this placebo test to workers who are unlikely to have a disability. This restriction, however, raises the possibility that the results are driven by positive selection into employment. In Appendix Table A4, we vary the set of controls—including no controls (except the necessary fixed effects), the baseline controls (from Table 2, column 3), and the baseline controls along with occupation fixed effects—and find that the estimates are qualitatively unchanged.

Table 5
Placebo tests (ACS 2001–2019).

	(1)	(2)	(3)
Sample:	Employed	Mothers of infants	Age 62 and above
Dependent variable:	Log hourly wage	Worked last week	Social Security Income receipt
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	−0.8951 (2.072)	−1.0155 (9.224)	−2.5364 (2.278)
Observations	2,310,807	56,351	584,290
Adjusted R-squared	0.296	0.131	0.304
Dependent variable (mean)	2.526	0.403	0.638

Notes. See Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. In column 1 the sample is restricted to individuals who worked last year and reported a positive income from work. In column 2 the sample is restricted to women with a child under one year old in the household. In column 3 the sample is restricted to individuals 62 or above years old. Estimates are weighted using the appropriate person-level weights provided by the ACS. We cluster the standard errors by state, year, and country of origin cells. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

from the population driving our baseline results: those with an SSDI-qualifying disability who are at the margin of applying for benefits. We next consider work-related responses to economic downturns among two populations most often found outside the labor force, other than the disabled (Schanzenbach et al., 2017): likely caregivers and likely retirees.

Like workers with a disability, mothers of infants may work only if they are sufficiently well compensated for doing so. Suppose our baseline results are explained by immigrants in high-SSDI groups working in more cyclically sensitive jobs, so that those with weak labor market attachment (i.e. those with a disability) leave the labor force when they lose their jobs or see their pay fall. We might then also expect immigrant mothers in these same high SSDI groups to be more likely to stop working during a downturn, choosing to care for a newborn rather than return to work quickly. If instead they are not, differential cyclical exposure becomes a less plausible explanation for our baseline results.

In column 2 of Table 5, we use a sample of immigrant women with a child under age one in the household and estimate Eq. (1) with a dummy equal to one if the woman worked last week as the dependent variable. The estimated coefficient on the interaction between average SSDI take-up and the unemployment rate is statistically insignificant. In other words, we find no evidence that mothers of infants from high-SSDI countries are especially likely to remain on leave, or to leave the labor force entirely, when unemployment increases. To the extent that women with young children work in occupations similar to others in their group, this provides an additional check on the occupational-exposure channel, though we acknowledge that this test is based on a small sample.

For a final placebo test, we turn to a much larger population that is similarly likely to be weakly attached to the labor market and also likely to include many people with a disability: individuals of retirement age. Just as SSDI applications rise during downturns (Maestas et al., 2015), people are more likely to leave the labor force and claim retirement benefits when a recession coincides with their reaching retirement age (Coile and Levine, 2011). By examining the work-related decisions of this population, we can again assess whether our baseline results reflect differential sensitivity to the business cycle. If our SSDI results were driven by greater job loss among working-age immigrants in high-SSDI groups, we would likewise expect more job loss among older workers in these same groups.

Studying this population also helps address concerns about differential levels of disability. If working-age immigrants in high-SSDI groups are more likely to go on disability during downturns simply because they are more likely to be disabled—perhaps due to their job histories—then immigrants in these same high-SSDI groups should also be more disabled at older ages, and so more likely to retire earlier than immigrants in low-SSDI groups. If our results are not driven by differential disability, we should not observe older immigrants in high-SSDI groups retiring at especially young ages.

To address both concerns, we could simply have used labor force participation as our measure of retirement. Instead, we examine the likelihood that older individuals receive Social Security Retirement income. This lets us address differential job loss and differential disability as before, and, because of the structure of the Social Security program, it also lets us address concerns that eligibility for SSDI—rather than network effects—is driving our results.

Following Furtado and Theodoropoulos (2016), this works because eligibility rules for Social Security retirement benefits are very similar to those for disability benefits. Social Security retirement and SSDI are both administered by the Social Security Administration under the same Old-Age, Survivors, and Disability Insurance (OASDI) program, require nearly identical work histories, and generally make identical monthly payments.[17] As with SSDI, undocumented immigrants, and documented immigrants who have worked off the books, are ineligible for retirement benefits. The key difference is that disability applicants must demonstrate a qualifying disability, while retirement applicants need only meet the age requirement.

All of this implies that we can address three alternative explanations for our baseline results at the same time by analyzing Social Security Retirement income take-up in this older population. First, if our SSDI results reflect differential cyclical exposure, we would also expect larger increases in retirement claiming among these same high SSDI groups during recessions. Moreover, if immigrants from high-SSDI countries simply have more underlying health limitations, they should also be more likely to claim retirement benefits when job prospects worsen, since retirement is more attractive to those in poor health. Finally, if our results instead reflect differences in eligibility arising from work history or documentation status, we would again expect more Social Security retirement claiming among high-SSDI immigrants, since the same documentation and employment histories determine eligibility for both programs.

