Why Aren't More People Working in Low- and Moderate-Income Areas?

By Kelly D. Edmiston

Although the U.S. labor market has seen strong growth in recent years, labor market conditions have been weaker in low- and moderate-income (LMI) communities. In particular, residents in LMI communities are much less likely to work than residents in higher-income (non-LMI) communities. As of 2017, 35 percent of residents in LMI communities age 18–64 were not working compared with 24.9 percent in non-LMI communities.

In this article, I use a formal text analysis of a unique set of survey comments to examine prominent obstacles to working, and compare the prevalence of these obstacles, or "employment barriers," in LMI and non-LMI communities. I find that lower educational attainment and lack of access to transportation and childcare are among the most prominent barriers to employment, and these problems are especially prevalent in LMI communities. Although public assistance, disabilities, and chronic health conditions are considerably more prevalent in LMI communities, they are not especially prominent barriers in the text analysis.

Section I documents the difference in employment rates between LMI and non-LMI communities, showing persistent gaps that are increasing over time. Section II conducts a formal text analysis of survey comments to identify the most prominent barriers to employment. Section III compares statistics on the prevalence of these employment

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barriers and finds that barriers to work are much more prevalent in LMI communities than non-LMI communities.

I. The Employment Share of the Working-Age Population

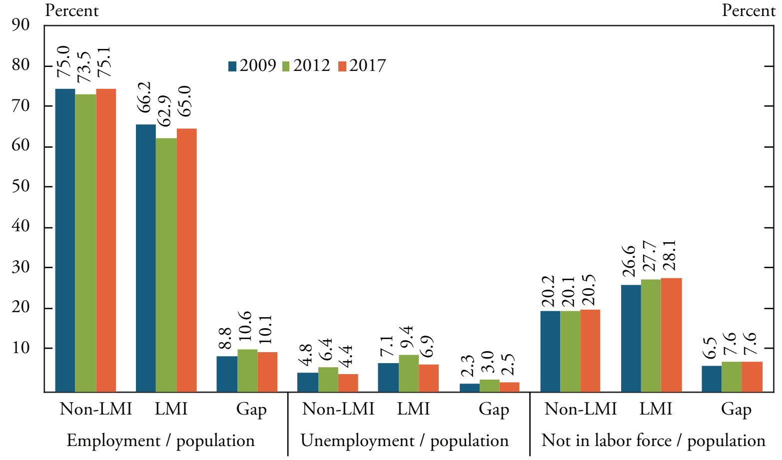
To measure differences in employment between LMI and non-LMI communities, I consider only working-age individuals (18–64) and define "communities" as census tracts.[1] Restricting my analysis to the 18–64 population excludes those who are weakly attached to the labor force, such as full-time students and retirees.[2] Defining communities as census tracts (hereafter, "tracts") allows me to use residence-based employment measures from the U.S. Census Bureau's American Community Survey, which also contains a wealth of socioeconomic data on demographics, disabilities, and work histories. LMI tracts have median incomes below 80 percent of area median income and make up roughly one-third of all tracts. Tract-level data are available only as five-year averages, the latest of which cover 2013−17 (hereafter, "the 2017 ACS").

The primary statistic of interest is the employment-to-population ratio (hereafter, "epop ratio"), which is the share of the 18−64 population that is working. In the 2017 ACS, the epop ratio was about 65 percent in LMI tracts, compared with 75.1 percent in non-LMI tracts—a gap of 10.1 percentage points.

Although the epop ratio provides a good aggregate measure of labor market differences in these communities, it does not differentiate between individuals who are not working but actively seeking work ("unemployed") and individuals who are neither working nor seeking work ("not participating in the labor force"). Quantifying the relative contributions of unemployment and labor force nonparticipation to differences in epop ratios is important because some employment barriers are more likely to affect individuals when looking for a job (such as a criminal conviction), while other barriers may prevent an individual from working altogether (such as a severe disability).[3]

Separating these contributions reveals that differences in labor force nonparticipation explain about three-quarters of the gap in epop ratios between LMI and non-LMI communities, while differences in unemployment explain only one-quarter. Chart 1 shows the epop ratios in LMI and non-LMI communities, the gap between the two, and the

Chart 1
Epop Ratios and Their Components over Time



Notes: Data are five-year averages, so the Great Recession and its anemic early recovery are largely captured in the 2012 ACS, which covers 2008–12, not the 2009 ACS, which covers 2005–09. The first ACS five-year averages were published in 2009.
Sources: U.S. Census Bureau and author's calculations.

components of the epop ratios from the 2009, 2012, and 2017 ACS. The first set of bars show the epop ratio and associated gap for each ACS period. The second set of bars show that in the 2017 ACS, 6.9 percent of the working-age population in LMI tracts was unemployed compared with 4.4 percent in non-LMI tracts.[4] Consequently, unemployment explains only 2.5 percentage points (6.9 – 4.4) of the total 10.1 percentage point gap in epop ratios between LMI and non-LMI tracts. The third set of bars in Chart 1 shows that in the 2017 ACS, 28.1 percent of the working-age population in LMI tracts did not participate in the labor market compared with 20.5 percent in non-LMI tracts. Thus, nonparticipation explains about 7.6 percentage points (28.1 – 20.5) of the total 10.1 percentage point gap.

Chart 1 also shows that the disparity in labor market outcomes between LMI tracts and non-LMI tracts is persistent. In particular, the gap in the epop ratio is sizeable in all three periods, widening slightly after the Great Recession. Although epop ratios declined for all income groups between the 2009 ACS and 2012 ACS, the decline was somewhat steeper for LMI tracts. In non-LMI tracts, the epop ratio fell by 1.5 percentage points, from 75.0 percent to 73.5 percent. In LMI tracts, the epop ratio declined by 3.3 percentage points, from 66.2 percent to 62.9

percent. As a result, the gap in the epop ratio between non-LMI tracts and LMI tracts widened from 8.8 percentage points to 10.6 percentage points (after rounding).

The epop ratio recovered for all income groups by the 2017 ACS, but the gap between non-LMI and LMI tracts remained elevated. Although the employment gap narrowed slightly between the 2012 and 2017 ACS, the gap remained 1.3 percentage points higher than in the 2009 ACS. While changes in the epop ratio may be cyclical, the gap between non-LMI and LMI tracts was substantial throughout the business cycle. Specifically, the widening gap in labor force nonparticipation accounted for about 85 percent of the total increase in the employment gap between the 2009 ACS and the 2017 ACS.

