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Prospects for Poor Neighborhoods in the Broadband Era: Neighborhood-Level Influences on Technology Use at Work

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Abstract

This research explores the role of place in Internet use at work, investigating the role that neighborhood context may play in opportunities to gain technology skills and access to relatively better paying jobs. Examining both individual and neighborhood attributes, the authors carry out a comprehensive survey of individuals within three distinct cities in Northeast Ohio combined with a methodology that allows generation of location-specific contextual information. Together, these data are modeled in a series of logistic regressions that compare the importance of both individual and contextual attributes. The findings demonstrate that individual characteristics, especially job type, education, and income, are strongly related to workplace Internet use and that neighborhood unemployment is associated with lower probabilities of technology use at work.

Keywords

community development, labor force issues, technology policy

What are the prospects for residents of poor urban neighborhoods in the increasingly digital economy? Recent public investments in broadband aim to spur economic development and to benefit workers affected most by the recession. The American Recovery and Reinvestment Act provides $7.2 billion for broadband infrastructure and technology inclusion initiatives. In March 2010, a National Broadband Plan was announced to guide long-term promotion of broadband development and more widespread adoption among individuals as well as businesses and community institutions. The plan includes an array of national purposes for broadband use, among them the expansion of economic opportunities for small business entrepreneurship, worker training, and local and regional economic development (Federal Communications Commission, 2010). These broadband investments follow decades of technological change in the workforce and have the potential to affect regional economic development (Gillett, Lehr, Osorio, & Sirbu, 2006). For individual workers, the use of information technology has become a key aspect of human capital.

What sort of influences, both individual and contextual, are associated with Internet use at work? How are poor neighborhoods positioned to participate in the information economy? Theory and research on neighborhood effects identify a geographic dimension to exclusion from better jobs, and this study seeks to update this literature to better understand how this relates to participation in the information economy. Internet use is conditioned somewhat by location (Fong & Cao, 2008; Mossberger, Kaplan, & Gilbert, 2008; Mossberger, Tolbert, & Gilbert, 2006), and we seek to discover whether place plays a role in Internet use at work beyond individual-level factors and whether residents of high-poverty neighborhoods are particularly disadvantaged in opportunities to use information technology on the job.

To explore these questions, we rely on a unique survey of individuals in three Northeast Ohio communities: Youngstown, Shaker Heights, and East Cleveland. In addition to the survey responses, we also are able to model location-specific information for each individual that allows us to separate out the contextual factors. We construct half-kilometer geographic buffers using census data to create these individuals contexts. Neighborhood-level data are often unavailable to test contextual effects (Ihlanfeldt & Sjoquist, 1998), and this study presents an opportunity to update existing theories of concentrated poverty.

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Technology Use and Economic Opportunity

The ability to use information technology on the job is increasingly important in the workforce, as technology applications grow throughout the economy, including in "old economy" sectors (Litan & Rivlin, 2002). Productivity growth since the 1990s has been linked to information technology use (Stiroh, 2004), and some economists argue that it will be the source of innovation and productivity growth in industries throughout the economy in the coming decades (Byrnjolfsson & Saunders, 2010).

What does this mean for less educated workers, with a high school diploma or less? Information technology can displace less skilled workers if it substitutes for their labor (Autor, Levy, & Murnane, 2003), and the literature on inequality and skill-based change in the labor market emphasizes the increasing returns to education accompanying technological change (Acemoglu, 2002; Autor, Katz, & Krueger, 1998). Yet there is evidence that technology skills are needed in many jobs requiring only a high school degree or less. The 2003 Current Population Survey (CPS), which was the last to measure Internet usage at work, indicated that 35% of the employed with a high school education or less used computers at the workplace, and 21% of these less skilled workers used the Internet for their jobs. This is much lower than for workers with more than a high school diploma, as 72% of these more educated workers use computers at work and 58% use the Internet on the job. A much more recent survey, from 2009 (U.S. Department of Commerce, 2010), does not explicitly address workplace usage but shows a sizeable gap between different educational levels. Just slightly more than half of those with a high school education or less reported Internet use anywhere. This contrasted with more than 85% of respondents who reported at least some college. This discrepancy in Internet use echoes the earlier findings from 2003.

Technology skills may allow less educated workers to have a greater choice of jobs, including those with higher wages or better benefits. A four-city study of employers indicated that information technology skills were required among less educated workers (Holzer, 1996; Moss & Tilly, 2001) and that computer use on the job was one of a number of statistically significant predictors of higher wages, along with soft skills (Holzer, 1996). According to an analysis of the 2003 CPS, computer and Internet use at work are related to higher wages for less educated workers as well as for all workers. The returns for Internet use averaged $118 per week for all workers and $111 per week for less educated workers, controlling for other factors. The premium for technology use at work boosted the earnings of less educated African American and Latino workers more than similarly situated Whites, because it represented a higher percentage of the wages for these lower earning groups (Mossberger, Tolbert, & McNeal, 2008).[1] Other studies indicate that the benefits for technology use are less evident for noncollege workers. Firm-level panel data in Canada showed no significant effect for less educated workers, but the analysis was restricted to wage growth over a 2-year period for workers who remained with the same employer (Zhogi & Pabilonia, 2006). Technology use on the job may be only one of the workforce skills necessary to compete economically, but its role is bound to increase over time even for less skilled positions.