By contrast, the information-sharing and stigma mechanisms underlying our network interpretation are specific to disability insurance. Establishing a qualifying disability is the most demanding part of the SSDI process, often requiring extensive documentation and medical evidence, and contacts who have navigated this process can offer real informational advantages. These advantages have little relevance for retirement benefits, since the application process is far simpler. Stigma is also likely to differ across the two programs. Claiming retirement at or after normal retirement age is common and socially accepted, even following job loss, whereas applying for disability with only a marginal impairment may carry meaningful stigma in low-SSDI-take-up circles but little in high-take-up ones. If information sharing or stigma related to disability claims drive our SSDI results, we should therefore see little corresponding effect on retirement claiming.

As shown in column 3 of Table 5, this is precisely what we find. Among immigrants aged 62 and above, the estimated coefficient on the interaction between the unemployment rate and average SSDI take-up is statistically indistinguishable from zero, small relative to the mean of the dependent variable, and negatively signed. The standard error is rather large relative to the coefficient, but the point estimate runs

[17] The only difference in work history requirements is that SSDI has a recent-work-experience requirement and retirement benefits do not. In terms of benefit amounts, retirement claimed at or after full retirement age—65 or 66 during our sample period since it has gradually increased depending on birth year—pays the same amount as SSDI, while retirement claimed at 62 pays less, with smaller reductions for those claiming closer to full retirement age.

opposite to what differential cyclical exposure, differential underlying disability, or differential eligibility for SSDI would predict.[18]

We next ask whether the timing of the estimated relationship behaves the way a genuine response to labor market conditions should. Increases in unemployment should lead to more SSDI take-up in subsequent years, given how long applications take to file and decide, but should have no relationship with take-up in prior years. In Table 6, we examine the robustness of our results to using different leads and lags of the unemployment rate. The estimate on our interaction term remains positive and of roughly the same magnitude if we use a two- (column 3) or three- (column 2) year lag instead of the one-year lag (column 4, our baseline), but in these specifications, the estimate is only statistically significant at the 10 percent level. In contrast, when we use a four-year lag (column 1), the estimate falls by about half and is no longer statistically significant at conventional levels. This might make sense given that initial decisions on SSDI applications are typically made within 6–8 months. Even applications that go to the highest level of appeal (federal court) take about four years. Reassuringly, the specifications using current or leads of unemployment rate show no significant coefficients (columns 5 to 7).[19]

Next, for even further evidence that our results are driven by ethnic networks, we examine whether those immigrants that are likely more socially connected to their ethnic communities are indeed more likely to go on disability when hit with economic shocks if they are in high SSDI groups. We start by splitting the sample by whether the immigrant is fluent in English, expecting those who are more fluent in English to be less sensitive to ethnic network effects. Immigrants who are less fluent in English are likely to have more co-ethnic friends in their social circles, and so would be more likely to acquire information about the SSDI program from co-ethnics and be more sensitive to any stigma about SSDI within their ethnic groups. Comparing columns 1 and 2 of Table 7, we can see that impacts are slightly weaker in magnitude for immigrants who are fluent in English (as defined by "speaking English very well" or "speaking only English at home") than those who are not (as defined by speaking English "not at all," "not well" or "well"), but the difference between the two estimates is statistically insignificant.

In the last two columns of Table 7, we compare immigrants who are geographically isolated from co-ethnics to those who live closer to other immigrants born in the same country. Immigrants living in states alongside many others from their country of origin may be more likely to have their social circles comprised predominantly of co-ethnics while those living in states with few others from their origin country are likely to have friends who are either native born or are foreign born from different origin countries. If our results are explained mostly by ethnic networks, we should expect stronger results for immigrants surrounded by co-ethnics. As can be seen in column 3 of Table 7, the estimate of the interaction coefficient is positive but statistically insignificant when using a sample of immigrants living in a state where the share of same-origin inhabitants is less than the median in the overall sample (0.05). In contrast, for non-isolated immigrants (in column 4 of Table 7), the estimate of the interaction coefficient is positive, statistically significant, and considerably larger in magnitude compared to our baseline estimate shown in column 3 of Table 2.

Taken together, we view these results broadly as evidence in favor of a role played by ethnic networks. Immigrants connected to groups with high SSDI take-up may face less stigma for exiting the labor force to receive SSDI benefits (despite having only a marginal disability)—a result consistent with findings in Furtado et al. (2022) considering the role of work norms. It is also possible that ethnic network effects are driven by information sharing about the SSDI program. While we cannot differentiate between these two mechanisms, both of which are likely to occur at the same time, we can provide a rather informal test for information sharing by separating the sample by education level. Under the assumption that people with higher levels of education can retrieve information about SSDI and the application process without relying as much on information shared within social circles, we would expect to see larger estimates for people with lower levels of education if information sharing plays an important role. Columns 1 and 2 in Table 8 are consistent with this hypothesis. The estimated coefficient of interest is positive and statistically significant for non-college graduates (column 1) and negative and statistically insignificant for college graduates (column 2), results consistent with information sharing. We attempted a similar test using variation in the languages into which SSA materials are translated, though that exercise proved harder to interpret.[20]

To assess whether stigma contributes to our results, we again turn to WVS/EVS data on work norms. Immigrants from countries with stronger work norms may face greater emotional or social barriers to leaving the labor force to apply for and receive SSDI benefits. However, if co-ethnics from these countries nonetheless exhibit high SSDI take-up,[21] this may