II. Identifying Prominent Barriers to Work in Low- and Moderate-Income Areas

The persistent, widening gap in employment between LMI and non-LMI tracts suggests that LMI tracts may face structural barriers to work. To identify potential barriers to work in these communities, I use a unique data set of 258 comments garnered from respondents to the Federal Reserve Bank of Kansas City's LMI Survey. The LMI Survey is distributed twice yearly to community organizations that work directly and regularly with the LMI population or in LMI communities. The survey uses community organizations as proxies for LMI individuals because surveying LMI individuals on a regular basis can be difficult (Edmiston 2018).

The LMI Survey asks respondents whether economic conditions for the LMI population—including job availability, housing availability, and access to credit—are better, worse, or about the same as the previous quarter. Each of these questions includes a comment box so that respondents can provide further details. In addition, some surveys ask special questions beyond the standard set; the January 2018 survey asked about factors that keep men and women in LMI communities from working.

I use text analysis algorithms on responses to this special survey question to identify common barriers to work. The text analysis is based on natural language processing, which allows computers to understand, interpret, and manipulate human language by applying a numeric structure to text-based data. I first identify the fundamental argument(s) in each comment and summarize them in a single text (see Appendix A for details on the process, called "latent semantic analysis").

I then develop a set of terms that match related words in the summarized text. For example, I combine any word related to children, childcare, daycare, parenting, or family responsibilities into the single term "childcare/family." Similarly, I combine words related to substance abuse and criminal history—both background issues affecting employability—into the term "crime/drugs," and combine words related to education and training into "ed/training" because of their similar objectives. Aggregating terms in this way ensures that the prominence of a barrier to work is not lost in the many word forms used to describe it.

A word cloud provides a clear way to illustrate the broad themes (terms) as well as the frequency of these themes. Figure 1 shows a word cloud created by feeding the fully prepped text—largely, a long list of terms—to an algorithm. The larger the size of the term in the word cloud, the more frequently the term appears in the text corpus.

Based on the word cloud, the most prominent themes are "jobs," "qualifications," and "ed/training." In the survey, references to "jobs" or related words usually referred to the availability of jobs, though another factor that may have influenced its top billing was the occasional use of "job" as a modifier, as in "job skills." References to "qualifications" and related words usually addressed inadequate skills for available jobs, while references to education and training usually articulated a need for more access or better quality.

The next most prominent themes, "transportation" and "childcare/family," could be considered the most direct barriers to employment—individuals cannot work at all without some way of getting to the workplace, and childcare is a necessity for working parents. "Crime/drugs" was the next most prominent theme. Both criminal convictions and substance abuse are "check-the-box" barriers, meaning that simply having a criminal record or failing a drug test often will immediately disqualify an applicant for a job.

"Pay" was the next most prominent theme, though it is difficult to discuss outside of the context of "jobs." Comments on pay were often about the general need for higher pay, but respondents also mentioned low pay as a disincentive to working. Both "public assistance" and

Figure 1
Word Cloud of Common Terms Used in LMI Survey Responses

Note: The size of the term is proportional to its frequency in the analyzed text.
Source: Author's calculations.

"housing," the next most prominent themes, commonly occur along with other barriers. For example, people with disabilities or minor children in the home are more likely to receive public assistance. Likewise, those with criminal convictions may have more difficulty getting approved for housing. Although "disability," "health," and "mental," indicating mental health, were less prominent themes in the word cloud, they are pervasive problems in LMI communities (Barr 2019; Marmot 2002).[5]

Table 1 ranks the most prominent themes drawn from the text analysis and represented in the word cloud. My analysis excludes some words in the table. I exclude "affordable," for example, because it was used exclusively as a modifier for other terms, such as "affordable childcare" or "affordable housing," and has little meaning out of context. I also exclude "motivation," which sometimes referred to individuals being motivated to work but being unsuccessful, but more commonly referred to an individual lacking the motivation to seek a job. Little can be done with this concept in terms of a quantitative analysis, as distinguishing the context in which the word was used is unfeasible and I am not able to measure motivation. Finally, I exclude "government" or similar terms that were explicitly political or that referred to funding available to the

Table 1
Major Themes from the Text Analysis and Associated Words

Rank	Term	Examples of associated words (not comprehensive)
1	Jobs	Jobs, work, employment, unemployment, layoffs, positions
2	Qualifications	Qualifications, qualify, qualified, skills, skill sets, mismatch, employable, requirements, credentials, unskilled, marketable, standards
3	Ed/training	Education, training, workforce development, mentoring, literacy, GED, educate, high school, graduate, educational, train, degree(s)
4	Transportation	Transportation, transit, car(s), proximity, close
5	Childcare/family	Childcare, daycare, children, family, families, kids, parent(s), pre-school
6	Crime/drugs	Criminal record(s), criminal history, felony, conviction(s), ex-offender, drug(s), substance, alcohol, addiction, background issues
7	Pay	Pay, paying, wage(s), salaries
8	Public assistance	Government benefits, benefits, assistance, SSI, welfare, dependence
9	Housing	Housing, homeless(ness), home
10	Mental	Mental health, mental illness, mental, mentally, low functioning
11	Motivation	Want to work, unwilling to work, initiative, willingness, work ethic
12	Government	Government, federal, state, politics, political, city, funds, resources
13	Health	Health, medical, physical illness, illness, sick, healthy
14	Disability	Disability, disabilities, disabled, impairment
15	Affordable	Affordable, afford, cost

Notes: The "motivation," "government," and "affordable" themes are not specifically analyzed in the text. Associated words are identified through lemmatization, a linguistic process that groups together the inflected forms of a word (for example, "run" and "ran") for analysis as a single item.

organizations that responded to the survey, which is outside the scope of this article.

III. Prevalence of Barriers to Work in LMI and Non-LMI Communities

To better understand the importance of the employment barriers identified in the text analysis, I compare the prevalence of these barriers in LMI tracts with their prevalence in non-LMI tracts. These comparisons require that I transform qualitative responses from the sentiment analysis into quantitative measures. Thus, for each barrier, I locate or construct a quantitative indicator, or proxy. As an example, I use the share of households in the tract without access to a vehicle as a quantitative indicator for "transportation." For robustness, I consider multiple indicators for most terms based on how well the quantitative indicator represents the qualitative sentiment and on the availability of data.

Table 2 provides statistics for the indicators used to measure each barrier. Column 1 shows the mean value of these indicators in LMI tracts, column 2 shows the mean value of these indicators in non-LMI tracts, and column 3 shows the difference in the means of the indicators between LMI and non-LMI tracts. The difference in means for every indicator is statistically significant, meaning I can conclude with meaningful certainty that the true difference in the barrier's prevalence between LMI tracts and non-LMI tracts is not zero. In the vast majority of cases, barriers are more prevalent and severe in LMI tracts. A statistically significant difference is not necessarily economically significant, however. To gauge economic significance, I also report the ratio of the difference in means to the mean in non-LMI tracts in column 4.