In the broadband economy, Internet use represents a potentially marketable skill, with the expansion of e-commerce, the use of e-mail and social networks for communication, and the possibility of researching almost any issue online. In addition to technical skills, Internet use requires some basic educational competencies for online information literacy—the ability to search for, evaluate, and apply information (Mossberger, Tolbert, & Stansbury, 2003; Van Dijk, 2005; Warschauer, 2003). It is also a more demanding measure of technology use on the job, especially in lower skilled occupations (Goss & Phillips, 2002). Jobs that involve Internet use generally require more technology skill than the use of scanners in retail or other minimally skilled tasks that may be counted as computer use. As technology use becomes more prevalent in the workforce, residents of poor neighborhoods may experience further exclusion from opportunities even within entry-level jobs. Some research on technology disparities indicates that neighborhood effects are significant for Internet use and home Internet access, controlling for individual-level variables (Fong & Cao, 2008; Mossberger et al., 2006; Mossberger, Kaplan, et al., 2008). Does place of residence influence opportunities to secure jobs that include technology skills and higher wages? To understand the potential intersection between technology skills, place, and employment, we turn to the literature on neighborhood effects.

Neighborhood Effects and Technology Use

Theories of concentrated poverty (Jargowsky, 1997; Wilson, 1987) suggest that neighborhood-level factors may present additional constraints on access to jobs using technology, beyond individual-level characteristics such as education, age, occupation, race, or ethnicity. The double burden of being poor and living in a poor neighborhood (Federal Reserve & Brookings Institution, 2008) includes greater exposure to crime and drug abuse, poor quality schools and high dropout rates, a higher incidence of mental and physical health problems, inflated prices for goods and services, a lack of local job opportunities and commerce, and social isolation (Federal Reserve & Brookings Institution, 2008; Jargowsky, 1997; Massey & Denton, 1993; Orfield & Lee, 2005; Wilson, 1987). Research has found evidence of neighborhood influences on employment (Bayer, Ross, & Topa, 2008; Case & Katz, 1991; Elliott, 1999, 2000; Greene, Tigges, & Brown, 1995; Tigges, Brown, & Greene, 1998; Topa, 2001). Place effects on employment disparities in poor neighborhoods may involve the information available within social networks, unequal educational opportunities, or employer attitudes. We briefly review this literature, elaborating more specifically on possible linkages to jobs involving technology use.

Much of the theory and research in both sociology and economics regarding neighborhood effects on employment refers to the social networks within high-poverty neighborhoods and the job information flowing through those networks. In a recent review, Ioannides and Topa (2009) conclude that "a consensus estimate, coming from studies that span the past three decades and use a variety of data sources from both the U.S. and from other countries, is that half of all jobs are typically found through informal contacts" (p. 14). These networks tend to be localized. In one study of labor market referrals, neighborhood networks for job information were confined to the immediate block (Lee & Campbell, 1999), whereas other studies have found frequent interactions within a one-mile radius or less (Guest & Lee, 1983; Wellman, 1996). Neighborhoods are therefore an important source of job network participants.

In poor communities, these networks are lacking the contacts and information that could lead to better paying jobs, and these may include positions that use technology. Widespread unemployment in some neighborhoods may limit resources for employment referrals, and unemployment has become geographically concentrated since 1980, despite falling levels of unemployment overall (Wheeler, 2007). Social isolation of poor communities may also have an impact. Granovetter's (1973) argument about the strength of weak ties indicates that job seekers with broader networks have better access to information for securing employment. More recent studies find that residents of public housing and high-poverty neighborhoods tend to rely on strong ties for their job search (Elliott, 1999; Kleit, 2001) and so have more limited job information. But, there has also been evidence from the Moving to Opportunity experiment that simply relocating to less impoverished areas may not improve the prospects of jobseekers, because those who move do not automatically develop new networks for job information and may have educational and other barriers to employment as well (Kling, Liebman, & Katz, 2007; Ludwig et al., 2008; Turney, Clampet-Lundquist, Edin, Kling, & Duncan, 2006).

Unequal educational opportunities in poor communities may constrain the skills needed for technology jobs. Dependence on local funding introduces place-based disparities in education, which are aggravated by higher needs for remedial education and other services in poor neighborhoods (Bahl, 1994; Bahl, Martinez-Vazquez, & Sjoquist, 1992; Orfield & Lee, 2005). The federal E-rate program subsidizes Internet service for low-income schools, although challenges remain for providing and maintaining hardware and software and for integrating technology into the curriculum for students who lack Internet connections at home. More fundamentally, levels of student achievement in basic skills such as reading comprehension affect the development of Internet literacy and technical skills (Warschauer, 2003), and this may have longer-term effects on adults who attended schools in high-poverty neighborhoods in the past. Holloway and Mulherin (2004) find long-term disadvantages in the labor market for individuals who lived in high-poverty neighborhoods during adolescence. Although there are multiple possible causes for these long-term effects, the quality of education is one potential explanation.

Finally, employers may assume that residents of poor neighborhoods do not have the skills needed for technology jobs, whether or not, in fact, this is the case. Those who list addresses in highly distressed (and usually segregated) neighborhoods may experience a territorial stigma (Bauder, 2002; Holzer, 1996; Kirschenman & Neckerman, 1991; Wacquant, 1993), diminishing the likelihood of employment in higher skilled jobs.

The survey data we present do not allow us to distinguish the mechanisms that may be operating as neighborhood-level constraints in the case of technology use at work. We can, however, examine patterns across individual-level and contextual factors that may open the door for future research.

