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Abstract

Although the association between industrial agglomeration and productivity has been widely examined and documented, little work has explored the possibility that these 'external' productivity shifts are the product of more advanced technologies. This paper offers a look at this hypothesis using data on individual-level computer usage across a sample of U.S. metropolitan areas over the years 1984, 1989, 1993, and 1997. The results indicate that, for a wide array of industries at the two-, three-, and four-digit SIC level, an industry's scale within a metropolitan area is positively associated with the frequency of computer use by its workers. However, in spite of these observable differences in workplace technology, I also find that estimated localization effects on wages are largely *not* explained by computer usage. Even after controlling for computer use, there remain significant own-industry scale effects in labor earnings.

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1 Introduction

One of the more robust findings emerging from studies of industrial agglomeration is the positive association between an industry's scale within a local market and its productivity. This relationship has been shown to hold both at the 'aggregate' level, where the productivity of an entire city-industry is considered (e.g. Carlino (1979) and Henderson (1986)), and the micro level, where plant-level productivity (e.g. Henderson (2003)) or the wages of individual workers (e.g. Wheeler (2004)) are considered. Although the exact magnitudes of these 'localization effects' vary somewhat depending on the unit of analysis, most studies find them to be both statistically and economically significant.[1]

These empirical results are often interpreted as evidence of Marshall's (1920) scale economies; that is, positive productivity shifts associated with the localization of industry. Marshall (1920), of course, suggested three primary sources for these shifts: the spillover of industry-specific knowledge across producers, greater efficiency in the firm-worker matching process, and the creation of an extensive array of specialized input providers. In each instance, the hypothesis is that, holding producer and worker characteristics constant, an increase in the magnitude of an economic agent's own local industry is associated with higher productivity.

There is, however, an issue that has not received much attention (at least empirically) in the localization - or more generally, agglomeration - literature: technological differences between producers in small and large markets. In particular, one reason for the observed positive productivity shifts among both producers and workers in localized markets may be

[1]Henderson (1986), for example, estimates output-employment elasticities near 0.1 (that is, a 10 percent increase in own-industry employment corresponds to a 1 percent increase in output) for U.S. and Brazilian manufacturing. Also using manufacturing, Wheeler (2004) estimates wage-employment elasticities between 0.02 and 0.08, while Henderson (2003) finds that a 10 percent increase in the number of own-industry plants within the same county increases an establishment's total factor productivity by 0.2 to 0.8 percent.

the use of more advanced technologies.

Two well-established empirical findings serve as the basic motivation for this conjecture. First, several recent papers (e.g. Kim (1995), Holmes and Stevens (2002), and Wheeler (2004)) have shown that localization is positively associated with average plant size. That is, large clusters of industry - measured either by total employment within a local market or by the extent to which an industry is over-represented in local employment relative to the aggregate U.S. level - tend to be characterized by plants which are, on average, larger. Second, larger producers tend to make greater use of advanced production technologies than their smaller counterparts. For example, looking at a sample of manufacturing establishments, Dunne (1994) finds that large plants are more likely to adopt relatively sophisticated technologies such as computer aided design and engineering, lasers, and robotics than small plants. Given the positive association between the use of these technologies and various measures of productivity (e.g. Doms et al. (1997), Black and Lynch (2001), Bresnahan et al. (2002)), the use of more advanced capital may be an important aspect of industrial localization.

To date, most studies of either city-industry (e.g. Carlino (1979) and Henderson (1986)) or plant-level data (e.g. Henderson (2003)) have not attempted to account for technological differences across producers in markets of varying sizes. Capital and labor are usually treated as homogeneous, regardless of the extent of the local industry. Studies of individual-level wage earnings (e.g. Wheeler (2004)) tend to be based upon a similar premise. Although the influence of various observable measures of skill (e.g. education and experience) is usually taken into account when estimating the localization-wage relationship, estimation still proceeds under the assumption that the nature of a job in a particular industry, including its degree of technological sophistication, is the same across markets of varying sizes.