Although Table 2 includes multiple indicators for each barrier, I examine only a few indicators in detail in the subsequent analysis for tractability. The indicators in Table 2 that are not discussed serve as "robustness checks," providing additional support for the conclusions drawn. See Appendix B for the data sources and Appendix C for details on the construction of each indicator.

Jobs and pay

Although "jobs" was the most common barrier cited in the LMI survey, the context of job-related comments varied widely. Some comments implied plenty of jobs were available, while others implied an insufficient number of jobs were available. To draw conclusions from these conflicting assessments, I use the LMI Job Availability Index, which tracks the diffusion of survey responses to a question about the availability of jobs in LMI communities over time. Any index value above 100 (neutral) means that more survey respondents stated jobs were more available than stated jobs were less available. Chart 2 shows the index relative to the previous year (blue line) and quarter (green line) alongside expectations for the following quarter (orange line). All three indexes were above neutral in every quarter after 2012, which means the balance of survey opinion has been that jobs are plentiful in LMI-relevant sectors—or at least increasingly so.

Measuring job availability in LMI tracts relative to non-LMI tracts is challenging because residents in these tracts essentially face the same geographic labor market. Most people do not live and work in the same

Table 2
Barriers to Employment in LMI and Non-LMI Census Tracts

Variable	Mean (LMI) (1)	Mean (non-LMI) (2)	Difference in means (3)	Percent difference (4)
Jobs and pay				
Workers in tract / residents (W/P)	0.73	1.00	−0.268***	−26.7
Health workers / residents	0.13	0.16	−0.031*	−19.5
Retail workers / residents	0.09	0.12	−0.032***	−25.5
Accommodations and food service workers / residents	0.08	0.10	−0.017***	−17.7
Median earnings (age 16+)	$41,977	$58,375	−$16,398***	−28.1
Qualifications				
Percent age 25+ with less than 9th grade	8.2	3.7	4.5***	120.3
Percent age 25+ with no high school diploma	19.4	9.6	9.8***	102.2
Percent age 25+ with associate degree or some college	28.4	28.7	−0.2***	−0.8
Percent age 25+ with bachelor's degree or more	20.1	33.9	−13.9***	−40.9
Percent age 18–64 with no work in past 12 months	30.2	21.7	8.6***	39.5
Percent residents age 15–29	23.0	18.7	4.3***	23.1
Ed/training				
Miles to closest training center	6.8	7.9	−1.0***	−13.2
Density of training centers (per square mile)	0.07	0.04	0.023***	53.3
Transportation				
Percent households with no vehicle	16.5	6.6	9.9***	149.7
Percent age 18–64 self-employed	6.7	6.9	−0.1***	−1.7
Childcare/family				
Childcare facilities per square mile	1.8	1.1	0.7***	59.4
Average family size	3.3	3.1	0.2***	6.6
Percent households with children age <18	26.6	26.9	−0.3***	−1.1
Percent female-headed households with children age <18	10.0	5.0	5.0***	99.7
Percent male-headed households with children age <18	2.8	2.0	0.7***	34.3
Childcare costs (U.S. average)/earnings (percent)	24.1	16.3	7.8***	47.9
Crime/drugs				
Crime rate (annual per 10,000 people)	93.7	57.2	36.5***	63.7
Drug deaths (annual per 10,000 people)	2.38	2.33	0.05***	2.0
Alcohol deaths (annual per 10,000 people)	1.18	1.14	0.04***	3.7
Annual opioid prescription / 100 residents	61.1	60.6	0.5*	0.8
Housing				
Percent households renters	49.5	28.0	21.6***	77.2
Percent households paying >35 percent of income in rent	42.6	31.8	10.8***	34.1
Percent households in different house in same county	10.3	7.0	3.3***	46.2
Percent households with more people than rooms	4.9	2.2	2.7***	124.3

Table 2 (continued)

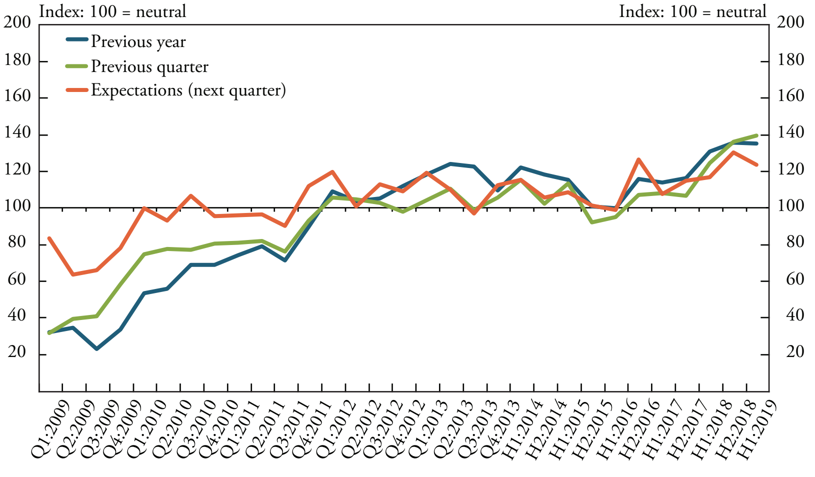
Variable	Mean (LMI) (1)	Mean (non-LMI) (2)	Difference in means (3)	Percent difference (4)
Homeless per 100 residents	0.19	0.16	0.03***	16.3
Homeless per square mile	10.54	6.52	4.02***	61.7
Chronically homeless per 100 residents	0.03	0.02	0.005***	19.7
Chronically homeless per square mile	0.9	0.7	0.2***	28.2
Disability/mental/health				
Percent age 18–64 with disability	14.6	9.9	4.7***	47.1
Percent age 18–64 with ambulatory disability	7.7	4.8	3.0***	62.1
Percent age 18–64 with cognitive disability	6.5	4.1	2.5***	47.1
Age-adjusted mortality rate (annual, per 100,000)	77.8	74.9	2.9***	3.9
Public assistance				
Percent households receiving public assistance	24.1	9.4	14.6***	155.1
Percent households receiving TANF	4.3	1.9	2.4***	125.9
Percent households receiving SNAP	23.3	8.8	14.4***	163.7
Percent households receiving SSI	8.9	4.3	4.5***	104.5

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Notes: The difference in means may not align with the reported means due to rounding. F-fold statistics reject variance equality for virtually all variables, where $F' = \max(s_{12}, s_{22}) / \min(s_{12}, s_{22})$ and s_{ij} is the row i, column j element of the covariance matrix. Therefore, t-statistics (not reported) use Satterthwaite's approximation for degrees of freedom. Statistical significance is determined using Cochran p-values.