[18] An ideal placebo test of our network interpretation would examine how average group SSDI take-up influences the impact of the unemployment rate on SSDI take-up using groups whose members share characteristics that make them similarly vulnerable to economic, health, and other shocks but who are unlikely to interact socially. Groups formed on the basis of age or education come close to this ideal. People of the same age or education level share many characteristics that could drive similar SSDI take-up rates, and because these categories contain so many people, it seems unlikely that their members interact socially. We therefore constructed average SSDI take-up within age-group–state and education-group–state cells, following the same procedure as our baseline measure, and used these in place of average co-ethnic take-up. As reported in columns 2 and 3 of Appendix Table A3, the estimated coefficients on the interaction terms are positive and significant under both groupings. Under the assumption that there is no social contact among people in these groups, these results might be interpreted as evidence that our baseline results are driven by correlations in health level, SSDI eligibility or exposure to the business cycle within groups, rather than any network effects. That said, the network interpretation cannot be ruled out entirely, since immigrants' social circles are not composed only of co-nationals but also people of the same age and education level. Under that interpretation, these results might instead be read as evidence that information sharing and stigma operate within age and education groups as well as within country-of-origin groups.

[19] Since SSDI is close to an absorbing state, states of residence with high SSDI rates in one year are likely to also have high SSDI in the following year (i.e., observations from different years may not be independent). To check for serial correlation, we cluster standard errors in different ways. Table A5 in the Appendix (columns 2-6) shows that the results remain robust in all cases. Our estimates are also robust to including country-specific time trends as extra controls (Table A5, column 1).

[20] The SSA website is fully available in Spanish, and anyone who calls the SSA at any time can request a Spanish-speaking representative. With a few additional steps, translations and interpreters are available in sixteen further languages. If (i) information sharing drives our results, (ii) the relevant information were available from the SSA, and (iii) the choice of translated languages were unrelated to group characteristics, we would expect the smallest network effects among Spanish speakers, larger effects among speakers of the sixteen additional languages, and the largest effects among all others. As reported in Table A6, the estimate is indeed larger for non-Spanish speakers than for Spanish speakers, consistent with this reasoning, but speakers of the sixteen additional languages have larger estimated coefficients than other non-Spanish speakers (although the difference is not statistically significant). However, we note that neither condition (ii) nor (iii) is likely to hold. Much of what plausibly circulates through networks is not on the SSA website—how severe an impairment must be to qualify, which attorneys handle these cases well, how often appeals succeed—so official materials may substitute poorly for informal information. Moreover, translations are presumably provided in languages with many likely beneficiaries, which are precisely the groups where within-network information is likely to be richest. We therefore do not read this set of results as strong evidence for or against the information-sharing channel.

[21] Again, an immigrant group may have high SSDI take-up rates because they have longer work histories, tend to work in occupations that cause disabilities, or any other idiosyncratic reason that has nothing to do with work norms.

Table 6
Choosing unemployment rate lag structure (ACS 2001–2019).

Dependent variable: SSDI receipt	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells four years prior to the survey	0.3193 (0.351)						
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells three years prior to the survey		0.6407+ (0.385)					
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells two years prior to the survey			0.6646+ (0.386)				
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells one year prior to the survey (baseline)				0.7095* (0.349)			
Average state-origin group SSDI in 2000 × Current unemployment in state-year cells					0.3946 (0.318)		
Average state-origin group SSDI in 2000 × Lead unemployment in state-year cells one year after the survey						0.0804 (0.320)	
Average state-origin group SSDI in 2000 × Lead unemployment in state-year cells two years after the survey							−0.4338 (0.322)
Observations	2,912,665	2,973,278	3,033,689	3,085,321	3,140,585	2,940,227	2,737,448
Adjusted R-squared	0.079	0.079	0.079	0.078	0.077	0.078	0.078
Dependent variable (mean)	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143

Notes. See Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. Column 4 is identical to column 3 of Table 2. The other columns replicate this column but replace the interaction term with the one listed. Estimates are weighted using the appropriate person-level weights provided by the ACS. We cluster the standard errors by state, year, and country of origin cells. Levels of significance: ** p < 0.01, * p < 0.05, + p < 0.1.

Table 7
Immigrants' connection to their ethnic communities (ACS 2001–2019).

	(1)	(2)	(3)	(4)
Dependent variable: SSDI receipt	Sample: Fluent in English	Sample: Not fluent in English	Sample: Share same country of origin in state below median	Sample: Share same country of origin in state above median
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	0.6214+ (0.349)	0.7154 (0.716)	0.4431 (0.304)	2.3867* (1.147)
Observations	1,572,871	1,512,450	1,615,924	1,469,397
Adjusted R-squared	0.088	0.075	0.077	0.084
Dependent variable (mean)	0.0125	0.0160	0.0141	0.0145

Notes. See Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. 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 where the share from the same country of origin is below the median (below 0.05) and column 4 to those individuals living in states where the share from the same country of origin is above the median (above 0.05). Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the ACS. We cluster the standard errors by state, year, and country of origin cells. Levels of significance: ** p < 0.01, * p < 0.05, + p < 0.1.

attenuate stigma within the ethnic community, making individuals especially responsive to adverse labor market conditions. In contrast, immigrants from countries with weaker work norms are likely to apply for SSDI in response to poor labor market conditions regardless of SSDI take-up among their co-ethnics, as stigma is less binding to begin with. Therefore, if stigma operates through the share of network members receiving SSDI and helps explain our findings, we expect stronger network effects among immigrants from countries with stronger work norms. Columns 3 and 4 of Table 8 test this prediction by splitting the sample according to whether immigrants originate from countries below

Table 8
Partial evidence on information sharing and stigma (ACS 2001–2019).