Admittedly, such an approach is understandable given the general lack of easily-accessible data covering technological use among either producers or workers within small geographic areas. However, one commonly used data set, the Current Population Survey (CPS), does provide some information about the use of information technology in places of work. Beginning in 1984, a series of supplements to the usual monthly survey asked individuals whether they used a computer at work or not.[2] Because information about an individual's metropolitan area of residence and detailed industry of employment can also be identified for the majority of the respondents, the CPS provides a means of examining the relationship between industrial localization and technological 'sophistication.' This paper seeks to estimate this relationship.

To what extent can computers really be considered an advanced technology? Although the effect of computer technology on productivity has been debated in recent years (e.g. Gordon (2000)), a number of studies have linked the recent rise in U.S. productivity to the growth of information technology. Indeed, a host of evidence supports this conclusion at both the aggregate national level (Oliner and Sichel (2000)) as well as across a wide array of industries (Stiroh (2002)). At the micro-level, Doms et al. (1997) report a similar result: wages are positively associated with the adoption of computer-based technologies across plants in U.S. manufacturing. Moreover, using the same CPS data employed here, Krueger (1993) shows that, after conditioning on a number of personal characteristics, workplace computer use is associated with a 10 percent increase in hourly wages.[3] While this result does not necessarily represent a purely causal association (see DiNardo and Pischke (1997)), it is certainly indicative of a strong correlation between the use of this particular technology and productivity.

Briefly summarizing the results, I find a statistically significant, positive association between the employment of a worker's own metropolitan area-industry and the frequency of

[2]Computer usage was covered in the October 1984, 1989, 1993, and 1997 surveys as well as August 2000, September 2001, and October 2003 surveys.

[3]Krueger (1993) actually reports many point estimates across a variety of specifications. This is merely an (approximate) average figure.

computer usage. Point estimates suggest that, on average, a 1 standard deviation increase in city-industry employment is associated with a 3 to 4.5 percentage point rise in the frequency of computer usage. These results are robust to a variety of alterations to the basic estimating equation, including the addition of controls for overall city size, density, economic diversity, local human capital, as well as time-, industry-, and city-specific fixed effects.

When I turn to the analysis of individual labor earnings, however, I also find that the association between the scale of a worker's own city-industry is affected only very little by the inclusion of computer usage in the regression. Hence, while there appear to be important observable differences in workplace technology across industrial clusters of varying sizes, those differences (at least as captured by computer use) do not, for the most part, explain localization effects.

The remainder of the paper proceeds as follows. The next section maps out the data and estimation techniques. Section 3 then describes the results. Section 4 concludes.

2 Data and Estimation

2.1 Data

The 1984, 1989, 1993, and 1997 October supplements to the Current Population Survey include information about workplace computer usage for nearly all respondents. The sample used here consists of all individuals between the ages of 18 and 65 who report having a job. The fundamental variable of interest from these files is the response to the question "Do you directly use a computer at work?" While questions about computer usage were also asked in later supplements (August 2000, September 2001, October 2003), I limit the sample to the years 1984 to 1997 to facilitate the construction of consistent city-industry employment series.[4]

As noted previously, the CPS identifies the metropolitan statistical area (MSA) or New England County Metropolitan Area (NECMA) of residence for many respondents. All individuals for whom this information is not reported are dropped. I then define an individual's local labor market either as his or her MSA or NECMA of residence or, in the event that the metropolitan area belongs to a consolidated metropolitan statistical area (CMSA), the CMSA of residence. While CMSAs (e.g. New York-Northern New Jersey-Long Island) may be somewhat large when considering local labor markets, they greatly facilitate the creation of geographic areas with consistent definitions over time.[5] Using large metropolitan areas also increases the likelihood that a worker's place of work is the same as his or her place of residence.[6]

In this paper, I define industries at the most detailed level available in the CPS. For the most part, these correspond to the three-digit SIC level of aggregation, although a number of the them represent either two- or four-digit sectors, or groups of three-digit sectors. In all, a total of 201 distinct industries drawn from all major private industry sectors are identified in one or more of the years.[7]

Data covering total employment within metropolitan areas for these industries are taken

[4]The principal concern involves the County Business Patterns (CBP) files (described below), which switched over from the Standard Industrial Classification (SIC) system to the North American Industry Classification System (NAICS) in 1998. Since the correspondence between the two is far from exact - particularly for the detailed industries examined here - I restrict the analysis to the pre-1998 data.