Chart 2

LMI Job Availability Index



Note: The survey asks respondents to assess conditions relative to the same period in the previous year, conditions relative to the previous quarter, and for their expectations for the following quarter relative to the current quarter.
Source: Federal Reserve Bank of Kansas City.

tract. The average commute distances for the 69 largest U.S. metropolitan areas range from 5.0 to 12.8 miles (Kneebone and Holmes 2015). The geographic labor markets, which I define as circles with radii equal to average commuting distances, would therefore include many tracts. For example, using a representative LMI neighborhood in Kansas City, Missouri, where the average commute is 8.9 miles, I measure a labor market area consisting of 213 tracts.

An analysis of more localized labor markets may offer some insight, at least to the extent that there are benefits to having jobs nearby. To measure job opportunities in a more localized labor market, I compare the number of people who *work in a tract* with the number of people who *live in the tract*. The premise underlying this measure is that the number of workers in a tract is a reasonable (albeit imperfect) indicator of the number of jobs available in the tract. If there are more workers in the tract, I presume there are more job opportunities in the tract. Importantly, workers/residents is different from residents with jobs/residents. Most of those who *work* in a tract live in a different tract. Likewise, most of those who *live* in a tract work in a different tract. My calculation of workers/residents shows that on average, people who live in non-LMI tracts have more nearby job opportunities. Specifically, Table 2 shows that LMI tracts have 0.73 workers per resident compared with 1 worker per resident in non-LMI tracts.[6]

Much like job availability, pay is a challenging indicator to evaluate because, again, residents in LMI and non-LMI tracts face essentially the same geographic labor market. The importance of pay as a barrier to employment depends on how responsive potential workers are to different rates of pay in deciding whether to work. Research suggests, for example, that marginally higher pay has little effect on this decision; most people would need to achieve a certain pay threshold to be induced to work (McClelland and Mok 2012). However, a nontrivial share of survey comments asserted that prevailing wages are disincentives to work, suggesting their constituents would need substantially higher pay. Indeed, specific comments mentioned that for many, working does not seem worthwhile when the pay is insufficient to sustain them or their families.

If self-sufficiency is required to make work worthwhile, then pay is likely a more significant barrier to work in LMI tracts than in non-LMI tracts. However, the difference in pay results from the types of jobs that are attainable based on qualifications, rather than wage differentials between distinct labor markets faced by those in LMI and non-LMI tracts.[7]

Although the text analysis suggests that job availability and pay may be critical factors in decisions about working for the LMI population, disparities between LMI and non-LMI tracts likely arise from differences in the types of jobs for which residents qualify and the compensation those jobs offer, not geographic differentials.

Qualifications, education, and training

Education and training, along with work experience, are unquestionably advantages in the labor market. Labor market statistics clearly document returns to educational attainment in the form of lower unemployment rates and higher average earnings. However, the type of education received is also important. Hanushek and others (2016) suggest that while specific skills gained in vocational training may ease the transition to a first job, the specificity of the training may make workers less adaptable for future work compared with those with a more general education.

To help quantify the importance of education differentials as barriers to employment, I compare educational attainment among individuals age 25 and older between LMI and non-LMI tracts. Table 2 shows that 19.4 percent of individuals in LMI tracts have not earned a high school diploma or equivalent, compared with only 9.6 percent of individuals in non-LMI tracts. The rates for those with an associate degree or "some college" are similar in LMI and non-LMI tracts, potentially reflecting a greater share of LMI individuals with vocational training. However, substantially fewer individuals in LMI communities have a bachelor's degree. Specifically, 20.1 percent of individuals in LMI tracts have a bachelor's degree or higher compared with 33.9 percent in non-LMI tracts.

Skills come not only from formal education and training but also from experience. Residents in LMI tracts typically have less experience than residents in non-LMI tracts, as indicated by the percentage of the population age 15–29 (presuming young people have less job experience) and the share who have not worked at all in the preceding 12 months (presuming skill atrophy or obsolescence).

Together, these statistics suggest that lacking qualifications is a substantial impediment to work. As the second most frequently mentioned employment barrier in LMI Survey comments, a lack of qualifications appears to be a widespread problem, compounded by large gaps in education and experience between LMI and non-LMI tracts.

The need for additional education and training opportunities was unsurprisingly a common refrain in LMI Survey comments. Because the majority of tracts contain no facility, I calculate the distance to the closest facility. The average distance to workforce training is only about a mile shorter, on average, in LMI tracts (6.8 miles) than in non-LMI tracts (7.9 miles). By these measures, the proximity of training opportunities does not appear to differ substantially in LMI and non-LMI tracts.

Transportation

Most people work in a different tract than the one in which they live, and commuting distance may be a significant barrier to work for many people. The average commute range of 5.0 to 12.8 miles reported by Kneebone and Holmes (2015) suggest significant hurdles for those with few transportation options. The greatest transportation barrier is likely lack of access to a vehicle (Baum 2009; Blumberg and Pierce 2014; King, Smart, and Manville 2019). Vehicle access is also arguably the most straightforward transportation barrier to measure, as the ACS reports the share of households without a vehicle.

The difference in vehicle access between LMI tracts and non-LMI tracts is quite stark. Table 2 shows that 16.5 percent of households in LMI tracts do not have access to a vehicle. By contrast, only 6.6 percent of households in non-LMI tracts lack access to a vehicle.

Households without a vehicle may prefer to work close to home, but data suggest this option is not as viable in LMI tracts as in non-LMI tracts. As noted in the discussion of job availability, the number of workers per resident is lower in LMI tracts. In addition, self-employment rates are also lower in LMI tracts. As with qualifications, a lack of transportation is both a pervasive employment barrier—as indicated by its ranking in the text analysis—and considerably more prevalent in LMI communities than non-LMI communities.

Childcare and family issues

Childcare availability and cost are frequent concerns for working parents and for parents who would like to work. In a recent poll, 70 percent of respondents reported location to be one of the most important factors they consider when choosing a provider (Dodge-Ostendorf and others 2019). On the cost side, Powell (2002) provides causal statistical evidence that the high cost of childcare reduces the probability of working. The cost of childcare may lead a parent to reasonably question whether working is financially worthwhile.