Three Communities and Survey Data

Examining three communities in Northeast Ohio, we explore relationships between neighborhood residence and information technology use at work. Computer and Internet use are now increasingly common in many occupations and industries, and some evidence suggests that technology use on the job is related to higher wages, even for less-educated workers. To the extent that entry-level jobs using technology are less accessible for residents in high-poverty neighborhoods, this may compound other disadvantages faced by these workers in the labor market.

We selected three distinct cities to represent a range of socioeconomic and racial characteristics. East Cleveland is an inner-ring suburb of Cleveland but is one of the poorest municipalities in the state, with many neighborhoods of extreme poverty. It also has a majority African American population. Educational attainment in East Cleveland is low, with only 9% college graduates. By contrast, Shaker Heights is one of the wealthiest suburbs of Cleveland. The poverty rate for Shaker Heights is 7%, and median household income is $64,000—much greater than in the other two cities. Almost two thirds of Shaker Heights residents have a college degree. Shaker Heights is racially mixed, with one third of the population being African American. Youngstown is larger than the other two cities. It is racially diverse as well and stands between East Cleveland and Shaker Heights socioeconomically. There is concentrated poverty in areas throughout the city but more variation in neighborhood poverty rates in Youngstown compared with East Cleveland. Youngstown is only slightly better off than East Cleveland in terms of

Table 1. Selected Characteristics of Study Cities, U.S. Census 2000

City	% Poverty	% Black	% High school graduate	% College graduate	Median household income ($)
East Cleveland	32	93	69	9	20,542
Youngstown	25	44	73	10	24,201
Shaker Heights	7	34	95	62	63,983

Table 2. Use of the Internet at Work and Demographic Factors (Among Respondents Reporting a Job)

	Race		Education		Income	
	% African American	% Non–African American	% No college diploma	% College diploma	% Earning $18,000 or less	% Earning more than $18,000
East Cleveland	17.1	40.0	13.8	48.1	2.6	27.7
Shaker Heights	43.3	57.7	26.4	61.5	16.7	54.7
Youngstown	27.3	26.6	21.1	40.4	14.7	31.2

Note. n = 531, employed respondents only.

educational attainment. Table 1 compares the cities on key demographic factors.

To gauge the extent of Internet and computer usage, we surveyed 962 people divided between the three communities. The survey used in our analysis, the 2005 Internet Usage Poll, was conducted for the researchers by the Center for Policy Studies, a division of the Institute for Health and Social Policy at the University of Akron. Households in Youngstown, East Cleveland, and Shaker Heights comprised the sampling frame. The samples for the research were generated by a nationally known supplier—Survey Sampling, Inc., of Fairfield, Connecticut. Using a random digit dialing protocol, the initial sampling procedures generated a representative sample of each of the areas to be sampled. In addition, further sample screening for disconnects was conducted to provide more accurate and efficient samples. Included in this sample were both listed and unlisted household telephone numbers. Each household was given an introduction explaining the purpose of the survey. The respondent from each household was chosen at random, ensuring a representative sample of the population. The survey instrument was tested prior to the interviewing phase. The interviewing process took nearly 2 months, beginning June 15, 2005, and ending August 12, 2005. The cooperation rate for the survey was 28%, which approximates typical response rates for national telephone surveys.[2]

Respondents' characteristics were similar to that of each city's overall population. The proportion of African Americans in the survey for each of the three cities is within 7 percentage points of the proportion of African Americans in the general population. Likewise, educational attainment, gender, and age are closely matched between survey sample and city population.[3] Although the sample corresponds to the census characteristics of these three cities, it is much more African American and poorer than the national population. The cities in this study represented two somewhat contrasting poor cities and an economically affluent but racially diverse city used for comparison.

Descriptive Data on Technology Use at Work

Fewer residents are employed at all in poorer communities, and of those who are employed, many fewer workers have Internet access on the job. The survey included a question, "Where have you accessed the Internet in the last month?" with various potential responses, including work. If we compare the populations of the three cities, only 11% of East Cleveland residents and 15% of Youngstown residents use the Internet at work, in comparison with 39% of generally more affluent Shaker Heights residents. If we select only those respondents who are engaged in full-time or part-time work, 20% of East Cleveland workers, 26% of Youngstown workers, and 52% of Shaker Heights workers report using the Internet at their place of employment. The Shaker Heights data are comparable with the national average of 58% for Internet use at work in the 2003 CPS.

We first used cross-tabulation analysis to determine individual and employment characteristics related to Internet access at work. Income, education, and full-time employment are associated with use of the Internet on the job in all three communities. Selecting only those respondents who reported a full- or part-time job, Table 2 presents some of the demographic factors that have been shown to be significantly associated with Internet use at work.

Table 3. Use of the Internet at Work and Types of Jobs

	Employment		Job Sector		
	% Full-time	% Part-time	% Managerial, professional	% Clerical, sales, service	% Blue-collar
East Cleveland	25.2	5.1	30.4	16.1	9.7
Shaker Heights	62.3	14.3	59.8	42.2	0.0
Youngstown	30.8	10.3	47.9	21.0	2.5

Note. The values show what percentage of workers in each city use the Internet at work. $n = 531$

Race is important in both East Cleveland and Shaker Heights, with African Americans less likely to use the Internet at their place of employment in both communities. Still, African Americans in Shaker Heights (who are higher income and more educated overall) are much more likely than African Americans in East Cleveland to go online at work. Interestingly, this factor is unimportant within Youngstown. Education is an important indicator of Internet use at work, no matter what level of education is selected. In each city, individuals with a college degree or higher are more than twice as likely to use the Internet on the job. Again, however, Shaker Heights workers report much higher rates than workers in the other two cities. Income is also a significant variable, with low-level wage earners far less likely to use the Internet than those who earn more than $18,000 a year. Even at the $36,000 yearly level, the relationship remains.

