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Abstract

Immigration legal services providers (ISPs) are a principal source of support for low-income immigrants seeking immigration benefits. Yet there is scant quantitative evidence on the prevalence and geographic distribution of ISPs in the United States. To fill this gap, we construct a comprehensive, nationwide database of 2,138 geocoded ISP offices that offer low- or no-cost legal services to low-income immigrants. We use spatial optimization methods to analyze the geographic network of ISPs and measure ISPs' proximity to the low-income immigrant population. Because both ISPs and immigrants are highly concentrated in major urban areas, most low-income immigrants live close to an ISP. However, we also find a sizable fraction of low-income immigrants in underserved areas, which are primarily in midsize cities in the South. This reflects both a general skew in non-governmental organization service provision and the more recent arrival of immigrants in these largely Southern destinations. Finally, our optimization analysis suggests significant gains from placing new ISPs in underserved areas to maximize the number of low-income immigrants who live near an ISP. Overall, our results provide vital information to immigrants, funders, and policymakers about the current state of the ISP network and opportunities to improve it.

Keywords: Immigration, Nonprofit organizations, Spatial Optimization

1 Introduction

Immigrants often navigate legal challenges most citizens never encounter, such as renewing visas, petitioning for family reunification, pursuing naturalization, or defending themselves against deportation in immigration courts. Navigating these complex bureaucratic and legal procedures competently requires assistance from legal professionals. Demand for immigrant legal assistance is higher than ever given the growing immigrant population and recent policy developments, such as half a million new deportation proceedings in 2019 ([Syracuse University, 2019](#)), changes to public charge rules that are affecting eligibility for permanent residency, and the proposed cancellation of various programs (e.g., Deferred Action for Childhood Arrivals and Temporary Protected Status) involving hundreds of thousands of immigrants. Yet the federal government provides no legal services directed to the needs of the immigrant population; its Legal Services Corporation, the nonprofit organization that administers federal funding for legal services, excludes immigration legal services ([Heeren, 2011](#)). Indeed, in 1996, Congress barred organizations that take federal funding from using their non-federal funds to represent most immigrant clients ([Heeren, 2011](#)).

In response, nonprofit organizations, which we call immigration legal services providers (ISPs), have filled the void. ISPs provide low- or no-cost legal services for immigrants and refugees. They include charities, ethnic associations, humanitarian organizations, churches, and law clinics. Even though ISPs have become a principal source of support for low-income immigrants facing legal issues, we have scant quantitative evidence on their prevalence and geographic distribution across the United States. While research has highlighted the important role ISPs can play in supporting low-income immigrants ([De Graauw, 2016](#); [Cortés, 1998](#); [Brown, 2014](#); [Wong and García, 2016](#); [Yasenov et al., 2019](#); [Ryo and Peacock, 2019](#); [Chand et al., 2020](#)), extant work typically has focused on specific ethnic groups and specific geographic areas and has not compiled comprehensive data on the nationwide network of ISPs. (See [Chand et al. \(2020\)](#) for an excellent first step in this direction.) Identifying this geographic distribution of ISPs and its coverage is of fundamental importance because ISPs

facilitate access to free or low-cost legal aid. Indeed, proximity to ISPs may be critical for the integration of immigrants into their communities (Allard, 2009; Owens and Smith, 2005; Roth and Allard, 2016). At the same time, research has raised the concern that there may be a geographic mismatch between the provision of service and the immigrant population most in need Roth and Allard (2016); Ryo and Peacock (2019).

In this study, we collect a comprehensive database of 2,138 geocoded, low- or no-cost immigrant legal service providers in the United States. We pair this new database with ZIP code-level data on the low-income immigrant population and leverage spatial optimization methods to analyze the geographic distribution of ISPs and their proximity to low-income immigrants. In particular, we answer three questions: What is the geographic distribution of ISPs? What are the most underserved, overserved, and well served areas? How can the ISP network be improved through the placement of new locations to maximize the number of low-income immigrants nearby? The answers to these questions matter for assessing and improving legal services provision for low-income immigrants.

We find that most low-income immigrants live relatively close to an ISP; 75% of foreign-born people whose household income is below 150% of the Federal Poverty Guidelines live within 6.6 miles of an ISP. This pattern reflects the fact that the immigrant population is highly concentrated in major urban areas, which also have dense ISP networks. Yet we also find that many low-income immigrants are not well covered by the current network. About 1.5 million low-income immigrants live in areas with no ISP within 12 miles, our criterion for access. Many of these areas with limited coverage are in midsize cities in the South. Further tests suggest that this pattern is partly driven by the fact that these areas generally have a lower presence of non-governmental service organizations and are relatively new immigrant destinations where the ISP network has lagged in development. Finally, our analysis finds that adding new ISPs in optimal locations could significantly increase the number of low-income immigrants who have access to services. In particular, adding just one more ISP optimally in each state could reduce the number of underserved low-income immigrants by

about 192,600 or approximately 12%. In addition, optimally rearranging the network of ISPs across the entire US would reduce the number of underserved low-income immigrants by about 1.1 million and close about 70% percent of the gap in the number of people served.

Theorists in sociology often have been skeptical about the effectiveness of ISPs due to their dependence on the state (Taylor et al., 2002), their tax status (which can prohibit advocacy activities (De Graauw, 2016)), and the growing strength of anti-immigrant organizations (Brown, 2014). Preliminary empirical research, however, is more encouraging. Even with limited data on the presence of ISPs, findings suggest that ISPs provide essential services, enabling immigrants to overcome legal hurdles in applying for naturalization (Yasenov et al., 2019), seeking adjustment of status (Wong and García, 2016), fighting deportation (Chand et al., 2020), obtaining release from detention (Ryo and Peacock, 2019), and procuring veterans' benefits (Cortés, 1998). Outside the legal realm, qualitative research points to ISPs' successes in teaching English, in pressing for wage increases, and in securing identity cards (De Graauw, 2016).

The lack of a comprehensive ISP database has been a persistent problem in the literature. While researchers have compiled lists of immigrant organizations using tax data, these lists have been either geographically constrained (Joassart-Marcelli, 2013; Gleeson and Bloemraad, 2013; Roth and Allard, 2016) or limited to specific immigrant groups (Cortés, 1998; Roth and Allard, 2016; Hung, 2007). Moreover, tax data undercount ISP presence by up to 50% (Gleeson and Bloemraad, 2013). The most extensive data collection that we are aware of is (Chand et al., 2020), who compiled a list of 1,079 ISPs. An important contribution of our study is that, using new methods, we have identified and validated a list of nearly twice as many active ISP offices.

2 Data and Methods

2.1 ISP Data

We defined ISPs as organizations that provide low- or no-cost assistance with official immigration-related documents or forms and/or legal representation in immigration proceedings. We used three criteria. The provider must (1) be an organization; (2) qualify by the broad US Federal Title 8 standards as a representative for immigration legal services ([Shannon, 2009](#)); and (3) advertise online as providing free or low-cost legal services to immigrants and/or refugees.