Although there is not an ideal measure of childcare costs on a geographic basis, I measure physical access to childcare by calculating the density of childcare establishments—that is, the number of childcare facilities per square mile in a tract. Childcare facilities are generally more accessible in LMI tracts, which have 1.8 childcare facilities per square mile, than in non-LMI tracts, which have 1.1 facilities per square mile (Table 2). Thus, physical access to childcare alone does not appear to be a greater barrier in LMI areas, though the cost of nearby facilities could alter the calculus.

Even if greater competition (as measured by density) effectively reduced costs, childcare likely would still be much less affordable in LMI tracts, where income is much lower. On average, childcare costs $8,606 annually in the United States, though there is substantial geographic variation (Child Care Aware 2017). Using this national average, childcare costs are 24.1 percent of median earnings in LMI tracts, compared with 16.3 percent of median earnings in non-LMI tracts.

Furthermore, working families in LMI tracts may have a greater need for childcare. The share of households with minor children is roughly the same across tracts, but households with minor children are twice as likely to be headed by a single mother in LMI tracts and therefore lack a spousal childcare option or spousal income support for childcare (single father households also are more common in LMI tracts, but rarer in general).[8]

Crime and substance abuse

People with criminal convictions have a significant disadvantage in finding employment compared with those without criminal convictions. Pager (2003) provides causal evidence that simply having a criminal record reduces employment opportunities irrespective of potential delays in education and experience due to incarceration or personality traits that may be common among those with criminal records but separate from their criminal behavior. References to this problem were prominent in LMI Survey comments and also pervasive in focus-group discussions with non-working LMI individuals recently hosted by the Federal Reserve Banks of Chicago and Kansas City.[9] The increasing use of criminal background checks in employment pre-screening makes the problem even more formidable (Blumstein and Nakamura 2009).

There is no practical way to determine how many people in a geographic area have criminal records, making this barrier especially difficult to evaluate.[10] However, Wiles and Costello (2000) find that offenders are most likely to commit crimes near their homes, which suggests crime rates are correlated with the presence of offenders. I estimate tract-level crime rates for 2008–12 and use them as a proxy for the prevalence of individuals with criminal convictions in 2013–17.

My estimates of crime rates are dramatically higher for LMI tracts than non-LMI tracts. From 2008 to 2012, LMI tracts had 93.7 crimes per 10,000 residents, compared with 57.2 crimes per 10,000 residents in non-LMI tracts (Table 2). If Wiles and Costello (2000) are correct that criminals tend to commit their crimes close to home—and if a higher crime rate in 2008–12 is associated with a higher percentage of the population having criminal convictions in 2013–17—then criminal convictions may be more prevalent barriers to employment in LMI tracts than non-LMI tracts.

In contrast, substance abuse may not be a substantially more prevalent barrier in LMI communities. In 2017, nonintentional drug-related deaths averaged 2.4 per 10,000 residents in LMI tracts and 2.3 per 10,000 residents in non-LMI tracts. Alcohol-related deaths were only modestly different, averaging 1.2 and 1.1 deaths per 10,000 residents in LMI tracts and non-LMI tracts, respectively.

Opioid use also appears to be similar in LMI and non-LMI communities. Opioid prescriptions are known to reduce labor force participation, making them an especially useful indicator of the connection between substance abuse and employment rates (Aliprantis and others 2019; Krueger 2017). The data, which are for 2015, show very little difference between LMI tracts, where 61.1 opioid prescriptions were written annually per 100 residents, and non-LMI tracts, where 60.6 prescriptions were written annually. While substance use may be an impediment to employment, the evidence does not point to substantially higher rates of substance abuse in LMI tracts. The differences are statistically significant but negligible in economic significance.

Housing instability

A lack of secure and stable housing may be a barrier to employment for multiple reasons. Housing instability can upset social ties or prevent the formation of social ties, which provide an important source of information about job opportunities and may help workers address sudden needs for transportation or childcare (Briggs 1998; Calvo-Armengol and Jackson 2004). In addition, housing instability consumes time and focus and can induce significant stress, making it more difficult to find or retain a job (Manzo and others 2008).

I evaluate housing instability using a variety of data from the ACS and consistently find greater instability in LMI tracts than non-LMI tracts. Perhaps most tellingly, households in LMI tracts are 34 percent more likely than households in non-LMI tracts to devote over 35 percent of their gross income to rent. Allocating such a large share of income to rent increases the likelihood that a household will be unable to make rent payments (Desmond and Shollenberger 2015). In addition, households in LMI tracts are more likely to live in renter-occupied units (49.5 percent versus 28.0 percent in non-LMI tracts), live in a different house in the same county than the year before (10.3 percent versus 7.0 percent), or live in housing units with more residents than rooms (4.9 percent versus 2.2 percent).[11] By every measure, housing appears to be more unstable in LMI tracts than in non-LMI tracts.

The extreme side of housing instability is, of course, homelessness. Homelessness can present unique barriers to employment, such as shelter policies that limit the ability to work odd hours (Poremski and others 2016). However, data on homelessness are unsurprisingly difficult to obtain, given that homeless people do not have a stable physical address. I use counts from the U.S. Department of Housing and Urban Development (HUD)'s Continuum of Care (CoC) Program to estimate the number of homeless people per square mile (homeless density) and the number of homeless people per 100 residents (homeless rate).

Homeless density is 10.54 per square mile in LMI tracts and 6.52 per square mile in non-LMI tracts. The homeless rate is 0.19 per hundred residents in LMI tracts and 0.16 per hundred residents in non-LMI tracts. Thus, homelessness appears to be moderately more prevalent in LMI tracts.

Disabilities and mental and physical health

Disabilities and poor health—both physical and mental—are direct barriers to work in that they put limits on what a worker is effectively able to accomplish. Some disabilities or illnesses may prevent workers from doing certain jobs at all.

Data from the ACS show that people in LMI tracts are much more likely to have disabilities than people in non-LMI tracts. The ACS measures the presence of any disability as a "yes" response to at least one of its six disability questions. In LMI tracts, 14.6 percent of the working-age population report having some disability, compared with 9.9 percent of the working-age population in non-LMI tracts.

The ACS also differentiates between cognitive and ambulatory disabilities, which helps capture the distinction made in LMI Survey comments between mental and physical health. Cognitive disabilities are more common among residents in LMI tracts (6.5 percent) than non-LMI tracts (4.1 percent). These disabilities may make finding and retaining a job more difficult. Among the most frequent work problems for those with cognitive disabilities are lack of motivation, side effects from medication, substance abuse, low self-confidence, stigma, treatment issues, and difficulties in identifying and achieving goals (Secker and others 2001; Bassett, Lloyd, and Bassett 2001). Ambulatory disabilities are also much more common among residents in LMI tracts (7.7 percent) than non-LMI tracts (4.8 percent). One frequent work-related problem for those with ambulatory or other physical disabilities is a limitation on the tasks they are physically able to complete. In addition, a lack of social acceptance by coworkers can keep employees with disabilities from staying in jobs, making their employment less stable (Shier, Graham, and Jones 2009).