The cross-tabulations also indicate how much these differences are because of employment status or to job sector (see Table 3).

In all three communities, full-time employment is significantly and positively related to Internet use at work. In these cases, full-time workers were more than 3 times more likely to use the Internet at work than were part-time employees. Again, though, the differences between the three communities emerged, with Internet use significantly greater for full-time workers in Shaker Heights. Also, managerial and professional employees in all three cities were far more likely to use the Internet at work than clerical, sales, and service workers. These in turn were more likely than blue-collar workers to use the Internet on their jobs. Clearly, Internet use at work is most strongly associated with full-time work, jobs that enable individuals to rise above the poverty level, and jobs that involve some postsecondary education, including managerial positions.

These patterns mirror trends in national data from the 2003 CPS, but some differences are evident across the three communities. For residents of Shaker Heights, many part-time jobs and service jobs include Internet use, whereas in the two poorer communities they do not. This may indicate variation in types of part-time and service-sector jobs, although we did not have that level of precision in our data set. Differences in educational attainment in the three communities may affect the range of variation in Internet use within job categories, such as within the management category. In Shaker Heights, there were 3 times as many employees listed as "professional" compared with managers or business owners.

Demographic and employment factors influence the differences between the three cities with regard to Internet use. There is also the question of how much the contextual environment may affect the level of Internet use at work. Location within the three cities has an important impact. Does place matter for technology use over and above what individual income, occupation, educational attainment, and other factors might predict?

Neighborhood-level data can provide an additional scale to explain some of the differences in Internet use at work. Context has been shown to matter with regard to poverty, crime, mortgage lending, access to quality food, and other important influences on quality of life and economic opportunity. Therefore, an individual's immediate context could affect whether he or she has access to the Internet in general and specifically access to jobs that include Internet use at work. As with our discussion of the differences between the three cities, our data set measures the geographical location of individuals at their places of residence rather than at their work sites. However, residential context could be important in shaping an individual's access to employment and work experience. We use geographic buffers to account for this context, as described below.

Method: Buffers, Neighborhood Data, and Multivariate Analysis

To measure these contextual variables, we took the geographical location of each respondent and then created a series of buffers around each respondent's residence. Information about the socioeconomic makeup of the buffer came from synthesizing block group information from the 2000 U.S. Census.[4] Many studies of neighborhood effects have used either block group or census tract to define the immediate neighborhood (Ioannides & Topa, 2009; Wheeler, 2007). These suffer from three basic problems. First, there are boundary issues that are inherent in the use of block groups or tracts, as location near one edge of a unit boundary reports the same context as location in the center of the unit or at the opposite edge. Second, census units are based on population and not areas, so

Table 4. Neighborhood Composition by Use of Internet at Work

	Internet use at work					
	Youngstown		East Cleveland		Shaker Heights	
Neighborhood composition	No	Yes	No	Yes	No	Yes
% Black in neighborhood	31.6	23.4	88.9	78.8	42.4	33.5
% Below poverty level in neighborhood	19.9	15.0	30.8	28.4	9.4	7.4
% College graduate in neighborhood	13.0	16.8	10.5	19.8	52.6	59.7
% Managerial/professional in neighborhood	21.4	25.1	21.9	29.5	56.5	61.2
% Unemployment in neighborhood	9.7	7.3	13.4	11.5	4.7	3.6

Note. The values show the percentage of each attribute within a respondent's neighborhood, depending on whether the respondent uses the Internet at work. Neighborhood is defined as within 0.5 kilometers of respondent's residence. *n* = 531.

their geographical size varies a great deal. Third, all respondents from the same unit will be assigned the exact same variable values. By using buffers, we avoid these problems. Each respondent has a unique context and so there are as many buffers as there were respondents. Furthermore, the context is equally calibrated at 0.5 kilometers in radius and there are no edge effects. Although buffers can be any size, we decided on the basis of past experience to use buffers with a radius of 0.5 kilometers to gauge the most immediate neighborhood context (Kaplan, 1999). This did a better job of approximating the field of likely interactions that could occur because of proximity.

Table 4 shows how these contextual variables play out in comparing respondents who use the Internet at work and respondents who do not have access to the Internet at work. So, for example, within Youngstown, respondents with Internet access at work live in neighborhoods where the unemployment rate is 7.3%. Those Youngstown residents without Internet access live in neighborhoods where the unemployment rate is 9.7%. East Cleveland and Shaker Heights demonstrate the same gap: higher unemployment rates within the immediate neighborhoods of those who *do not* have Internet access at work and lower unemployment rates among those respondents who *do* have use of Internet at work. In all instances, and for each city, the results are as might be expected. Respondents with workplace access to the Internet live in neighborhoods that have a smaller percentage of African Americans, a lower proportion of people in poverty, a higher percentage of college graduates, and a higher proportion of people who work in managerial and professional occupations. Respondents with workplace access also live in neighborhoods with lower unemployment rates.