We drew on three sources: (1) The Immigration Advocates Network’s National Immigration Legal Services Directory ([Network, 2019](#)), where ISPs can self-register (1,153 offices); (2) the Department of Justice (DOJ) list of Recognized Organizations and Accredited Representatives Roster ([Department of Justice, 2019](#)) (1,178 offices); and (3) a list of immigrant service organizations maintained by Aunt Bertha ([Aunt Bertha, 2019](#)) (2,042 offices). We geocoded all office addresses and clustered them by location to identify distinct offices. We then did two rounds of manual coding to check the organizations’ websites and added 336 ISP locations that were not listed in any of the three sources.

2.2 Low-income Immigrant Data

To examine proximity, we leverage counts of the low-income, foreign-born population in the 32,989 ZIP Code Tabulation Areas (ZCTAs; henceforth ZIPs) from the American Community Survey 2014–2018 5-Year sample ([Manson et al., 2019](#)). We define “low-income immigrants” as all foreign-born people with household incomes lower than 150% of the Federal Poverty Guidelines (FPG) (i.e., an annual income of \$25,860 for a household of two). We compute the “as the crow flies” distance between the ZIP code centroid and the closest ISP. (Immigrants’ locations within ZIP codes are not disclosed.) We then aggregate to the core-based statistical area (CBSA) level as our main definition of a “city.” If a ZIP code falls into multiple CBSAs, we assign it to the CBSA that contains the majority of its population. When aggregating

distances to the CBSA level, we weight each ZIP code by the size of its low-income immigrant population. See the Supplementary Materials (SM) for additional summary statistics and results: we also analyze alternative aggregations, such as commuting zones and counties, and alternative distances, such as driving distances and driving times, and find similar results.

2.3 Identifying Underserved Areas

We use two approaches to identify “underserved” areas with a high number of low-income immigrants but relatively few ISPs nearby. First, we identify CBSAs in the upper quartiles of two marginal distributions: the number of low-income immigrants and average distance to the closest ISP. Second, we compare the current number of ISPs in each CBSA to the number of ISPs implied by our optimization algorithm (described below).

2.4 Spatial Optimization Algorithm

We conduct two types of spatial optimizations. First, we identify the optimal locations for new ISPs such that we maximize the number of low-income immigrants who gain access to services. We take a service area approach and define the service area of an ISP as a 12 mile radius around its location. Low-income immigrants are counted as having access to service if their ZIP code centroid is within 12 miles of the closest ISP; otherwise they are counted as underserved. The 12 miles’ distance cutoff is motivated by the fact that this is about twice the average distance to the closest ISP for the low-income immigrant population. To identify the optimal placement for the next ISP, we loop through the centroids of all underserved ZIP codes and select the ISP placement where the maximum number of immigrants gain service. This assumes that ISPs can only be placed at ZIP code centroids for computational simplicity. In the SM we also use an alternative distance cutoff (15 miles) and results are similar.

Second, we identify an optimal network that maximizes the number of immigrants served by rearranging existing ISPs. This allows us to examine to what extent the spatial distribu-

tion of the existing network is suboptimal. We use an iterative, simulation-based approach to find an approximate maximum. In particular, we use the same service area approach and first generate 200,000 random ISP networks of the size of the existing ISP network by randomly sampling, without replacement, ZIP code centroids. We then select the network that maximizes the number of immigrants with access to services. We impose a capacity constraint such that the maximum number of low-income immigrants covered by any given ISP is at or below the maximum covered under the current network: 61,725 low-income, foreign-born people. We then use an iterative procedure and randomly rearrange the locations of the ISPs with the lowest number of immigrants served until no further improvements can be made (see SM for details).

We conduct both optimization analyses in two ways: nationwide and state-by-state. The nationwide analysis is informative about the overall skew in the current network (i.e. across and within states). The state-by-state analysis is informative about the skew of the network within each state and also policy relevant since funding for ISPs often depends on within-state sources.

3 Results

3.1 ISP Network

Our final database consists of 2,138 ISP offices, 1,178 of which are registered on the Board of Immigration Appeals. Figure 1 presents the network of ISPs across the conterminous United States along with the size of the low-income immigrant population. Some patterns stand out. First, the ISP network is widely distributed, covering all states. ISPs cover all major urban centers, and the largest traditional immigrant-receiving hubs, such as New York City, Los Angeles, and Chicago, have some of the densest ISP networks, with 264, 124 and 100 ISPs, respectively. Although rural areas generally have low coverage, some places with small immigrant communities do have ISPs. For instance, Jamestown, ND, Riverton, WY, and

Auburn, IN each host fewer than 100 low-income immigrants but contain an ISP. Second, as the concentration of red points in dark blue localities shows, both ISPs and low-income immigrants are highly concentrated in major urban areas. The correlations between these two variables range from 0.83 to 0.94, depending on the level of aggregation (e.g., county, commuting zone, CBSA, or state).

How close are low-income immigrants to an ISP? The left panel of Figure 2 presents the (empirical) quantile function of the average distance of low-income immigrants to their closest ISP. Most low-income immigrants reside relatively close to an ISP. The median low-income immigrant lives about 2.7 miles from an ISP, and 75% of the total population of about 12 million low-income immigrants live within 6.6 miles of an office. This pattern is driven by the fact that low-income immigrants are highly concentrated in major urban areas, which are covered by the densest ISP networks. For instance, the six largest immigrant cities—New York City, Los Angeles, Miami, Houston, Chicago, and Dallas—account for 40% of the low-income immigrant community nationwide. The same cities account for 37.4% of all ISPs. However, many low-income immigrants are not well covered by the current network. For example, there are about 1.5 million underserved low-income immigrants (or about 13% of the total population) who live more than 12 miles away from the closest office, suggesting potential gains from improving the network’s coverage.

3.2 Underserved Areas

What are some of the most underserved areas? The middle panel of Figure 2 shows a CBSA-level scatter plot of low-income immigrant population size and average distance to the closest ISP. The inverse relationship indicates that, on average, cities with more low-income immigrants are better connected to the ISP network. The cities in the lower right cluster have dense ISP networks and contain the majority of the low-income immigrant population, which explains the pattern discussed above—that most immigrants live close to an ISP. The upper middle cluster of cities identifies low-service areas: cities with larger numbers of

immigrants who, on average, live relatively farther from an ISP. The plot labels all cities that are above the 3rd quartile in the distributions of distance to the closest ISP (44 miles) and the size of the low-income immigrant population (3700 foreign-born people). These underserved areas are mostly in Southern midsize cities such as Augusta, GA, Huntsville, AL, and Gainesville, FL. In these areas, the median distance to the closest ISP is 60 miles, and the median number of low-income immigrants is 5562.