	(1)	(2)	(3)	(4)
Dependent variable: SSDI receipt	Sample: Non-college graduates	Sample: College graduates	Sample: Strong work norms	Sample: Weak work norms
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	1.2096* (0.543)	−0.3555 (0.330)	1.2300* (0.594)	0.2526 (0.499)
Observations	2,123,276	962,045	1,861,567	441,193
Adjusted R-squared	0.083	0.055	0.076	0.099
Dependent variable (mean)	0.0168	0.0076	0.0142	0.0167

Notes. See Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. Column 1 is restricted to individuals with less than a university degree. Column 2 is restricted to individuals with a university degree or above. Column 3 is restricted to individuals from countries where the share of WVS/EVS respondents who "strongly disagree" that work is a duty towards society is below the median (0.019) and column 4 to individuals where the share of respondents who "strongly disagree" that work is a duty towards society is above the median. Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the ACS. We cluster the standard errors by state, year, and country of origin cells. Levels of significance: ** p < 0.01, * p < 0.05, + p < 0.1.

(column 3) or above (column 4) the median value of our work-norm measure (share of respondents who say that they strongly disagree with the statement that work is a duty towards society). Consistent with this mechanism, the coefficient of interest is larger among immigrants from countries with stronger work norms (below the median share of strongly disagreeing that work is a duty towards society).

5. Heterogeneity by self-reported health (CPS data)

We now turn to Current Population Survey (CPS) data, which provides a better measure of SSDI receipt because it records whether a person received Social Security income for a *disability* in the previous

year. When we repeat Eq. (1) using CPS data in column 1 of Table 9 (using controls for a person's health level in place of the disability controls from the ACS), a larger coefficient on the interaction of average SSDI and lagged unemployment rate is found compared to the equivalent regression using ACS data, perhaps because there is less measurement error in the dependent variable now.

The CPS also includes information on the self-reported health of individuals. When the regression is repeated separately for each health status group in columns 2–6 of Table 9, a large and significant estimate (at the 5% level) of the coefficient on the average SSDI-unemployment rate interaction term is found for those with fair self-reported health whereas much smaller estimated coefficients are found for those with excellent, very good, good or poor health. The differences between excellent and fair health, and between good and fair health are significant at the 5% level. Although self-reported health at the time of survey is an imperfect proxy for documented disability on the SSDI application, this pattern is what we would expect if people in good health do not qualify for SSDI while those in the worst health apply and are awarded benefits regardless of economic conditions or take-up in their origin group. It is also consistent with Maestas et al. (2021), who find that applicants with marginal disabilities are the most likely to go on disability during economic downturns. On the other hand, such a pattern is difficult to reconcile with a story in which our estimates simply reflect differences across immigrant groups in the likelihood of having a qualifying disability. Under that interpretation, there is no particular reason to expect the effect to concentrate among people with marginal impairments, precisely the people most likely to be responsive to stigma and information within their social circles.

6. Conclusion

In December 2022, disability benefits were paid to about 8.9 million people and payments to disabled beneficiaries totaled almost $12.6 billion that month (Social Security Administration, 2023). In this paper, we find robust evidence that immigrants from groups with high SSDI take-up rates are especially likely to receive SSDI in response to increases in the unemployment rate. One explanation of this pattern is that there are correlations across ethnic groups in terms of eligibility for the program or sensitivity to business cycles. While we cannot rule this out, we view these results – at least in part – as evidence that SSDI take-up decisions exert spillovers within social networks. In particular, those with marginal disabilities are more likely to move onto disability when jobs are scarce if they belong to groups with high existing rates of SSDI receipt.

Importantly, individuals who withdraw from the labor market even temporarily while they are applying for benefits might experience deterioration of their human capital, making it more difficult for them to find a job when the economy improves (Autor et al., 2015) even if they are never awarded benefits. Those who are awarded benefits are themselves likely to leave the labor market permanently. Moreover, our results suggest that new beneficiaries induce others within their networks to apply for SSDI, potentially generating persistent reductions in employment that extend well beyond the economic downturn.

Policy implications, however, depend on whether low SSDI take-up ethnic groups have inefficiently low levels of SSDI take-up or, alternatively, high take-up groups have inefficiently high levels. From a social welfare perspective, would it be better to increase participation rates among Saudi Arabian immigrants (and other low take-up groups) or to decrease participation rates among the Portuguese (and other high take-up groups)? It is possible that some of those induced into SSDI participation after a job loss are genuinely only able to work for specific employers who can accommodate their disabilities. Many of these individuals in low take-up groups might not apply for SSDI benefits because they do not have access to information about how to navigate the very long and complicated application process, instead remaining unemployed and experiencing unnecessary poverty. If these applicants are driving most of our results, then a policy implication would be to provide more assistance with the application process—especially to those unable to acquire information within their social networks.