Modeling Internet Use at Work

Although most of the variables show expected linkages between Internet access at work and individual attributes, contextual attributes, and work distance, it can be helpful to determine which variables carry statistically significant independent effects. Logistic multivariate analysis can be used to understand how these variables might affect jobs and opportunities to use the Internet at work.

The dependent variable used in our models is binary, as are individual variables, with the exception of age. These were intended to measure income, job status, education, race, gender, and age. Demographic variables such as income, age, race, gender, and education have been used before and have been significant in other studies of Internet use, including our own (Mossberger, Tolbert, & McNeal, 2008; Mossberger, Kaplan, & Gilbert, 2008; Fairlie 2004; Fong & Cao, 2008). Internet use anywhere is more likely for younger, higher income, better educated, and White individuals. As shown in the literature review, Internet use is most common in jobs with higher educational requirements and higher pay, so individual education, income, and occupation could be expected to influence technology use at work. Gender may also affect Internet use on the job for less educated workers in particular. Clerical occupations, for example, are more likely to involve technology use despite relatively low levels of required education (Holzer, 1996). Income was coded as either less than $18,000 (0) or more than $18,000 (1); this is the cutoff poverty level for a family of three and appeared to be the cleanest method of measuring poverty. Job status was reduced to whether the respondent had a full-time job (1) or not (0). A further variable reflects whether the job was managerial/professional (1) or not (0). Education is based on the existence (1) or absence (0) of a college degree. Race was coded as a 1 for African American, 0 if not. Gender is listed as 1 for males and 0 for females. Age was recorded in years. The contextual variables are ratio-level measures. As might be expected, there was some multicollinearity among the variables, especially between an individual variable and the related contextual variable. For example, the African American proportion of a neighborhood correlates with whether an individual respondent is African American. This presents a problem for any study measuring the influence of segregated contexts. We introduce the contextual variables separately, in the second stage, in part for this reason. Some contextual variables, such as managerial/professional percentage and college-educated percentage, are correlated but still measure somewhat different phenomena.

We present this analysis in two stages. This was done to see how the addition of contextual variables affected the model not just in their potential significance but also in their effect on the model's overall explanatory power. The first stage shows only the impact of individual attributes. In this model, a statistically significant factor is whether the respondent has a full-time (as opposed to a part-time) job and also whether the job is managerial or professional in nature. Such employment would be more likely to encourage Internet use on the job. Income and education are also important barometers, as those who have a college education and an income that is higher than the poverty level for a family of three are more likely to use the Internet at work. Just as revealing are the variables that are not significant. Although African Americans are less likely to be employed in jobs with Internet access in two of the three cities, in a multivariate model, with all cities pooled, the respondent's race does not appear important. Also, despite the significance of age in determining Internet access in general (Fairlie, 2004; Mossberger, Tolbert, et al., 2008; U.S. Department of Commerce, 2010)—with older people less likely to use the Internet—age is not significant in determining Internet access at work. One possible explanation for this finding is that Internet use falls off substantially after the age of 65 years (Mossberger, Tolbert, et al., 2008), and so age effects may be less pronounced within the workforce.

The second stage of this model adds in some contextual variables. The expanded set of variables does increase the explanatory power of the model using two calculations of R^2. All of the individual variables continue to be significant in this expanded model, with the addition of age showing a negative relationship with Internet use at work. Of the contextual variables, the unemployment context of the immediate surroundings is also significant. Therefore, the likelihood of using the Internet at work is related to not only whether one has a full-time job but also the jobless rate of the neighborhood.

Although the unemployment rate is significantly related to Internet use, the other contextual variables are not significant. We maintain the continued importance of context but would argue that variables may exhibit different effects in different cities. Moreover, much of the difference in neighborhood context is explained by the very real differences between the three cities. East Cleveland is predominantly Black, whereas both Shaker Heights and Youngstown are racially mixed. Shaker Heights is much more affluent and better educated than East Cleveland or Youngstown.

To uncover these differences, one option is to assign a dummy variable for each city. We tried this, but it was not illuminating. Moreover, the inclusion of dummy variables constrains each of the explanatory variables to regress exactly the same way on the dependent variable. Instead, we opted to split the analysis and in this way tease out some of the important relationships that exist within each city and uncover whether certain regressors operate differently within each city.

Tables 5 and 6 compare the individual city results for the two-stage models. The first stage, showing only individual variables, shows that although the models as a whole suggest a fair degree of explanatory power, the number of significant variables drops precipitously from the pooled model. In Youngstown, having a full-time job and the managerial/professional variables are significant. This is not surprising in itself, except that we expected college and income variables to also show up. In East Cleveland, no variable is significant at the 5% threshold and only income is significant at the 10% threshold at the first stage. In Shaker Heights, age is significant but negatively associated with Internet use. Given that the average worker in this city (among our respondents) is 47 years old, this may reflect a predominance of significantly older workers in that city. Both the full-time job and the college variables are significant in the expected direction here.

The expanded model for each city shows a number of similarities to the individual model. The explanatory power of these models does increase a little with the inclusion of contextual variables. In Youngstown, the expanded model expands the overall significance of the model, and it adds the presence of a full-time job as another significant variable. However, no contextual variables are significant here. In East Cleveland, once again, the overall explanatory power of the model increases, but none of the individual variables are significant. In this case, however, the poverty context of the neighborhood shows up at a 10% level of significance but in an unexpected direction. The expanded model for Shaker Heights shows almost no change.