What might explain this clustering of underserved areas? While a full investigation of this question is beyond the scope of this study, we explore two hypotheses. The first is that the ISP network lags behind the diversification of immigrant settlement patterns, with less settlement in recent decades in traditional hubs and more in new destinations (Massey and Capoferro, 2008; Massey et al., 2016). The right panel of Figure 2 provides support for this idea by comparing the state-level average distance to the closest ISP with total immigration growth between 1990 and 2018. New destination states, which have experienced higher growth in immigration over this time period (e.g., Georgia, North Carolina, and Arkansas), are also, on average, relatively farther from an ISP. This suggests that the ISP network has not caught up with the diversification of immigrant settlement patterns.

A second hypothesis is that the underserved areas for immigrant legal aid reflect a general skew in nonprofit service provision, which in turn may reflect funding availability and the presence of lawyers engaged in pro bono services. To examine this, we compared the nationwide ISP density with that of all registered nonprofit public charities in the United States using the IRS Business Master File extract from August 2019. The correlation between the two variables was high, ranging between 0.87 and 0.92 depending on the level of geographic aggregation. In addition, in the SM we provide a regression analysis that suggests, controlling for pure demand factors such as low-income population size, that democratic vote share (likely proxying here for urban professionals) and the availability of funding (proxied by household income) are significant predictors of ISP locations. Overall, these findings suggest that both the lag and the general skew hypotheses help explain the cluster of underserved

areas. This indicates the mismatch is not self-correcting, but rather a persistent feature of service provision.

3.3 Optimization

Another method to identify under-served areas is to compute the optimal nationwide ISP network that maximizes service coverage for low-income immigrants and then compare the number of ISPs in the optimal and current networks. Figure 3 plots the current against the optimal number of ISPs for each CBSA (left panel) and state (right panel). Locations above (below) the 45 degree line are currently high (low) services areas relative to the optimal ISP distribution. The results suggest a clear skew in the current network. Large cities like New York City, NY, Los Angeles, CA, San Francisco, CA, Boston, MA, and Seattle, WA currently have many more ISPs than suggested by the optimal network that maximizes coverage. In contrast, Riverside, CA, Houston, TX, Phoenix, AZ, Bakersfield, CA, Virginia-Beach, VA, and Merced, CA currently have far fewer ISPs than suggested by the optimal network. The differences are similarly stark at the state level where the optimal network shifts many ISPs from relatively overserved states such as New York, California, Illinois, and Massachusetts to relatively underserved Southern states like Texas, North Carolina, Florida, Georgia, Tennessee, and Alabama. The differences are most striking in New York and Texas which have 119 fewer ISPs and 51 more ISPs in the optimal network compared to the current network, respectively.

How can the current network be improved to maximize access to service? Figure 4 presents the maps that results from our spatial optimization analyses in the four largest immigrant-receiving states: California, Texas, New York, and Florida, home to 57.5% of all low-income foreign-born. For each state we show the five optimal locations to add a single new ISP office (orange squares) to the existing network (red circles) to maximize access to service for the largest number of under-served low-income immigrants. For example, in California these optimal new locations are either in the area east of Los Angeles, in Santa

Barbara, or in the central valley. We also show the approximately optimal network that results from rearranging the existing ISPs in each state to maximize access to service (yellow diamonds). The optimal networks distributes many ISPs away from major urban centers to more peripheral areas and midsized cities that host many low-income immigrants. For example, in California the optimal network has many more offices distributed to the central valley area.

How large are the gains from optimally restructuring the ISP networks or adding an additional ISP location in each state? Figure 5 present the state-level gains in the number of low-income immigrants covered when placing an additional new ISP (top) and when restructuring the entire ISP network (bottom), plotted against the number of low-income immigrants currently served. States with larger immigrant populations experience, on average, larger gains in coverage in both types of analyses. On the one hand, New York and Illinois are well below the regression line, indicating a relatively efficient current ISP network and hence smaller gains from adding an additional new office. On the other hand, several Southern states, like Florida, Texas, Virginia and Georgia, can gain large numbers of newly covered immigrants by adding an ISP location. This pattern can be seen in the two right panels, where we show the gains by state and type of analysis. Four of the top five states in each panel are in the South, suggesting the greatest gains are in that region. The results also show considerable potential gains overall. Under the current nationwide network, about 10.4 million immigrants are covered by an ISP (i.e., they live within 12 miles of an ISP) and about 1.6 million are underserved (i.e., they live more than 12 miles from an ISP). By optimally rearranging the ISP locations within each state, 494,000 low-income foreign-born people can gain coverage in these four states, as can 1.1 million nationwide. These gains would reduce the number of underserved low-income immigrants in those areas by about 84% and 70%, respectively.

4 Discussion

By conducting the first comprehensive study of the nationwide network of ISPs, we provide vital information to low-income immigrants, funders, and policymakers about the current state of the ISP network. By identifying underserved areas with few ISPs but many low-income immigrants, we illuminate how the current network could be improved. Our optimization analysis identifies areas where placing additional new ISP offices would yield the highest returns in terms of number of newly served low-income immigrants. Lastly, our study also contributes to the literature on civil society organizations generally and ISPs specifically. Our work highlights how in one important area of service provision—legal aid to low-income immigrants—the nonprofit sector has built a comprehensive network that filled the void left by the federal government. That said, our study also highlights how the clustering of underserved areas reflects both a general skew in non-governmental organization service provision and the fact that the ISP network has not caught up with new immigrant settlement patterns, particularly in the South. Our work also paves the way for future research. In particular, researchers could build on our work and that of ([Chand et al., 2020](#)) to examine the broader impact of service providers on the success of immigrants in navigating the complex legal and bureaucratic obstacles they face.

Our study is not without limitations. First, we cannot guarantee that our list of ISPs is complete. Yet, given our triangulation of data sources, we are confident that our list does not miss large swaths of ISPs and that the broader patterns we have identified are robust to the inclusion of those ISPs that eluded our count. Second, the ongoing COVID-19 crisis might result in shifts to the ISP network that we cannot capture in our current data. Future work could investigate how the network might change in light of the crisis.

5 Figures

Figure 1: ISP network and low-income immigrant population size across the US. Red dots indicate ISP locations. Polygons are commuting zones.

Figure 2: Distance to the closest ISP at the individual (left plot), CBSA (middle) and state (right) levels. Left panel shows the fraction of low-income immigrants located within a distance to the closest ISP. Middle and right panels show distance to the ISP by size and growth of the immigrant population.

Figure 3: Number of current and optimal ISPs by CBSA (left panel) and state (right) (45 degree lines in black).

Figure 4: Current (red) and optimal (yellow) ISP networks in the four largest immigrant-receiving states. The optimal locations of the next five ISPs are shown in orange.

Figure 5: Currently covered low-income immigrant population size and gains in coverage from adding an additional new ISP location (Panel A) and rearranging the entire ISP network optimally (B). Gains in low-income immigrant coverage from adding an additional new ISP location (C) and rearranging the entire ISP network optimally (D) by state.

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13 Supporting Information Text

14 In this Appendix we present additional results organized in several subsections – identifying low and high service areas,
15 predicting immigrant service providers (ISP) presence, robustness checks, and optimizing the ISP network. Please refer to the
16 main text for details on data sources and variable definitions. All data and code necessary to replicate our main findings can
17 be obtained at XXXX.