On the other hand, if many of the applicants induced into SSDI as a result of a job loss can indeed work for a variety of employers, then a policy implication may be to improve SSDI screening. Redirecting them to the unemployment insurance system, with an accompanying reallocation of funding, might limit spillovers for SSDI take-up within social networks before they can begin. If it is too difficult to screen out applicants without denying benefits to those who are genuinely disabled, another policy might involve restructuring the SSDI system to incentivize returns to the labor force when jobs are relatively plentiful. Although spillovers might still drive entrants into the system during recessions under this approach, this effect might be at least partially offset during expansions. Unfortunately, previous attempts by the SSA to incentivize work among recipients have not had tremendous success (Thornton et al., 2007).

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT and Claude to assist with editing the text. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Delia Furtado: Writing – original draft, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Kerry L. Papps:** Writing – review & editing, Formal analysis, Conceptualization. **Nikolaos Theodoropoulos:** Writing – review & editing, Visualization, Methodology, Investigation, Formal analysis, Conceptualization.

Table 9
Business cycles and SSDI benefit receipt in the CPS sample by health status (CPS 2001–2019).

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: SSDI receipt	Sample: All health levels	Sample: Health excellent	Sample: Health very good	Sample: Health good	Sample: Health fair	Sample: Health poor
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	6.0768**	4.5764*	2.4884	8.5123*	27.4803*	−15.8467
	(1.584)	(2.269)	(2.025)	(3.891)	(12.342)	(70.514)
Observations	130,350	34,228	43,233	39,842	10,091	2,956
Adjusted R-squared	0.062	0.026	0.039	0.043	0.117	0.078
Dependent variable (mean)	0.0108	0.0019	0.0029	0.0087	0.0490	0.1285

Notes. See Table 1 for information on sample restrictions. The same control variables and fixed effects are included as in Table 2 (column 3) except that in column 1 we use controls for a person's health level in place of the disability controls from the ACS. To avoid including households twice, only observations from the first four months a household is in the CPS sample are included. Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the CPS. We cluster the standard errors by state, year, and country of origin cells. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Declaration of competing interest

The authors declare no competing interests.

Appendix tables

Table A1
Average origin group–state SSDI take-up in 2000 by country, ranked from highest to lowest (5% Sample Census 2000).

Country of origin	Average state-origin group SSDI in 2000	Average number of observations within country of origin-state cells
Portugal	0.063	144.5
St. Lucia	0.049	16.4
Slovakia	0.044	9.3
Croatia	0.041	25.4
Grenada	0.041	27.3
Italy	0.038	206.8
Paraguay	0.038	8.2
Macedonia	0.038	23.8
Yugoslavia	0.038	42.4
Fiji	0.037	21.7
Nepal	0.035	6.1
Albania	0.034	17.3
Latvia	0.034	11.0
Ecuador	0.034	157.7
Venezuela	0.031	45.9
Dominica	0.030	17.0
Burma (Myanmar)	0.030	24.3
Indonesia	0.030	30.9
Liberia	0.029	21.9
Algeria	0.028	7.5
Trinidad and Tobago	0.028	110.1
France	0.027	61.4
Ukraine	0.026	84.5
Colombia	0.022	243.5
Tonga	0.022	16.0
Netherlands	0.022	44.6
Germany	0.022	316.6
Turkey	0.022	38.8
Hungary	0.021	35.6
Cape Verde	0.021	37.6
Armenia	0.020	72.2
Guatemala	0.020	259.3
Israel/Palestine	0.020	68.3
Nicaragua	0.020	135.2
Greece	0.019	86.4
Senegal	0.019	9.0
Panama	0.019	60.2
Cuba	0.019	427.9
Norway	0.019	13.6
Belize/British Honduras	0.018	29.3
Thailand	0.018	67.5
Dominican Republic	0.018	380.4
Canada	0.017	353.5
Bermuda	0.017	6.2
Haiti	0.017	268.2
Jordan	0.017	32.3
Afghanistan	0.017	34.1
Austria	0.017	24.7
Sierra Leone	0.017	17.1
Guyana/British Guiana	0.016	125.7
Eritrea	0.016	13.8
Philippines	0.016	775.6
Uruguay	0.015	22.7
Iraq	0.015	50.9
Yemen	0.015	13.3
Cambodia (Kampuchea)	0.015	98.0
Honduras	0.014	141.7
Mexico	0.014	4672.6
Romania	0.014	57.0
Sri Lanka (Ceylon)	0.014	16.2
Ireland	0.013	71.7

(*continued on next page*)

Table A1 (*continued*)