Conclusion: Neighborhood Effects and the Workplace Digital Divide

This analysis lends support to the argument that place factors are related to the probability of Internet use at work, updating the literature on concentrated poverty. Our examination of descriptive data for the three cities showed substantial disparities, with predominantly low-income and African American East Cleveland trailing furthest behind. Only 25% of full-time workers in East Cleveland and 30% of full-time employees in Youngstown were in jobs involving Internet use in 2005—in comparison with the national average of 58% of all workers in 2003. At the city level, residents of East Cleveland and Youngstown are largely excluded from the information economy.

Table 5. Logistic Model of Internet Use at Work

	Stage 1			Stage 2		
Pooled Data	B	*SE*	Significance	B	*SE*	Significance
Full-time job	1.56	0.40	.000	1.76	0.37	.000
Managerial/professional	0.96	0.27	.000	0.81	0.26	.002
Age	–0.01	0.01	.221	–0.02	0.01	.023
Income >$18,000	1.24	0.57	.029	0.93	0.46	.043
Black	–0.05	0.25	.836	–0.05	0.31	.883
College	1.03	0.28	.000	0.72	0.29	.012
Black context				0.32	0.57	.577
Poverty context				1.15	2.22	.604
College context				0.09	2.19	.968
Unemployed context				–8.59	4.31	.047
Managerial context				1.04	2.66	.696
–2 Log likelihood		426			483	
Cox & Snell R^2		.22			.24	
Nagelkerke R^2		.30			.33	

Table 6. Logistical Regression by City

	Youngstown			East Cleveland			Shaker Heights		
	B	*SE*	Significance	B	*SE*	Significance	B	*SE*	Significance
Stage 1									
Full-time job	0.99	0.63	.120	1.09	0.82	.184	2.23	0.54	.000
Managerial/professional	1.67	0.42	.000	0.06	0.55	.909	0.72	0.47	.129
Age	–0.02	0.02	.174	0.02	0.02	.361	–0.04	0.02	.017
Income >$18,000	0.60	0.60	.313	1.88	1.07	.079	1.27	1.43	.373
Black	0.39	0.43	.370	–0.77	0.64	.233	–0.33	0.41	.427
College	0.35	0.46	.453	0.96	0.61	.113	0.97	0.48	.043
–2 Log likelihood		174			117			178	
Cox & Snell R^2		.17			.16			.25	
Nagelkerke R^2		.24			.26			.33	
Stage 2									
Full-time job	1.21	0.66	.068	1.45	0.94	.122	2.27	0.55	.000
Managerial/professional	1.60	0.44	.000	0.35	0.59	.551	0.67	0.48	.165
Age	–0.03	0.02	.157	0.02	0.02	.291	–0.03	0.02	.029
Income >$18,000	0.48	0.63	.445	1.67	1.08	.122	1.33	1.46	.362
Black	0.61	0.49	.217	–0.95	0.80	.233	–0.45	0.51	.370
College	0.47	0.48	.329	0.74	0.63	.244	0.99	0.50	.048
Black context	0.79	1.46	.591	5.30	4.82	.272	1.67	2.58	.518
Poverty context	–1.39	4.41	.753	11.99	6.97	.085	0.79	6.53	.903
College context	7.05	6.08	.246	1.91	10.52	.856	–0.08	4.06	.984
Unemployed context	–8.84	6.70	.187	–6.33	8.12	.436	–10.12	13.29	.447
Managerial context	–5.42	5.49	.323	11.70	8.77	.182	1.49	3.77	.693
–2 Log likelihood		165			110			177	
Cox & Snell R^2		.21			.20			.25	
Nagelkerke R^2		.30			.32			.34	

Do place characteristics explain these disparities? Our results in this exploratory study are consistent with theories of neighborhood effects insofar as one contextual factor was significant—the percentage of unemployment in the individual's immediate surroundings. Trends toward the concentration of unemployment (Wheeler, 2007) may be isolating some residents from opportunities to work in technology-related jobs. Several individual variables—especially type of job, education, and income—are also related to Internet use at work. Race and age appear to be less important for those who are already employed. Although individual-level factors account for most of the variation in Internet use at work, the presence of some contextual effects indicates that limited information networks or other neighborhood characteristics may exacerbate individual disadvantages.

Although our evidence is restricted to three communities in one hard-pressed geographic region, our study contains neighborhood-level data that are not always available in national studies. Understanding of the barriers to technology employment in poor communities could be further enhanced through national research using multilevel models for greater generalization and through case studies or interviews that might probe the experiences of community residents. If the results here are indicative of patterns in other urban neighborhoods, strategies should be considered to connect residents of high-poverty areas to technology-intensive jobs. This may include information, training, or business attraction.

Such strategies may contribute to more general workforce development and economic growth for regions as well as poverty alleviation for individuals in poor neighborhoods. Much of the rapid economic growth experienced during the decade of the 1990s resulted from increased productivity enabled by computer and Internet technologies. The effect of these gains was uneven, however, as some regions prospered whereas others were left behind. Some of the economic powerhouses of the early and mid 20th century, especially those in the industrial Midwest, have missed out in the growth of newer technologies. With greater federal attention to broadband and digital inclusion, there is new potential for regions to better position themselves in terms of human capital as well as the infrastructure and technology transfer that can foster economic growth in a digital economy.