18 Low and High Service Areas

19 In Table S1 we present summary statistics of the number of ISPs throughout the United States. Table S2 shows the list of
20 states with the highest number of ISPs and the corresponding size of the low-income immigrant population. California, New
21 York and Texas have the most ISPs – 426, 279 and 162 respectively. The three states are also the largest destinations for
22 low-income foreign-born (5.6 million).

23 Table S3 displays a list of Core-based statistical areas (CBSAs) without an ISP ordered by the size of the low-income
24 immigrant population. Palm Bay, FL, Deltona, FL and Hanford, CA are the largest cities (9958 or more low-income foreign
25 born) currently not hosting an ISP on our list. The closest ISP to each of these cities is located at least 35 miles away. Hence,
26 the gains from placing an ISP there could arguably be the largest.

27 In Table S4 we show the list of 20 CBSAs with at least one ISP and with the fewest ISPs per low-income immigrant.
28 The largest cities in this list are Miami, FL, Houston, TX and Phoenix, AZ where foreign-born communities are arguably
29 underserved in terms of low-cost or free legal immigration services. This problem is particularly severe in Las Vegas, NV and
30 Merced, CA which respectively contain only 3.2 and 3.8 ISPs per 100, 000 low-income immigrants. In agreement with the
31 results we present in the main text, Tables A1 and A2 show that many of the low service areas are mid-sized cities in the
32 South such as Palm Bay, FL, Deltona, FL, Gainesville, FL, Augusta, GA, Killeen, TX (Table S3) and El Paso, TX, McAllen,
33 TX, College Station, TX (Table S4).

34 Table S5 presents the list of CBSAs with the most ISPs. As expected, these are the largest major urban centers which have
35 been traditional immigrant receiving hubs for decades. In the last column we show the number of low-income immigrants
36 in each city. The New York City metro area leads the ranking with 264 ISPs; Los Angeles, CA is a distant second with 124
37 locations, while Chicago and San Francisco host 100 and 86 ISPs respectively.

38 Table S6 displays the list of CBSAs with the highest numbers of ISPs per low-income immigrant. Most cities in the list are
39 small and have only one ISP with the exception of Lebanon, NH-VT which has 8 ISPs and 1291 low-income immigrants.

40 Table S7 shows the list of cities with the lowest number of low-income immigrants which also host at least one ISP. Jamestown,
41 ND, Riverton, WY, and Auburn, IN (the top three cities in Table A4 as well) are home to fewer than 100 immigrants while
42 have an ISP. In the second column we present the total population in each city. The largest CBSA in the list is East Liverpool
43 – Salem, OH with 104,095 people.

44 Predicting ISP Presence

45 Table S8 presents the correlation coefficients between the number of low-income immigrants and the number of ISPs at various
46 geographic aggregation levels. The coefficients are positive indicating that localities with higher demand for ISPs have higher
47 ISP density. Expectedly, this correlation gets stronger as we move to larger units.

48 Figure ?? plots the empirical CDF of average distance to an ISP for low-income immigrants by region of origin. Aggregated
49 data on low-income immigrants by origin for each geographic location does not exist. We, therefore, used the individual level
50 American Community Survey (ACS) 2014-2018 IPUMS 5-Year sample (1) to get these counts at the CBSA level. We split the
51 low-income foreign-born population to 6 groups depending on their birthplace – Mexico, Central America, South America,
52 Caribbean, Asia and Africa. We then merged these counts to the CBSA level measure of average distance to the closest ISP.
53 The figure shows that immigrants from the Caribbean and South America are better connected to the ISP network than
54 foreign-born from Mexico and Africa at all levels of distance to the closest ISP. This finding perhaps reflects the fact that
55 immigrants from the Caribbean and South America tend to cluster in large urban centers with many ISPs (such as New York
56 City, NY and Miami, FL) while Mexicans employed in agricultural occupations can locate in more rural, underserved areas.

57 Figure ?? presents the same plots by education (Panel A) and income (B) level. Note that the foreign-born population here
58 is not filtered to low-income individuals only. As above, we merge the CBSA level counts of immigrants by education and
59 income to our measure of average distance to an ISP. In Panel A we see that foreign-born college graduates live in locations
60 that are closer to an ISP than foreign-born high school dropouts or high school graduates. Similarly, Panel B shows that
61 financially better off immigrants (income equal to 150% of the federal poverty line (FPL) or more) live, on average, closer to an
62 ISP than low-income foreign-born. These findings imply that those with lowest levels of education and lowest incomes are not
63 the ones best connected to the ISP network further suggesting potential benefits from optimizing the ISP locations.

64 What local factors can explain whether and how many ISPs are present in a CBSA? In Table S9 we present the results from
65 regressing ISP prevalence on several city level characteristics. The outcome variable in the first two columns is the number of
66 ISPs and in columns 3-6 it is a binary indicator for ISP presence. The unit of observation is a CBSA. The first two columns
67 present results from negative binomial models, the second two columns – from linear models and the last two from Logistic
68 regressions. The even-numbered columns control for state fixed effects. All coefficients reflect marginal effects. Standard errors
69 are clustered by state and shown in parenthesis.

All variables, unless otherwise noted, comes from the 2010 Census (2). The variable Obama shares measures the share of votes to the democratic candidate in the 2012 Presidential election. Number of low-income immigrants is measured in logarithm and so is population density which is defined as number of people per square mile. Household income is expressed in \$100,000s. Share of low-income naturalized and Obama share are proportions defined on a 0-1 scale. Lastly, income gap refers to the difference in log income between natives and foreign-born.

Most coefficients on the first three variables are positive and statistically significant. An increase of the vote share going to Obama by ten percentage points is associated with 0.12-0.13 more ISPs (columns 1-2) or around a 3.7-4.0% increase in the probability of having an ISP (columns 3-4). Moreover, a ten percent increase in the number of low-income immigrants is associated with 0.07 more ISPs and a 1.3% increase in the probability of having an ISP. Next, an increase of household income by \$10,000 per year is similarly related to 0.25-0.27 more ISPs locally as well as a 5-9% increase in the probability of having an office providing low-cost or free legal services to immigrants. Conditional on all other factors, cities with higher population density are not more likely to have an ISP (or additional ISPs). The last two variables are meant to measure immigrant integration but, conditional on the other factors, are not statistically significant in these models. In particular, we do not find evidence that ISPs tend to locate in areas where low-income immigrant naturalization rates are lower or where foreign-born lag behind natives in income levels. This suggests that demand factors are the strongest predictors of ISP presence.

In Table S10 we present the correlation between the number of ISPs and the number of non-governmental organizations (NGOs) at various geographic aggregation levels. Data on NGOs for year 2019 comes from IRS Business Master File Extract. We subset the data to only include public charities and then excluded churches, schools and hospitals. The correlation coefficients are positive and strong. Depending on the aggregation level, they range from 0.39 (ZIP) to 0.92 (CBSA), indicating that the ISP network follows closely the general skew in public services provision.