Health issues can also lead to less stable employment, and research documents a causal effect of health on employment rates. Wilson (2001) estimates that chronic adult-onset disease explains 10 percent of nonemployment among those age 35–74 in New Jersey. Zhang and others (2009) find significant causal effects of several chronic diseases on employment. For example, diabetes lowers the probability of employment by about 4 percentage points for men age 18–49 and by 11.5 percentage points for older men.

One general measure of health available for a large number of tracts is the age-adjusted mortality rate, which in 2017 was moderately higher in LMI tracts (77.8) than in non-LMI tracts (74.9).[12] Although data on specific health conditions are also available for multiple years, they are only available for tracts in the nation's 500 largest cities, which account for about one-third of the U.S. population. Table 3 shows that most specific health conditions are considerably more prevalent in LMI tracts than non-LMI tracts, the exception being cancer. Rates of self-reported physical and mental health are 51 percent and 41 percent higher in LMI tracts. Many unhealthy behaviors correlated with chronic illness are also much more common in LMI tracts. Obesity and smoking are 36 percent and 49 percent more prevalent in LMI tracts than in non-LMI tracts, respectively. An exception is binge-drinking, which is more common in non-LMI tracts.

Although disabilities and poor health were not among the most commonly cited barriers to employment in the LMI Survey, their greater prevalence in LMI communities, along with research showing significantly lower employment among the disabled and chronically ill, suggests they may be important nonetheless.

Public assistance

People who do not work—particularly those with disabilities, health problems, and minor children in the home—often receive public assistance, which may discourage working in the future. For example, Maestas, Mullen, and Strand (2013) find that the employment rate of beneficiaries on the margin of entry into the Social Security Disability Insurance (SSDI) program in 2005−06 would have been 28 percentage points higher two years later if they had never received SSDI benefits. But perhaps more importantly, most public assistance programs are structured in a way that discourages recipients from working even in the absence of any income effects.

Table 3
Prevalence of Health Problems in LMI and Non-LMI Census Tracts

Health indicator	Mean (LMI) (percent) (1)	Mean (non-LMI) (percent) (2)	Difference in means (3)	Percent difference (4)
Prevalence coronary heart disease	6.7	5.2	1.5	29.0
Prevalence poor mental health	15.4	10.9	4.5	41.4
Prevalence poor physical health	15.5	10.3	5.2	50.6
Prevalence arthritis	24.3	21.4	2.9	13.5
Prevalence asthma	10.9	9.0	1.9	21.7
Prevalence binge drinking	16.1	19.7	−3.6	−18.3
Prevalence cancer	5.1	6.0	−0.9	−15.7
Prevalence diabetes	13.3	8.7	4.7	53.9
Prevalence obesity	35.0	25.8	9.3	36.0
Prevalence smoking	22.1	14.8	7.2	48.6

Notes: The difference in means is significant at the 1 percent level and may not align with the reported means due to rounding. F-fold statistics reject variance equality for virtually all variables, where $F' = \max(s_{12}, s_{22}) / \min(s_{12}, s_{22})$ and s_{ij} is the row i, column j element of the covariance matrix. Therefore, t-statistics (not reported) use Satterthwaite's approximation for degrees of freedom. Statistical significance is determined using Cochran p-values.
Sources: Centers for Disease Control and Prevention and author's calculations.

A highly significant work disincentive built into public assistance programs is the benefit reduction scheme associated with earned income. Benefit reductions are similar to a tax on earned income. For example, at certain levels of income, Supplemental Nutrition Assistance Program (SNAP) benefits are reduced by 30 cents per dollar earned. Housing, childcare, or cash assistance through Temporary Assistance for Needy Families (TANF) also are reduced at some level of earned income. Benefit reduction rates vary widely by state. Some states have exemptions, usually time-limited and capped, but eventually benefit reductions come into play. The Earned Income Tax Credit is a substantial offset to these benefit reductions. Still, Maag and others (2012) document cases of marginal effective tax rates (tax rate on the next dollar inclusive of benefit reduction rates) greater than 100 percent. With such high marginal effective tax rates, beneficiaries may reasonably decide that work or additional work is not worthwhile, especially when they consider costs for childcare and transportation.

A considerably larger share of residents in LMI tracts receive public assistance than in non-LMI tracts. Overall, households in LMI tracts receive public assistance at 2.5 times the rate of households in non-LMI tracts. Differences in the rates at which households receive public assistance are similar across programs. The higher rate of Supplemental Security Income (SSI) receipt in LMI tracts results largely from a greater share of residents in LMI tracts providing care for disabled children.

Summary and Conclusions

Working-age residents in LMI tracts are less likely to work than working-age residents in non-LMI tracts. The gap in epop rates is quite large—10.1 percentage points in the latest available data—but also persistent. Moreover, in recent years, the gap has been growing, due mostly to differences in the share of the working-age population neither working nor looking for work.

Based on a text analysis of a unique set of survey responses to a question on relatively low employment rates in LMI communities, I identify several potential employment barriers, rank their prominence in the survey comments, and then compare their prevalence in LMI and non-LMI tracts. The analysis suggests that barriers are more prevalent in LMI tracts across the board, though educational attainment, transportation, and childcare are especially prominent and prevalent in LMI tracts. Although barriers such as mental and physical disabilities and poor health did not rank especially high in the survey comments, they are considerably more prevalent in LMI communities, suggesting they may nevertheless warrant close attention.

These results may be useful to agents in the social services sector seeking to allocate resources toward improving LMI employment outcomes. In particular, my analysis suggests that overcoming barriers to education and training, transportation, and childcare may help improve employment in LMI tracts. Restructuring public assistance programs to reduce disincentives for work and improving public health efforts in LMI communities may also help more individuals in LMI tracts enter the workforce.

Appendix A
Latent Semantic Analysis (LSA)

The first step in LSA is to "tokenize" the comments by chopping comments into pieces (often individual words) called tokens. Punctuation is removed, as are "stop words"—extremely common words such as "the" and "a" that would be of little value in understanding the text.

A process called "lemmatization" reduces inflectional forms and derivationally related forms of a word by grouping tokens to a common base word. For example, lemmatization would reduce "run," "running," and "ran" to the word "run," and "am," "are," and "is" to the word "be." The resulting tokens are then encoded as numbers but maintain their association with the sentence or passage from which they originated in the form of a numeric matrix. The matrix is manipulated for use in LSA. Specifically, a term-weighted matrix is created based on the frequencies of words co-occurring, and a singular value decomposition is performed on the resulting matrix. A topic is identified purely on the likelihood of words co-occurring and has no basis in connotation.