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Notes

1. More generally, there is a substantial literature indicating that technology use on the job is associated with higher wages (Autor et al., 1998; Goss & Phillips, 2002; Krueger, 1993; for a cross-national review, see Arabsheibani, Emami, & Marin, 2004). Debate exists, however, over the extent to which higher wages can be attributed to technology use (DiNardo & Pischke, 1997). Controls for endogeneity, such as fixed effects and panel studies, tend to diminish the size of the wage premium, although recent studies have shown statistically significant effects for technology even with these controls (Arabsheibania et al., 2004; Entorf, Gollac, & Kramarz, 1999; Pabilonia & Zhogi, 2005; Zoghi & Pabilonia, 2006).
2. See, for example, reports from the Pew Internet and American Life Project at pewinternet.org.
3. Income is more difficult to compare because of our categorical income data, but the samples appear representative in this respect: For example, about half of the East Cleveland sample and about 40% of the Youngstown sample have annual incomes of $18,000 or less, in comparison with median household incomes of $20,000 and $24,000 reported in the census.
4. Since each buffer could contain portions of several surrounding block groups, we calculated the attributes for each buffer by using the areal proportions of the block groups contained within the buffer. For example, if a buffer covered 25% of a block group and that block group contained 40 college graduates, then we would allocate 25% of 40, or 10 graduates, to that buffer. The sum of these proportions was aggregated to equal the proportion of college graduates within each buffer.

References

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature, 40*, 7-72.

Arabsheibani, G. R., Emami, J. M., & Marin, A. (2004). The impact of computer use on earnings in the UK. *Scottish Journal of Political Economy, 51*, 82-94.

Autor, D. H., Katz, L., & Krueger, A. (1998). Computing inequality: Have computers changed the labor market? *Quarterly Journal of Economics, 113*, 1169-1213.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration, *Quarterly Journal of Economics, 118*, 1279-1333.

Bahl, R. (1994). Metropolitan fiscal disparities. *Cityscape: A Journal of Policy Development and Research, 1*, 293-306.

Bahl, R., Martinez-Vazquez, J., & Sjoquist, D. L. (1992). Central-city suburban fiscal disparities. *Public Finance Quarterly,* 20, 420-432.

Bauder, H. (2002). Neighborhood effects and cultural exclusion. *Urban Studies, 39*, 85-93.

Bayer, P., Ross, S., & Topa, G. (2008). Place of work and place of residence: Informal hiring networks and labor market outcomes, *Journal of Political Economy, 116*, 1150-1196.

Brynjolfsson, E., & Saunders, A. (2010). Wired for innovation: How information technology is reshaping the economy. Cambridge: MIT Press.

Case, A. C., & Katz, L. (1991, May). *The company you keep: The effects of family and neighborhood on disadvantaged youths* (NBER Working Paper No. 3705). Cambridge, MA: National Bureau of Economic Research.

DiNardo, J. C., & Pischke, J. S. (1997). The returns to computer use revisited: Have pencils changed the wage structure too? *Quarterly Journal of Economics, 112,* 291-303.

Elliott, J. R. (1999). Social isolation and labor market insulation. *The Sociological Quarterly, 40*, 199-216.

Elliott, J. R. (2000). Class, race and job matching in contemporary urban labor markets. *Social Science Quarterly, 81*, 1036-1052.

Entorf, H., Gollac, M., & Kramarz, F. (1999). New technologies, wages, and worker selection. *Journal of Labor Economics,* 17, 464-491.

Fairlie, R. (2004). Race and the digital divide. *B. E. Journal of Economic Analysis & Policy, 3*(1), 1-35. Retrieved from http://www.bepress.com/bejeap/contributions/vol3/iss1/art15/

Federal Communications Commission. (2010). *The national broadband plan: Connecting America.* Retrieved from http://www.broadband.gov

Federal Reserve & Brookings Institution. (2008). *The enduring challenge of concentrated poverty in America: Case studies from across the U.S.* Washington, DC: The Brookings Institution.

Fong, E., & Cao, X. (2008). Bridges across the racial digital divide: Residential ecology of internet use. *Canadian Studies in Population, 35*, 243-268.

Gillett, S. E., Lehr, W. H., Osorio, C. A., & Sirbu, M. A. (2006). *Measuring broadband's economic impact: Final report* (National Technical Assistance, Research, Training and Evaluation Project No. 99-07-13829). Retrieved from http://www.eda.gov/PDF/2006%20Measuring%20Broadband%20Report.pdf

Goss, E., & Phillips, J. (2002). How information technology affects wages: Evidence using internet usage as a proxy for IT skills. *Journal of Labor Research, 23*, 463-474.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology, 78*, 1360-1380.

Green, G. P., Tigges, L. M., & Browne, I. (1995). Social resources, job search, and poverty in Atlanta. *Research in Community Sociology, 5*, 161-182.

Guest, A. M., & Lee, B. A. (1983). The social organization of local areas. *Urban Affairs Quarterly, 19*, 217-240.

Holloway, S. R., & Mulherin, S. (2004). The effect of adolescent neighborhood poverty on adult employment. *Journal of Urban Affairs, 26*, 427-454.

Holzer, H. J. (1996). *What employers want: Job prospects for less-educated workers*. New York, NY: Russell Sage Foundation.

Ihlanfeldt, K. R., & Sjoquist, D. L. (1998). The spatial mismatch hypothesis: A review of recent studies and their implications for welfare reform. *Housing Policy Debate, 9*, 849-892.