Robustness Checks

In Table S11 we display correlation matrices between three distance measures – as-the-crow-flies distance, driving distance and driving time at various geographic aggregation levels. The latter two are obtained via Google Maps API. All measures correspond to distance to the closest ISP. In the bottom two panels we show the correlations for rural and urban counties defined as above/below median population density. All correlation coefficients regardless of the geographic unit are very high, ranging from 0.85 to 0.99.

All distances used in the paper are as-the-crow-flies distances. Figure ?? presents the conversion factors between this “crow distance” and driving distance (left) and driving time (right). The median (standard deviation) conversion factors are 1.31 (0.13) for driving distance and 1.03 (0.19) for driving time. Overall, with the exception of Alaska, there is little variation in this conversion factor across states.

To verify the robustness of our results to these alternative distance measures we replicated Figure 2 from the main text using each of them. Figure ?? present the results. All in all, the patterns we observe in Figure 2 are present here as well - (i) most immigrants live relatively close to an ISP, (ii) many of the underserved areas are midsized cities in the South and (iii) there is a positive state-level correlation between recent total immigration growth and distance to an ISP regardless of how the latter is measured.

Optimization

We conduct two types of approximate spatial optimization exercises. First, we identify the optimal locations for adding a single new ISP to the current network such that we maximize the number of low-income immigrants who gain access to services. Second, we identify an approximately optimal network that maximizes the number of immigrants served by rearranging existing ISPs.

Both types of analysis are based on a service area approach. We define the service area of an ISP as a 12-mile radius around its location. Low-income immigrants are counted as having access to service if their ZIP code centroid is within 12 miles crow-distance of the closest ISP. Below we also use an alternative 15-mile radius and the results are similar. To reduce computational complexity, we assume that ISPs can only be placed at ZIP code centroids. This assumption reduces complexity for the computation, but still provides informative results since ZIP codes are relatively small.

Also, we conduct both optimization analyses in two ways: nationwide and state-by-state. The nationwide analysis is informative about the overall skew in the current network (i.e. across and within states). The state-by-state analysis is informative about the skew of the network within each state and also policy relevant since funding for ISPs often depends on within-state sources. Note that in the state-by-state analysis we assume that ISPs can only be placed within each state and immigrants can only access an ISP within their state of residence.

Algorithm to Identify the Next Optimal ISP Location. To find the optimal locations to place a single new ISPs to the existing network we loop through the centroids of all underserved ZIP codes and select the ISP placement where the maximum number of low-income immigrants gain service. In the state specific maps, we show the top five locations to add a single new ISP. If these locations are clustered together, this indicates that there is a single area where a placement of a new ISP would maximize access to service. If these locations are clustered in various different areas this indicates that there are various areas where the new ISP could be placed, and we would see fairly similar gains in terms of the number of people newly served.

Algorithm to Identify the Optimal Network by Rearranging ISPs. To identify an optimal network that maximizes the number of immigrants served by rearranging existing ISPs, we follow an iterative, simulation-based approach to find an approximate maximum. Our optimization algorithm follows the following steps:

- 1 Generate 200,000 random ISP networks of the size of the existing ISP network by randomly sampling, without replacement, ZIP code centroids where ISPs are placed.
- 2 Compute the number of low-income immigrants served under each of the 200,000 randomly generated ISP networks using our service area approach.
- 3 Select the network that maximizes the number immigrants served as the current best candidate network.
- 4 Starting with this current best candidate network, repeat the following steps until end.
 - a Compute the total number of immigrants served by the current best candidate network
 - b Compute the number of immigrants served by each ISP in the current best candidate network
 - c Rank the ISPs by the number of immigrants served in decreasing order such that the ISP with rank one is the one serving the lowest number of immigrants, rank two the one serving the second lowest number of immigrants, etc.
 - d Create 200,000 new candidate ISP networks by taking the ISPs that are ranked first to K in the current best candidate network and replace their locations with a randomly drawn location. Locations are randomly sampled without replacement from the zip code centroids of zip codes that have no ISPs in the current best candidate network.
 - e Select among the 200,000 new candidate networks the network that maximizes the number of immigrants served. Call this the best new candidate network.
 - f Compare the number of immigrants served by the best new candidate network and the current candidate network (from step 4a)
 - i If the best new candidate network serves more immigrants than the current candidate network: replace the current candidate network with the best new candidate network and move back to step 4a
 - ii If the best new candidate network serves fewer immigrants than the current candidate network:
 - 1 If $K > 1$: keep the current candidate network, decrement K by one, and move back to step 4a
 - 2 If $K = 1$: declare the current candidate network as the final best network and end.

For the state-by-state optimization we start K at 15 (or the number of current ISPs if that is lower than 15). For the nationwide optimization, we start K at 150 and begin at step 4 with the results from the state-by-state optimizations as our initial candidate network.

Note that for this optimization we impose a capacity constraint such that the maximum number of low-income immigrants served by any given ISP is at or below the maximum covered under the current network: 61,725 low-income, foreign-born people. To accommodate this constraint, we simply discard from evaluation all candidate networks in steps 1 and or step 4e that violate the constraint (see below for more details on the distributions of number of people served by each ISP).

In our optimization routine, we impose a capacity constraint such that the maximum number of low-income immigrants covered by any given ISP is at or below the maximum covered under the current network: 61,725 low-income, foreign-born people. This does not mean that we would expect a single ISP to provide services to tens of thousands of people. Rather, it can be thought of the market of potential clients. We believe it is reasonable to set this constraint such the optimal network would not place an ISP in a service area exceeding the current maximum number of low-income, foreign-born people in an ISP service area.

Note that our iterative, simulation-based procedure will find an approximate maximum (which for simplicity we refer to as the optimal network), but we cannot guarantee that our algorithm reaches the global maximum (which is computationally not tractable). Nevertheless, the number of low-income immigrants in the US (11.9 million) provides a natural upper bound on the number of people served under any given network. As we show below, in our nationwide optimization our algorithm finds an approximately optimal network that covers over nearly 97% of that population, suggesting that our iterative approach performs well.

Results.

Alternative Distance Cutoff for Service Areas. To check the robustness of our results we also replicated this analysis using an alternative distance cut-off of 15 miles. This second cut-off is motivated by the fact that the average one way commute time in the US is 26.1 minutes. In our ZIP data, there is a linear relationship between travel time (computed from the Google Maps API) and as-the-crow-flies distance between Zip codes and the closet ISP, where one minute of travel time corresponds to 0.6 miles of crow distance. Therefore, an average one way commute time in the US of 26.1 minutes corresponds to about 15 miles of distance in our data. Note that when using this alternative cutoff we again impose the constraint that the maximum number of low-income immigrants covered by any given ISP is at or below the maximum covered under the current network: in this case 62,784 low-income, foreign-born people.