Appendix B

Table B-1
Data Sources

Variable	Source
Employment rate (by residence)	2017 ACS 5-Year Estimates, Table 2301
Unemployment rate (by residence)	2017 ACS 5-Year Estimates, Table 2301
Labor force participation rate (by residence)	2017 ACS 5-Year Estimates, Table 2301
Population 18–64	2017 ACS 5-Year Estimates, Table DP02
Workers in tract	U.S. Census Bureau, County Business Patterns (Complete ZIP Code Industry Detail File)
Median earnings (16+)	2017 ACS 5-Year Estimates, Table S2001
Educational attainment	2017 ACS 5-Year Estimates, Table DP02
Worked in past 12 months	2017 ACS 5-Year Estimates, Table S2303
Location of training centers	National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS)
Household with no vehicle	2017 ACS 5-Year Estimates, Table DP04
Self-employment	U.S. Census Bureau, Survey of Business Owners and Self-Employed Persons
Location of childcare facilities	U.S. Census Bureau, County Business Patterns (Complete ZIP Code Industry Detail File)
Land area	ESRI
Average family size	2017 ACS 5-Year Estimates, Table DP02
Percent household children <18	2017 ACS 5-Year Estimates, Table DP02
Percent household female, with children <18	2017 ACS 5-Year Estimates, Table DP02
Percent household male, with children <18	2017 ACS 5-Year Estimates, Table DP02
Childcare costs (U.S. average)	Child Care Aware of America (2017)
Crime rates (2000)	National Neighborhood Crime Study (NNCS), 2000, Inter-university Consortium for Political and Social Research [distributor], 2010-05-05
Drug death rate	Centers for Disease Control and Prevention, National Center for Health Statistics, 2018. Compressed Mortality File, 1999-2017 (data file and documentation). Extracted from CDC WONDER Online Database
Alcohol death rate	Centers for Disease Control and Prevention, National Center for Health Statistics, 2018. Compressed Mortality File, 1999–2017 (data file and documentation). Extracted from CDC WONDER Online Database
Opioid prescription rate	Federal Reserve Bank of Cleveland (acquired from Centers for Disease Control and Prevention; original source: IQVIA Xponent 2006–2017)
Renter household	2017 ACS 5-Year Estimates, Table DP04
Household rent >35 percent of income	2017 ACS 5-Year Estimates, Table DP04
Household different house same county	2017 ACS 5-Year Estimates, Table DP02
Household with people > rooms	Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program. Social Vulnerability Index

Table B1 (continued)

Variable	Source
Homeless counts	U.S. Department of Housing and Urban Development, Office of Policy Development and Research, Enterprise Geospatial Information System, Continuum of Care (CoC) Grantee Areas
Percent 18–64 with disability	2017 ACS 5-Year Estimates, Table DP02
Percent 18–64 with ambulatory disability	2017 ACS 5-Year Estimates, Table S1810
Percent 18–64 with cognitive disability	2017 ACS 5-Year Estimates, Table S1810
Age-adjusted mortality rate	Centers for Disease Control and Prevention, National Center for Health Statistics, 2018. Compressed Mortality File, 1999-2017 (data file and documentation). Extracted from CDC WONDER Online Database
Disease prevalence (Table 3)	CDC, 500 Cities Initiative
Percent household public assistance	2017 ACS 5-Year Estimates, Table B19058
Percent household TANF	2017 ACS 5-Year Estimates, Table DP03
Percent household SNAP	2017 ACS 5-Year Estimates, Table DP03
Percent household SSDI	2017 ACS 5-Year Estimates, Table DP03

Appendix C
Variable Construction

The survey comments and analyzed text associated with those comments are qualitative data. However, a meaningful analysis of differences between LMI and non-LMI tracts requires a quantitative comparison. Therefore, I identify quantitative data that reflect the sentiments expressed in the qualitative comments. In some cases, these quantitative measures are easy to identify and use. For example, the census asks directly about the presence of a disability and whether or not households have access to a vehicle. In other cases, quantitative proxies for the qualitative data are not readily available and must be constructed. I construct several of the proxies used in the text by constructing new data from existing data. This appendix provides details about the construction of the quantitative proxies for qualitative responses in these cases.

Workers per resident in a tract

I construct the number of workers per resident in a tract from Zip-code-level data in the U.S. Census Bureau's County Business Patterns (CBP) and the ACS. I determine the number of people who work in a Zip code from CBP and divide that number by the resident population in the Zip code from the ACS. The result is the number of people who work in the tract per person living in the tract. I then overlay a census tract layer on a Zip code layer in geographic information systems (GIS) software and assign to the tract the average value of workers per resident for the Zip codes in which it intersects.

Minimum distance to training facility

Information about education and training facilities is extracted from the Integrated Postsecondary Education Data System (IPEDS). IPEDS includes several tables of institutional characteristics. Among these are the programs offered and the geographic coordinates of each education and training institution in the United States. Using the geographic coordinates, I create a GIS layer with the physical location of the institutions meeting my criteria—specifically, institutions that offer no degree higher than an associate's degree and that offer occupational and basic adult education. To compute the density, I count the number of facilities in each tract and divide that number by the land area of the tract in square miles.

For proximity, I identify the distance between each tract and the closest institution to that tract. The relevant distance is determined by the minimum perpendicular distance from points representing institutions to any boundary line of the tract. The distance is calculated relative to the boundary of the tract, not the centroid of the tract. This distinction is of little consequence in urban areas where census tracts are quite small in land area, but could be meaningful in rural areas with especially large census tracts. If an institution is within the boundaries of the tract, the tract is assigned a distance of zero.

Self-employment rates

Data useful for calculating self-employment rates are available at the county level from the U.S. Census Bureau's Survey of Business Owners and Self-Employed Persons. Data are derived from a survey of a random sample of businesses selected from a list of all firms operating during the year with receipts of $1,000 or more, except those classified in a small set of North American Industry Classification System (NAICS) industries. The firms list is compiled largely from IRS data, such as Schedule C filings. I calculate the number of business establishments with no payroll in each county and divide by the working-age population in the county. The resulting self-employment rates are assigned as the self-employment rate for all census tracts in the county.