Ioannides, Y. M., & Topa, G. (2009, April). *Neighborhood effects: Accomplishments and looking beyond them*. Paper presented at the *Journal of Regional Science* 50th anniversary conference, New York, NY.

Jargowsky, P. A. (1997). *Poverty and place: Ghettos, barrios and the American city.* New York, NY: Russell Sage Foundation.

Kaplan, D. (1999). The uneven distribution of employment opportunities: Neighborhood and race in Cleveland, Ohio. *Journal of Urban Affairs*, *21*, 189-212.

Kirschenman, J., & Neckerman, K. M. (1991). We'd love to hire them, but . . . The meaning of race for employers. In C. Jencks & P. E. Peterson (Eds.), *The urban underclass* (pp. 203-232). Washington, DC: The Brookings Institution.

Kleit, R. G. (2001). The role of neighborhood social networks in scattered-site public housing residents' search for jobs. *Housing Policy Debate, 12*, 541-573.

Kling, J. R., Liebman, J. B., & Katz, L. F. (2007). Experimental analysis of neighborhood effects. *Econometrica, 75*, 83-119.

Krueger, A. B. (1993). How computers have changed the wage structure: Evidence from microdata, 1984-1989. *Quarterly Journal of Economics, 109*, 57-68.

Lee, B. A., & Campbell, K. E. (1999). Neighbor networks of black and white Americans. In B. Wellman (Ed.), *Networks in the global village: Life in contemporary communities* (pp.119-146). Boulder, CO: Westview Press.

Litan, R. E., & Rivlin, A. M. (Eds.). (2002). *The economic payoff from the internet revolution*. Washington, DC: Brookings Institution Press.

Ludwig, J., Kling, J. R., Katz, L. F., Liebman, J. B., Duncan, G. J., & Kessler, R. C. (2008). What can we learn about neighborhood effects from the Moving to Opportunity program? *American Journal of Sociology, 114*, 144-188.

Massey, D. S., & Denton, N. A. (1993). *American apartheid: Segregation and the making of the underclass.* Cambridge, MA: Harvard University Press.

Moss, P., & Tilly, C. (2001). *Stories employers tell: Race, skill, and hiring in America.* New York, NY: Russell Sage Foundation.

Mossberger, K., Kaplan, D., & Gilbert, M. A. (2008). Going online without easy access: A tale of three cities. *Journal of Urban Affairs, 30*, 469-488.

Mossberger, K., Tolbert, C. J., & Gilbert, M. A. (2006). Race, place, and information technology. *Urban Affairs Review, 41*, 583-620.

Mossberger, K., Tolbert, C. J., & McNeal, R. S. (2008). *Digital citizenship: The Internet, society and participation.* Cambridge: MIT Press.

Mossberger, K., Tolbert, C. J., & Stansbury, M. (2003). *Virtual inequality: Beyond the digital divide.* Washington, DC: Georgetown University Press.

Orfield, G., & Lee, C. (2005). *Why segregation matters: Poverty and educational inequality*. Cambridge, MA: The Civil Rights Project, Harvard University. Retrieved from http://www.eric.ed.gov/PDFS/ED489186.pdf

Pabilonia, S. W., & Zhogi, C. (2005). Returning to the returns to computer use. *American Economic Review, 95*, 314-317.

Stiroh, K. (2004). *Reassessing the impact of IT on the production function: A meta-analysis and sensitivity tests* (Working Paper). New York: Federal Reserve Bank of New York.

Tigges, L. M., Browne, I., & Green, G. P. (1998). Social isolation of the urban poor: Race, class, and neighborhood effects on social resources. *The Sociological Quarterly, 39*, 53-77.

Topa, G. (2001). Social interactions, local spillovers and unemployment. *Review of Economic Studies, 68*, 261-295.

Turney, K., Clampet-Lundquist, S., Edin, K., Kling, J. R., & Duncan, G. J. (2006). *Neighborhood effects on barriers to employment: Results from a randomized housing mobility experiment in Baltimore* (Working Paper No. 511). Princeton, NJ: Industrial Relations Section, Princeton University.

U.S. Department of Commerce, National Telecommunications and Information Administration. (2010). *Digital nation: 21st century America's progress toward universal broadband internet access.* Retrieved from http://www.ntia.doc.gov/report/2010/digital-nation-21st-century-americas-progress-towards-universal-broadband-internet-acces

Van Dijk, J. A. G. M. (2005). *The deepening divide: Inequality in the information society*. Thousand Oaks, CA: SAGE.

Wacquant, L. J. D. (1993). Urban outcasts: Stigma and division in the black American ghetto and the French urban periphery. *International Journal of Urban and Regional Research, 17*, 366-383.

Warschauer, M. (2003). *Technology and social inclusion: Rethinking the digital divide*. Cambridge: MIT Press

Wellman, B. (1996). Are personal communities local? A dumptarian reconsideration. *Social Networks, 18*, 347-354.

Wheeler, C. H. (2007). Trends in neighborhood-level unemployment in the United States: 1980-2000. *Federal Reserve Bank of St. Louis Review, 89*, 123-141.

Wilson, W. J. (1987). *The truly disadvantaged: The inner city, the underclass and public policy*. Chicago, IL: University of Chicago Press.

Zhogi, C., & Pabilonia, S. W. (2006, June). *Which workers gain upon adopting a computer?* (Working Paper No. 395). Washington, DC: U.S. Department of Labor, U.S. Bureau of Labor Statistics, Office of Productivity and Technology.

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