Country of origin	Average state-origin group SSDI in 2000	Average number of observations within country of origin-state cells
Zimbabwe	0.013	6.3
Barbados	0.013	41.6
Bahamas	0.013	17.3
Costa Rica	0.013	41.5
United Kingdom	0.013	254.2
South Africa (Union of)	0.013	29.7
Spain	0.013	40.2
Laos	0.012	125.2
Kenya	0.012	21.4
Bolivia	0.012	32
Belgium	0.012	14.9
Vietnam	0.011	585.8
China	0.011	439.0
Lithuania	0.011	10.9
India	0.011	482.5
Lebanon	0.011	66.1
Uganda	0.011	8.4
South Korea	0.010	428.4
El Salvador	0.010	476.8
Iran	0.010	169.9
Japan	0.010	136.2
Byelorussia	0.010	19.5
Poland	0.010	201.4
Ghana	0.009	38.9
Nigeria	0.009	69.0
Syria	0.009	35.1
Brazil	0.009	84.4
Sudan	0.009	6.7
Somalia	0.008	11.1
Antigua-Barbuda	0.008	18.7
Jamaica	0.008	298.0
Switzerland	0.008	19.2
Egypt/United Arab Rep.	0.008	59.7
Czech Republic	0.008	22.2
Malaysia	0.007	28.9
Argentina	0.007	64.9
Sweden	0.007	22.1
Chile	0.006	44.5
Hong Kong	0.006	128.0
Peru	0.006	157.7
Australia	0.006	27.3
Bosnia	0.006	16.7
Ethiopia	0.006	36.8
Bangladesh	0.006	42.2
New Zealand	0.005	12.7
Uzbekistan	0.005	13.9
Singapore	0.005	11.0
Moldavia	0.005	13.1
Cameroon	0.005	7.4
Denmark	0.004	13.9
Serbia	0.004	8.9
Kosovo	0.004	8.0
Finland	0.004	11.8
St. Kitts-Nevis	0.003	11.3
Republic of Georgia	0.003	8.6
Kuwait	0.003	11.2
Azerbaijan	0.003	7.7
Bulgaria	0.003	13.7
Morocco	0.003	22.1
Pakistan	0.002	112.8
Taiwan	0.002	192.6
St. Vincent	0.001	22.8
Tanzania	0.001	8.8
Cyprus	0.001	10.3
Saudi Arabia	0.000	5.3

Notes. 5% sample of the 2000 U.S. Census.

Table A2
Extra robustness checks (ACS 2001–2019).

	(1)	(2)	(3)	(4)	(5)
Dependent variable: SSDI receipt	Drop Mexico	Drop Portugal	Drop Saudi Arabia	Drop Armenia	Drop Yemen
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	0.7112*	0.5977+	0.7159*	0.7135*	0.8341*
	(0.355)	(0.347)	(0.349)	(0.353)	(0.347)
Observations	2,163,308	3,067,614	3,083,701	3,078,534	3,082,886
Adjusted R-squared	0.076	0.077	0.078	0.078	0.078
Dependent variable (mean)	0.0149	0.0141	0.0143	0.0143	0.0143

Notes. See Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. Coefficients are estimated using linear probability models. In column 1 we drop the largest country in terms of observations (Mexico), in column 2 we drop the country with the highest average SSDI take-up (Portugal), in column 3 we drop the country with the lowest SSDI take-up (Saudi Arabia). In column 4 we drop the country with the highest value of the Herfindahl index across states (Armenia) and in column 5 we drop the country with the highest value of the Herfindahl index across industries (Yemen). 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 cluster the standard errors by state, year, and country of origin cells. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table A3
Supplementary specifications.

	(1)	(2)	(3)
Dependent variable:	Unemployed	SSDI receipt	SSDI receipt
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	3.3554**		
	(0.648)		
Average state-age group SSDI in 2000 × Lagged unemployment in state-year cells		3.0377**	
		(0.509)	
Average state-education group SSDI in 2000 × Lagged unemployment in state-year cells			2.4500**
			(0.713)
Observations	3,085,321	3,085,321	3,085,321
Adjusted R-squared	0.011	0.077	0.077
Dependent variable (mean)	0.0462	0.0143	0.0143

Notes. See Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. In column 2, state-country of origin fixed effects are replaced by state-age group fixed effects. In column 3, state-country of origin fixed effects are replaced by state-education group fixed effects. Coefficients are estimated using linear probability models. In column 1 the dependent variable is a dummy variable if the individual is unemployed. In columns 2 and 3 the dependent variable is SSDI. In column 1 average SSDI is constructed at country of origin-state of residence cells. In column 2, average SSDI is constructed at the age-by-state-of-residence level, with age measured in two-year increments over the range 25–61. In column 3, average SSDI is constructed at the education-by-state-of-residence level, using 11 education categories ranging from no education to Master's/PhD. Estimates are weighted using the appropriate person-level weights provided by the ACS. Standard errors are clustered by state, year, and country of origin cells in column 1; by state, year, and age group cells in column 2; and by state, year, and education group cells in column 3. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table A4
Log wage regressions with varying set of controls.

	(1)	(2)	(3)
Dependent variable: Log hourly wage	No controls	Baseline controls	Add occupation fixed effects
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	−0.8217	−0.8951	−1.2198
	(2.348)	(2.072)	(1.933)
Observations	2,310,807	2,310,807	2,310,807
Adjusted R-squared	0.165	0.296	0.350
Dependent variable (mean)	2.526	2.526	2.526

Notes. In all columns, the sample is restricted to individuals who worked last year and reported a positive income from work. See Table 1 for information on sample restrictions. In column 1 we include only the interaction term and state-year and state-country of origin fixed effects. In column 2 we include the baseline controls (Table 2, column 3), and in column 3 we add 23 occupation dummies (omitted category: military). Estimates are weighted using the appropriate person-level weights provided by the ACS. Standard errors are clustered by state, year, and country of origin cells. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table A5
Country-specific time trends and clustering standard errors at different levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: SSDI receipt	Country-specific time trends	Cluster on state	Cluster on country of origin	Cluster on state-country of origin	Cluster on state-year	Cluster on year-country of origin
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	1.9626**	0.7095+	0.7095+	0.7095*	0.7095*	0.7095+
	(0.245)	(0.416)	(0.362)	(0.354)	(0.361)	(0.362)
Observations	3,085,321	3,085,321	3,085,321	3,085,321	3,085,321	3,085,321
Adjusted R-squared	0.078	0.078	0.078	0.078	0.078	0.078
Dependent variable (mean)	0.0143	0.0143	0.0143	0.0143	0.0143	0.0143

Notes. See Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the ACS. Column 1 uses the baseline clustering on state, year, and country of origin cells. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table A6
Heterogeneity by language spoken at home.