Density of childcare establishments

The density of childcare facilities is the number of childcare facilities per square mile. These establishments primarily engage in providing daycare of infants or children and are listed under NAICS code 624410. To construct this measure, I collect data on the number of childcare establishments in each Zip code from CBP. I then divide by the land area of the Zip code (in square miles) to get a density. Data on childcare establishments are not available in some Zip codes. In these cases, I compute the density of childcare establishments at the county level and assign that value to Zip codes where Zip-code-level data are not available. Finally, using GIS, I overlay a census tract layer and assign to each tract the average density of the Zip codes in which it intersected.

Childcare costs

The national average reported in the text is "an average of averages"—that is, the average of the average cost of childcare for infants, toddlers, and four-year-olds in center-based and family child care homes. The data come from surveys of state Child Care Resource and Referral agencies reported in Child Care Aware of America (2017). States were asked to provide 2015 cost data for infants, toddlers, four-year-old children, and school-age children for licensed programs or child care programs that are legally exempt from licensing. I use the 2015 average for consistency with the 2017 ACS data, which cover 2013–2017.

Tract crime rates

Crime statistics are not routinely collected at the tract level. I build a predictive model using tract-level crime rates from the 2000 National Neighborhood Crime Study (NNCS) conducted by Peterson and Krivo (2000). I estimate the model using year 2000 data. I then estimate tract crime rates for 2008–12 by employing data from that period in the estimated model. I use 2008–12 data (commensurate with the 2012 ACS) because the goal is to proxy for people with criminal convictions who are free to seek work. These individuals presumably would have already endured the consequences of their crimes, meaning the crime would have been committed well in the past.

The model I construct follows the general logic in the NNCS study. The variables used to predict crime rates are represented by Z. The model for estimating year 2000 crime rates is:

$$\mathrm{CR}_{2000,i} = \mathbf{\Phi}'\mathbf{Z}_{2000,i} + u_i\,, \tag{C-1}$$

where $CR_{2000,i}$ is the crime rate in tract i in 2000, which comes directly from the NNCS data set, Z_{2000} represents the factors expected to be predictive of the crime rates in 2000, and Φ is the set of coefficients for the factors in Z_{2000} that I estimate. Because the purpose of the analysis is to obtain crime rate estimates, not to uncover the determinants of crime rates, I do not discuss the results in this appendix. However, the variable list, sample statistics, and model estimates are available from the author upon request. Estimated crime rates for 2008–12 are calculated using the estimates from equation (C-1):

$$\widetilde{\mathrm{CR}}_{2008-12,i} = \tilde{\mathbf{\Phi}}'\mathbf{Z}_{2008-12,i} \tag{C-2}$$

where the tilde represents a bootstrap estimate.

Rates and densities of homelessness

The only available, consistent source of data on homelessness are counts of people experiencing homelessness that occur as part of the HUD's CoC Program. Using GIS and CoC region boundary files that include point-in-time homeless counts, I calculate the density of homeless people per square mile (homeless density) and the number of homeless people per 100 residents (homeless rate) for each CoC region, which can be quite small in some cities but quite large in many outlying areas. The counts include both sheltered and unsheltered homeless. I then overlay census tract boundary files and assign the homeless density and homeless rate in the CoC region in which the census tract is located to that tract. Similar values are calculated for the chronically homeless. A "chronically homeless" person has a disability and has lived in a "shelter, safe haven, or place not meant for human habitation" for 12 continuous months or on four separate occasions in the previous three years that total at least 12 months ("Continuum of Care," 24 CFR 578 Revised July 31 2012).

Endnotes

[1]Census tracts are similar to communities in that they were designed to be as homogeneous as possible in their sociodemographic characteristics.

[2]The working-age population in most official U.S. labor market statistics is the civilian population age 16 and older. Most people age 16–17 are full-time students, while most people 65 and older are retired. In early 2019, only 22.5 percent of people age 16–17 and only 20 percent of people 65 and older were either working or looking for work.

[3]Dynamically, unemployment and labor force nonparticipation are not entirely separable. Individuals with criminal convictions may become so discouraged by their inability to find a job that they quit looking altogether. In that case, they are "discouraged workers" who would be considered "marginally attached" to the labor force but classified for statistical purposes as "not in the labor force." To be officially classified as unemployed, individuals must have looked for work—specifically, they must have filed a job application—in the past four weeks.

[4]This statistic should not be confused with the unemployment *rate*, which is the share of those in the labor force (employed or officially unemployed) who are officially unemployed. In November 2019, the U.S. unemployment rate was 3.5 percent.

[5]I use "mental" as a single term in the text analysis to better distinguish between mental health and physical health concerns.

[6]Certain types of industries are more likely to offer lower-skill jobs that LMI workers, who generally have lower job qualifications, can attain. As used here, a "low-skill" job is one that does not require a formal credential or specific experience. These jobs are relatively more common in the health-care, retail, and accommodations and food services industries. Even within industries more likely to hire LMI workers, jobs seem to be more widely available in non-LMI tracts.

[7]As a rough estimate of the variation in wages for jobs in LMI tracts compared with jobs in non-LMI tracts, I divide the total payroll of business establishments in each county by the number of establishments with paid employees in the county. Employer-based wage data are available only at the county level, and for this exercise I consider the labor market to be the county in which a tract is located. Under this accounting, the average wage is $41.43 in LMI tracts and $42.10 in non-LMI tracts. My interpretation is that LMI tracts are only modestly more likely to be in low-wage counties than are non-LMI tracts. The data for this calculation are from the Survey of Business Owners and Self-Employed Persons (U.S. Census Bureau).

[8]The latest available data (2015) indicate that 50.2 percent of custodial parents (the parent living in the household) have either legal or informal child support agreements with the noncustodial parent (Grall 2018). Just over 80 percent of custodial parents are mothers, 52.7 percent of whom have child support agreements. Among custodial parents with child support agreements, 69.3 percent

receive some payments for child support, but only 43.5 percent receive full child support payments.

[9]The focus groups were held in March and April 2019 in Chicago, Denver, Detroit, and Kansas City. Transcripts are currently being analyzed; we are not yet able to draw conclusions from the data.

[10]Due to registries, an exception is sex offenders, but the registries are maintained by individual counties and collecting this data would be intractable. Moreover, most crimes are not sex crimes, and little direct evidence suggests a correlation between the location of sex offenders and non-sexually motivated crimes.

[11]Renter-occupants are more mobile than owner-occupants. Moving to a different house in the same county proxies for reluctant moves. Desmond and Gershenson (2016) find the likelihood of workers who experienced a forced move losing their jobs to be between 11 and 22 percentage points higher than for comparable workers who did not.

[12]Age adjustment eliminates the effects of age from crude mortality rates to allow for meaningful comparisons across populations with different underlying age structures. For example, comparing the crude rate of heart disease in Florida to that of most other states would be misleading because of the relatively older population in Florida.

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