180 As shown in Figures ?? and ??, the results are broadly similar when using this alternative 15-mile distance cutoff for service
181 areas. As expected, some of the locations to place the next ISPs slightly differ but the overall gains from the optimization and
182 the overall optimal network does not change much.

183 **Nationwide Optimization.** In Figure ?? we show the results for a nationwide optimization where we replicate the same optimization
184 approaches without the constraint that ISPs have to be placed within a specific state (and using the 12-mile distance cutoff
185 and the maximum capacity constraint).

186 The top panel shows the next twenty optimal locations to add an additional ISP to the existing network. These locations
187 include the area east of Los Angeles, the central valley in California, between Orlando and Tampa in Florida, the Houston area,
188 Norfolk VA, and Charlotte NC.

189 The lower panel shows the optimal nationwide network from rearranging all ISPs. The results here suggest additional gains
190 in coverage from removing the state by state restriction. Under the optimal network about 11.6 million or about 97% of the
191 11.9 million low-income immigration population would gain access to service, compared to only 10.5 million who have access to
192 service under the current network. In other words, the nationwide optimal network would close the gap of the 1.4 million
193 low-income immigrants who are currently underserved by about 75

194 Figure ?? compares the distribution of the number of ISPs in the optimal versus the current network to illuminate the skew
195 of the current nationwide network since we now relax the restriction that the rearrangement of ISPs has to take place state by
196 state. The plots shows how the optimal nationwide network maximizes coverage by shifting ISPs from relatively overserved
197 states like NY, IL, CA, and MA to relatively underserved southern states like TX, NC, FL, GA, TN, and AL. Under the
198 optima network NY has 119 fewer ISPs (compared to 279 under the current network), while TX gains 51 ISPs (compared to
199 currently 62).

200 **Capacity Constraint.** Related to this, Figure ?? presents the histograms of the number of low-income immigrants served in the
201 current (red) and optimal (green) ISP networks. Note, that if a zip code centroid falls within the service area of multiple ISPs,
202 then the low-income immigrant population for that zip code is assigned to the service area of the closest ISP. The distributions
203 for the optimal and actual networks are similar, and just as in the actual network, very few ISPs have service areas that
204 approach the maximum capacity constraint. The key takeaway is that the major gains we see are coming from increasing the
205 number of people served for ISPs on the lower end of the service area distribution. In other words, most of the gains are coming
206 from placing many ISPs better such that they have a few thousand more people served compared to their current service areas.

207 **State by State Maps.** Following Figure 4 in the main text, Figures ??-?? present the current and optimal ISP network in every
208 state. In the left panels, current ISP locations are denoted with red circles while orange squares indicate the optimal locations
209 of the next five additional ISPs. In the right panels, we present with yellow diamonds how the state level ISP would look like if
210 it was rearranged optimally - that is to maximize the number of low-income immigrants within a 12-mile radius. This 12-mile
211 radius is motivated by the fact that 12 miles amounts to twice the average distance to the closest ISP for the low immigrant
212 population across all ZIP codes in our data.

213 **ZIP Codes Area Size.** For computational simplicity, in the optimization algorithm we consider only ZIP code centroids, and not
214 any points within ZIP codes. Lastly, in Table S12 we present summary statistics for ZIP code area size measured in square
215 miles. The top panel presents the statistics for all 32,989 ZIP codes. In the bottom panel we show the same statistics form ZIP
216 Codes with at least 100 low-income immigrants. The median area among this subset of ZIP codes is 57.4 square miles, while
217 the interquartile range is 14.2-54.6 square miles.

Fig. S1. Distance to an ISP for Low-income Immigrants by Region of Origin. Notes: This figure is produced at the CBSA level (and not the individual level) – hence the discontinuous jumps in the CDF. Data on the number of low-income immigrants by origin at the CBSA level comes from the individual level American Community Survey 2014-2018 5-Year sample. Each line represents a different region of origin immigrant group denoted in the legend. The thick blue dashed line shows the distance to an ISP for the overall immigrant population. Distance to an ISP is top-coded at 40 miles.

Fig. S2. Distance to an ISP for Immigrants by Education and Income. Notes: This figure is produced at the CBSA level (and not the individual level) – hence the discontinuous jumps in the CDF. Data on the number of low-income immigrants by origin at the CBSA level comes from the American Community Survey 2014-2018 5-Year sample. Each line represents a different education (Panel A) or income (B) group denoted in the legend. Distance to an ISP is top-coded at 40 miles.

Fig. S3. Converting from As-the-crow-flies to Alternative Distance Measures. Notes: Conversion factors from "crow" distance to driving distance (left) and driving (time). These are derived from binary regressions within each state without an intercept.

Fig. S4. Replicating Figure 2 with Alternative Distance Measures. Notes: Same as Figure 2 but distance measured as driving distance (top) and driving time (bottom).

Fig. S5. Gains from Optimization with 15 Mile Distance Cutoff. Notes: Currently covered low-income immigrant population size and gains in coverage from adding additional new ISP location (Panel A) and rearranging the entire ISP network optimally (B). Gains in low-income immigrant coverage from adding an additional new ISP location (C) and rearranging the entire ISP network optimally (D) by state. Results are based on 15 mile distance cut-off.

Fig. S6. Optimization Maps with 15 Mile Distance Cutoff. Notes: As in Figure 4, but the distance cutoff to define coverage is changed to 15 miles.

Fig. S7. Results from Nationwide Optimization. Notes: As in Figure 1 but optimization is conducted nationwide, and not state-by-state.

Fig. S8. Change in Number of ISPs by State: Optimal Network vs Current Network. Notes: State level difference in the number of optimal and current ISPs. Negative (positive) values correspond to currently having more (fewer) ISPs than what our optimization algorithm suggests.

Fig. S9. ISP Capacity in Current and Optimal Networks. Notes: Histograms of number of low-income immigrants served (i.e., located within a 12-mile radius) in the current (red) and optimal (green) ISP networks.