	(1)	(2)	(3)	(4)
Dependent variable: SSDI receipt	Sample: Speaks Spanish at home	Sample: Does not speak Spanish at home	Sample: Speaks any of the 16 languages	Sample: Does not speak Spanish nor any of the 16 languages
Average state-origin group SSDI in 2000 × Lagged unemployment in state-year cells	0.3376	0.7354+	0.9047	0.6903
	(0.626)	(0.411)	(0.686)	(0.487)
Observations	1,393,037	1,692,284	777,401	914,883
Adjusted R-squared	0.082	0.076	0.067	0.087
Dependent variable (mean)	0.0140	0.0145	0.0141	0.0149

Notes. See Table 1 for information on sample restrictions and Table 2 (column 3) for information on the control variables and fixed effects included. Coefficients are estimated using linear probability models. Estimates are weighted using the appropriate person-level weights provided by the ACS. We cluster the standard errors by state, year, and country of origin cells. Levels of significance: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Data availability

We have uploaded the code and documentation to the journal's data repository.

References

Autor, D.H., Dorn, D., Hanson, G.H., 2013. The China syndrome: local labor market effects of import competition in the United States. Am. Econ. Rev. 103 (6), 2121–2168.

Autor, D.H., Duggan, M.G., 2003. The rise in the disability rolls and the decline in unemployment. Q. J. Econ. 118 (1), 157–206.

Autor, D.H., Maestas, N., Mullen, K.J., Strand, A., 2015. Does delay cause decay? The effect of administrative decision time on the labor force participation and earnings of disability applicants. NBER Working Paper 20840.

Battisti, M., Peri, G., Romiti, A., 2022. Dynamic effects of co-ethnics on immigrants' economic success. Econ. J. 132 (641), 58–88.

Bertrand, M., Luttmer, E.F.P., Mullainathan, S., 2000. Network effects and welfare cultures. Q. J. Econ. 115 (3), 1019–1055.

Black, D., Daniel, K., Sanders, S., 2002. The impact of economic conditions on participation in disability programs: evidence from the coal boom and bust. Am. Econ. Rev. 92 (1), 27–50.

Borjas, G.J., 2017. The labor supply of undocumented immigrants. Labour Econ. 46, 1–13.

Borjas, G.J., Slusky, D.J.G., 2022. Health, employment, and disability: implications from the undocumented population. Am. J. Health Econ. 8 (1), 1–29.

Carey, C., Miller, N.H., Molitor, D., 2022. Why does disability increase during recessions? Evidence from Medicare. NBER Working Paper 29988.

Charles, K.K., Li, Y., Stephens, M., 2018. Disability benefit take-up and local labor market conditions. Rev. Econ. Stat. 100 (3), 416–423.

Coile, C.C., Levine, P.B., 2011. Recessions, retirement, and Social Security. Am. Econ. Rev. Pap. Proc. 101 (3), 23–28.

Cutler, D.M., Donahoe, J.T., 2025. Addiction, thick market externalities and the persistence of the opioid epidemic. NBER Working Paper 32055.

Cutler, D.M., Glaeser, E.L., 2010. Social interaction and smoking. In: Wise, D. (Ed.), Research Findings in the Economics of Aging. University of Chicago Press, Chicago, pp. 123–141.

Dahl, G.B., Kostøl, A.R., Mogstad, M., 2014. Family welfare cultures. Q. J. Econ. 129 (4), 1711–1752.

Deri, C., 2005. Social networks, information and health care utilization. J. Health Econ. 24 (6), 1076–1107.

Deshpande, M., Li, Y., 2019. Who is screened out? Application costs and the targeting of disability programs. Am. Econ. J.: Econ. Policy 11 (4), 213–248.

Deshpande, M., Lockwood, L.M., 2022. Beyond health: non-health risk and the value of disability insurance. Econometrica 90 (4), 1781–1810.

Devillanova, C., 2008. Social networks, information and health care utilization: evidence from undocumented immigrants in Milan. J. Health Econ. 27 (2), 265–286.

Duflo, E., Saez, E., 2003. The role of information and social interactions in retirement plan decisions: evidence from a randomized experiment. Q. J. Econ. 118 (3), 815–842.

Duggan, M., Imberman, S., 2009. Why are the DI rolls skyrocketing? The contribution of population characteristics, program changes, and economic conditions. In: Cutler, D., Wise, D. (Eds.), Health at Older Ages. University of Chicago Press, Chicago.

Eisenberg, D., Golberstein, E., Whitlock, J.L., 2014. Peer effects on risky behaviors: new evidence from college roommate assignments. J. Health Econ. 33, 126–138.

Figlio, D., Hamersma, S., Roth, J., 2015. Information shocks and the take-up of social programs. J. Policy Anal. Manag. 34 (4), 781–804.

Fletcher, J.M., 2010. Social interactions and smoking: evidence from multiple student cohorts, instrumental variables and school fixed effects. Health Econ. 19 (4), 464–484.

Flood, S., King, M., Rodgers, R., Ruggles, S., Warren, J.R., 2020. Integrated Public Use Microdata Series, Current Population Survey: Version 7.0. University of Minnesota, Minneapolis. https://doi.org/10.18128/D030.V7.0.

Furtado, D., Papps, K.L., Theodoropoulos, N., 2022. Who goes on disability when times are tough? The role of work norms among immigrants. Eur. Econ. Rev. 143, 103983.

Furtado, D., Theodoropoulos, N., 2013. SSI for disabled immigrants: why do ethnic networks matter? Am. Econ. Rev. Pap. Proc. 103 (3), 462–466.

Furtado, D., Theodoropoulos, N., 2016. Immigrant networks and the receipt of disability programs: evidence from the United States. Econ. Inq. 54 (1), 247–267.

Gee, E.R., Giuntella, O.G., 2011. Medicaid and ethnic networks. BE J. Econ. Anal. Policy 11 (1), 1–31.

Hoynes, H., Miller, D.L., Schaller, J., 2012. Who suffers during recessions? J. Econ. Perspect. 26 (3), 27–48.

Inglehart, R., Haerpfer, C., Moreno, A., Welzel, C., Kizilova, K., Diez-Medrano, J. (Eds.), 2014. World Values Survey: All Rounds — Country-Pooled Datafile.. JD Systems Institute, Madrid. http://www.worldvaluessurvey.org/WVSDocumentationWVL.jsp (accessed 24 June 2020).

Kearney M.S., Price B.M. and Wilson R., 2021. Disability insurance in the Great Recession: ease of access, program enrollment, and local hysteresis. NBER Working Paper 28725.

Kremer, M., Levy, D., 2008. Peer effects and alcohol use among college students. J. Econ. Perspect. 22 (3), 189–206.

Liebman, J.B., 2015. Understanding the increase in disability insurance benefit receipt in the United States. J. Econ. Perspect. 29 (2), 123–150.

Maestas, N., Mullen, K.J., 2024. Economic conditions, the COVID-19 pandemic recession, and implications for disability insurance in the US. In: Mitchell, O.S., Sabelhaus, J., Utkus, S. (Eds.), Real-World Shocks and Retirement System Resiliency. Oxford University Press, Oxford. https://doi.org/10.1093/oso/9780198894131.003.0010 accessed 26 May 2024.

Maestas, N., Mullen, K.J., Strand, A., 2013. Does disability insurance receipt discourage work? Using examiner assignment to estimate causal effects of SSDI receipt. Am. Econ. Rev. 103 (5), 1797–1829.
Maestas, N., Mullen, K.J., Strand, A., 2015. Disability insurance and the Great Recession. Am. Econ. Rev. Pap. Proc. 105 (5), 177–182.
Maestas, N., Mullen, K.J., Strand, A., 2021. The effect of economic conditions on the disability insurance program: evidence from the Great Recession. J. Public Econ. 199, 104410.
Manski, C.F., 1993. Identification of endogenous social effects: the reflection problem. Rev. Econ. Stud. 60 (3), 531–542.
Mueller, A.I., Rothstein, J., von Wachter, T.M., 2016. Unemployment insurance and disability insurance in the Great Recession. J. Labor Econ. 34 (1), S445–S475.
Powell, L.M., Tauras, J.A., Ross, H., 2005. The importance of peer effects, cigarette prices and tobacco control policies for youth smoking behavior. J. Health Econ. 24 (5), 950–968.
Ruggles, S., Flood, S., Sobek, M., Backman, D., Cooper, G., Rivera Drew, J.A, Richards, S., Rodgers, R., Schroeder, J., Williams, K.C.W., 2025. IPUMS USA: Version 16.0. IPUMS, Minneapolis. https://doi.org/10.18128/D010.V16.0.
Schanzenbach, D.W., Bauer, L., Nunn, R., Mumford, M., 2017. Who is out of the labor force? Economic Analysis. The Hamilton Project, Brookings Institution, Washington, DC.
Social Security Administration, 2017. Annual Statistical Supplement to the Social Security Bulletin, 2017. https://www.ssa.gov/policy/docs/statcomps/supplement/2017/supplement17.pdf (accessed 8 July 2024).
Social Security Administration, 2023. Annual Statistical Report On the Social Security Disability Insurance Program. https://www.ssa.gov/policy/docs/statcomps/di_asr/2022/di_asr22.pdf (accessed 8 July 2024).
Social Security Administration, 2024. The 2024 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds. https://www.ssa.gov/oact/TR/2024/tr2024.pdf (accessed 8 July 2024).
Thornton, C., Livermore, G., Fraker, T., Stapleton, D., O'Day, B., Wittenburg, D., Weathers, R., Goodman, N., Silva, T., Martin, E.S., Gregory, J., Wright, D., Mamun, A., 2007. Evaluation of the Ticket to Work Program: Assessment of Post-Rollout Implementation and Early Impacts, Volume 1. Mathematica Policy Research. https://files.eric.ed.gov/fulltext/ED498941.pdf (accessed 8 July 2024).