Fig. S10. Current and Optimal ISP Networks: Alaska

AL: Current Network & Next Optimal

AL: Optimal Network

Fig. S11. Current and Optimal ISP Networks: Alabama

AR: Current Network & Next Optimal

AR: Optimal Network

Fig. S12. Current and Optimal ISP Networks: Arkansas

AZ: Current Network & Next Optimal

AZ: Optimal Network

Fig. S13. Current and Optimal ISP Networks: Arizona

CA: Current Network & Next Optimal

CA: Optimal Network

Fig. S14. Current and Optimal ISP Networks: California

Fig. S15. Current and Optimal ISP Networks: Colorado

CT: Current Network & Next Optimal

CT: Optimal Network

Fig. S16. Current and Optimal ISP Networks: Connecticut

DE: Current Network & Next Optimal

DE: Optimal Network

Fig. S17. Current and Optimal ISP Networks: Delaware

Fig. S18. Current and Optimal ISP Networks: Florida

GA: Current Network & Next Optimal

GA: Optimal Network

Fig. S19

HI: Current Network & Next Optimal

HI: Optimal Network

Fig. S20. Current and Optimal ISP Networks: Georgia

Fig. S21. Current and Optimal ISP Networks: Iowa

ID: Current Network & Next Optimal

ID: Optimal Network

Fig. S22. Current and Optimal ISP Networks: Idaho

IL: Current Network & Next Optimal

IL: Optimal Network

Fig. S23. Current and Optimal ISP Networks: Illinois

IN: Current Network & Next Optimal

IN: Optimal Network

Fig. S24. Current and Optimal ISP Networks: Indiana

Fig. S25. Current and Optimal ISP Networks: Kansas

Fig. S26. Current and Optimal ISP Networks: Kentucky

Fig. S27. Current and Optimal ISP Networks: Louisiana

Fig. S28. Current and Optimal ISP Networks: Massachusetts

Fig. S29. Current and Optimal ISP Networks: Maryland

Fig. S30. Current and Optimal ISP Networks: Maine

Fig. S31. Current and Optimal ISP Networks: Michigan

Fig. S32. Current and Optimal ISP Networks: Minnesota

Fig. S33. Current and Optimal ISP Networks: Missouri

MS: Current Network & Next Optimal

MS: Optimal Network

Fig. S34. Current and Optimal ISP Networks: Mississippi

Fig. S35. Current and Optimal ISP Networks: Montana

Fig. S36. Current and Optimal ISP Networks: North Carolina

Fig. S37. Current and Optimal ISP Networks: North Dakota

Fig. S38

NH: Current Network & Next Optir NH: Optimal Network

Fig. S39. Current and Optimal ISP Networks: Nebraska

NJ: Current Network & Next CNJ: Optimal Network

Fig. S40. Current and Optimal ISP Networks: New Jersey

Fig. S41. Current and Optimal ISP Networks: New Mexico

NV: Current Network & Next Optimal

NV: Optimal Network

Fig. S42. Current and Optimal ISP Networks: Nevada

Fig. S43. Current and Optimal ISP Networks: New York

OH: Current Network & Next Optimal

OH: Optimal Network

Fig. S44. Current and Optimal ISP Networks: Ohio

Fig. S45. Current and Optimal ISP Networks: Oklahoma

OR: Current Network & Next Optimal

OR: Optimal Network

Fig. S46. Current and Optimal ISP Networks: Oregon

Fig. S47. Current and Optimal ISP Networks: Pennsylvania

RI: Current Network & Next Optimal

RI: Optimal Network

Fig. S48. Current and Optimal ISP Networks: Rhode Island

Fig. S49. Current and Optimal ISP Networks: South Carolina

Fig. S50. Current and Optimal ISP Networks: South Dakota

Fig. S51. Current and Optimal ISP Networks: Tennessee

Fig. S52. Current and Optimal ISP Networks: Texas

Fig. S53. Current and Optimal ISP Networks: Utah

Fig. S54. Current and Optimal ISP Networks: Virginia

VT: Current Network & Next Optimal VT: Optimal Network

Fig. S55. Current and Optimal ISP Networks: Vermont

Fig. S56. Current and Optimal ISP Networks: Washington

Fig. S57. Current and Optimal ISP Networks: Wisconsin

Fig. S58. Current and Optimal ISP Networks: West Virginia

Fig. S59. Current and Optimal ISP Networks: Wyoming

Table S1. Summary Statistics of the Number of ISPs

	Min	Median	Mean	Max	SD	N
ZIP	0	0	.07	9	.35	32,989
County	0	0	.68	95	3.54	3,143
PUMA	0	0	.90	22	1.61	2,351
CBSA	0	0	2.24	364	11.44	942
State	2	21	41.92	426	71.76	51

Table S2. States with the Most ISPs

State	Number of ISPs	Low-income Immigrants
California	426	2,872,695
New York	279	1,206,605
Texas	162	1,545,067
Florida	105	1,256,070
Illinois	104	430,981
Massachusetts	75	253,361
Washington	74	234,442
New Jersey	50	262,907
North Carolina	50	413,396
Michigan	49	183,985

Table S3. Low Service Areas – the largest CBSAs without an ISP

CBSA Name	Low-income Immigrants	Total Population	Distance to Closest ISP (km)
Palm Bay-Melbourne-Titusville, FL	14526	576988	60
Deltona-Daytona Beach, FL	13366	527585	47
Hanford-Corcoran, CA	9958	149764	35
Gainesville, FL	8902	280434	103
Augusta-Richmond County, GA-SC	8479	586647	81
Killeen-Temple-Fort Hood, TX	7868	437655	68
Ocala, FL	7352	348200	79
Moses Lake, WA	6270	94821	69
Longview, TX	6195	219532	41
Clewiston, FL	6093	40635	37
Huntsville, AL	5956	450244	79
Goldsboro, NC	5824	123293	39
Savannah, GA	5552	381925	49
Bloomington, IN	5521	198788	78
State College, PA	5092	161204	83
Sebastian-Vero Beach, FL	4808	150940	32
Lake Havasu City-Kingman, AZ	4763	205851	135
Thomasville-Lexington, NC	4586	166245	25
Key West, FL	4183	76313	120
Ames, IA	3857	97104	43

Table S4. Low Service Areas – CBSAs with the lowest number of ISPs per capita

CBSA Name	ISPs per 100,000 Low-income Immigrants	Low-income Immigrants	ISPs
Las Vegas-Paradise, NV	3.2	123543	4
Merced, CA	3.8	26584	1
Miami-Fort Lauderdale, FL	4.6	735654	34
Houston-Sugar Land-Baytown, TX	5.3	468408	25
El Paso, TX	6.7	88950	6
Kennewick-Pasco-Richland, WA	7.0	14234	1
McAllen-Edinburg-Mission, TX	7.2	124882	9
Atlantic City-Hammonton, NJ	7.3	13777	1
Madera-Chowchilla, CA	7.7	13071	1
Phoenix-Mesa-Glendale, AZ	7.7	221821	17
Stockton, CA	7.7	51766	4
Visalia-Porterville, CA	7.8	51533	4
Columbus, OH	7.9	50607	4
Provo-Orem, UT	7.9	12612	1
College Station-Bryan, TX	8.3	12016	1
Bakersfield-Delano, CA	8.4	71440	6
Beaumont-Port Arthur, TX	8.5	11788	1
Orlando-Kissimmee-Sanford, FL	8.6	128578	11
Lakeland-Winter Haven, FL	8.8	22731	2
Rio Grande City-Roma, TX	8.8	11357	1

Table S5. High Service Areas - CBSAs with the highest number of ISPs

CBSA Name	ISPs	Low-income Immigrants
New York-Northern New Jersey-Long Island, NY-NJ-PA	264	1436421
Los Angeles-Long Beach-Santa Ana, CA	124	1282161
Chicago-Joliet-Naperville, IL-IN-WI	100	397176
San Francisco-Oakland-Fremont, CA	86	258200
Washington-Arlington-Alexandria, DC-VA-MD-WV	71	239513
Boston-Cambridge-Quincy, MA-NH	52	198957
Seattle-Tacoma-Bellevue, WA	49	134484
Dallas-Fort Worth-Arlington, TX	44	384911
Miami-Fort Lauderdale-Pompano Beach, FL	34	735654
San Diego-Carlsbad-San Marcos, CA	33	207220
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	33	158244
San Jose-Sunnyvale-Santa Clara, CA	30	110423
Riverside-San Bernardino-Ontario, CA	26	290399
Houston-Sugar Land-Baytown, TX	25	468408
Tampa-St. Petersburg-Clearwater, FL	22	118761
Atlanta-Sandy Springs-Marietta, GA	21	209633
Minneapolis-St. Paul-Bloomington, MN-WI	20	104446
Sacramento-Arden-Arcade-Roseville, CA	19	123911
Detroit-Warren-Livonia, MI	18	114903
Phoenix-Mesa-Glendale, AZ	17	221821

Table S6. High Service Areas – CBSAs with the highest number of ISPs per capita

CBSA Name	ISPs per 100,000 Low-income Immigrants	Low-income Immigrants	ISPs
Jamestown, ND	4000.0	25	1
Riverton, WY	3125.0	32	1
Auburn, IN	1162.8	86	1
Marion, IN	990.1	101	1
Wilmington, OH	900.9	111	1
Defiance, OH	833.3	120	1
Madison, IN	740.7	135	1
East Liverpool-Salem, OH	630.9	317	2
Lebanon, NH-VT	619.7	1291	8
Hays, KS	555.6	180	1
Ashtabula, OH	514.1	389	2
Natchitoches, LA	478.5	209	1
Safford, AZ	425.5	235	1
Oneonta, NY	413.2	484	2
Juneau, AK	400.0	250	1
Batavia, NY	392.2	255	1
Williston, ND	387.6	258	1
Silver City, NM	381.7	262	1
Beeville, TX	362.3	276	1
Mason City, IA	346.0	289	1

Table S7. High Service Areas - Smallest CBSAs with an ISP

CBSA Name	Low-income Immigrants	Total Population	ISPs
Jamestown, ND	25	21221	1
Riverton, WY	32	40079	1
Auburn, IN	86	42632	1
Marion, IN	101	66440	1
Wilmington, OH	111	42092	1
Defiance, OH	120	37857	1
Madison, IN	135	32233	1
Hays, KS	180	28729	1
Natchitoches, LA	209	39287	1
Safford, AZ	235	47706	1
Juneau, AK	250	32330	1
Batavia, NY	255	57624	1
Williston, ND	258	34109	1
Silver City, NM	262	28043	1
Beeville, TX	276	32678	1
Mason City, IA	289	50427	1
Lewisburg, TN	291	31893	1
Tiffin, OH	310	54550	1
East Liverpool-Salem, OH	317	104095	2
Ada, OK	328	38223	1

Table S8. Correlation between Low-income Immigrants and ISP Prevalence

	Correlation Coefficient	N
ZIP	0.40	32,989
County	0.83	3,143
PUMA	0.43	2,351
CBSA	0.90	942
State	0.94	51

Table S9. Predicting ISP Presence

	Negative Binomial		Linear [0,1]		Logit [0,1]	
	(1)	(2)	(3)	(4)	(5)	(6)
Obama Share	1.352*** (0.458)	1.222 (0.801)	0.370*** (0.118)	0.403*** (0.109)	2.142** (0.842)	2.297** (0.938)
# Low-Income Immigrants	0.676*** (0.035)	0.701*** (0.037)	0.129*** (0.010)	0.130*** (0.009)	0.910*** (0.109)	1.056*** (0.092)
Household Income	2.670*** (0.546)	2.511*** (0.648)	0.916*** (0.230)	0.541** (0.251)	6.400*** (1.529)	4.412** (1.932)
Population Density	0.040 (0.052)	0.071 (0.061)	-0.014 (0.024)	0.034 (0.021)	-0.106 (0.141)	0.310** (0.133)
Share Low-Income Naturalized	0.606 (0.468)	0.196 (0.533)	0.030 (0.080)	-0.059 (0.070)	0.388 (0.792)	-0.598 (0.773)
Income Gap	-0.017 (0.235)	-0.175 (0.282)	0.019 (0.053)	0.029 (0.047)	0.003 (0.500)	0.011 (0.430)
Observations	886	883	886	886	886	879
R^2			0.363	0.456		
Pseudo R^2	0.355				0.336	0.402
Log Likelihood	-950.859	-778.639	-434.182	-364.293	-401.504	-272.105
State FE		X		X		X

Notes: All coefficients are average marginal effects. All data comes from the 2010 ACS, except for Obama share which refers to the 2012 Presidential election. The unit of observation is an MSA. The outcome variable in columns (1) - (2) is the number of ISPs and in columns (3)-(6) it is a binary indicator for having at least one ISP. Standard errors clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Variables denoting shares are on the 0-1 scale; population density is measured in log people per square mile; household income is expressed in \$100,000; low income immigrant population is measured in log; income gap is the difference in the log income of natives and immigrants.

Table S10. Correlation between ISP and NGO Prevalence

	Correlation Coefficient	N
ZIP	0.39	32,989
County	0.87	3,143
CBSA	0.92	942
State	0.91	51

Table S11. Correlation between Various Distance Measures

County (N=3,143)				
	As-the-Crow-Flies	Driving Distance	Driving Time	
As-the-Crow-Flies	1.00	—	—	
Driving Distance	0.98	1.00	—	
Driving Time	0.85	0.88	1.00	
PUMA (N=2,351)				
	As-the-Crow-Flies	Driving Distance	Driving Time	
As-the-Crow-Flies	1.00	—	—	
Driving Distance	0.99	1.00	—	
Driving Time	0.90	0.93	1.00	
CBSA (N=942)				
	As-the-Crow-Flies	Driving Distance	Driving Time	
As-the-Crow-Flies	1.00	—	—	
Driving Distance	0.97	1.00	—	
Driving Time	0.96	0.99	1.00	
Rural Counties (N=1,551)				
	As-the-Crow-Flies	Driving Distance	Driving Time	
As-the-Crow-Flies	1.00	—	—	
Driving Distance	0.95	1.00	—	
Driving Time	0.92	0.98	1.00	
Urban Counties (N=1,585)				
	As-the-Crow-Flies	Driving Distance	Driving Time	
As-the-Crow-Flies	1.00	—	—	
Driving Distance	1.00	1.00	—	
Driving Time	0.91	0.93	1.00	

Table S12. Summary Statistics of ZIP Codea Area Sizes (miles²)

All ZIP Codes						
Min	P25	Median	Mean	P75	Max	N
0.002	7.595	30.084	72.651	74.383	11260.670	32,989
100+ Low-income Immigrants						
Min	P25	Median	Mean	P75	Max	N
0.017	5.471	14.208	57.403	54.566	4011.020	9,545

218 **References**

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