[5]Individuals assigned to one metropolitan area within a CMSA in one year, for example, may be assigned to a different metropolitan area (within the same CMSA) in another year simply as a result of changes in geographic definitions.

[6]For example, it is possible that workers residing in Oakland work in San Francisco. Assigning these workers to the San Francisco-Oakland-San Jose CMSA avoids incorrectly specifying the Oakland MSA as the place of work.

[7]Major sectors are identified in Table 5.

from County Business Patterns (CBP) files for the same four years: 1984, 1989, 1993, 1997. After constructing industry groupings to match the CPS industry codes, I aggregate the county-level employment figures reported in the CBP to the metropolitan area level.[8] These are then matched to each individual in the CPS to provide a measure of scale for every worker's own city-industry. Further details about these data are provided in the Appendix.

Additional data on metropolitan areas (e.g. population, education) is derived from a variety of sources produced by the U.S. Census Bureau. Annual figures on resident population for each county in the U.S. are estimated by the Census Bureau's Population Estimates Program.[9] Education data is available for the years 1980, 1990, and 2000 from the USA Counties 1998 CD-ROM (U.S. Bureau of the Census (1999)) and the Census Bureau's Summary File 1 of the 2000 Census of Population. From these county-level observations, I aggregate the data to the metropolitan area level for all years using definitions from the year 1995. Because the CPS data fall between Census years, I estimate educational attainment at the metropolitan area level in the years 1984, 1989, 1993, and 1997 by linearly interpolating between Census years.

Some basic summary statistics describing computer usage appear in Table 1A.[10] These demonstrate a number of relatively well-known (or, at least, intuitive) patterns. Computer use at the workplace has grown over time, rising from 30 percent in 1984 to 53 percent by 1997. Moreover, sizable differences in computer usage can be linked to gender, race, education, union membership, and broad occupational category.

There are also important differences in the extent of computer use across the industries in the sample. Table 1B reports average frequencies over all four years for the 20 industries with the highest usage rates and the 20 with the lowest rates. Not surprisingly, industries

[8] Correspondence between the CPS and CBP (i.e. SIC) industry codes is provided by the Bureau of Labor Statistics at www.bls.census.gov/cps/bindcd.htm.

[9] See www.census.gov/popest/estimates.php.

[10] Overall summary statistics appear in Table A1 of the Appendix.

like computer and data processing, banking, and accounting all have rates in excess of 80 percent. Shoe repair, retail bakeries, and taxicab services by contrast are each characterized by a usage rate less than 10 percent.

2.2 Statistical Methods

To model computer usage statistically, I follow two common approaches: a linear probability model (LPM) and a probit specification. Letting y^j_{ict} represent a computer-use indicator variable for worker j of industry i in city c at time t, the LPM implies

$$\begin{aligned} &\text{Prob}(y^j_{ict} = 1 | \mathbf{x}^j_{ict}, \mathbf{z}_{ct}, \log\,(\text{Emp}_{ict}); \beta_t, \gamma, \theta, \mu) \\ &= \beta_t \mathbf{x}^j_{ict} + \gamma \mathbf{z}_{ct} + \theta \log\,(\text{Emp}_{ict}) + \mu_i + \mu_c + \mu_t \end{aligned} \tag{1}$$

where $\mathbf{x}^j_{ict}$ is a vector of personal covariates, including four educational attainment dummies (no high school, some high school, high school, some college, college), a quartic in potential work experience, race, gender, marital status, union membership, and 11 occupation indicators;[11] $\mathbf{z}_{ct}$ is a vector of city-level variables which vary over time; Emp_{ict} is the total employment of the worker's city-industry; and μ_i, μ_c, μ_t denote industry-, city-, and time-specific fixed effects. These last three terms are intended to capture the fact that, as seen in Tables 1A and 1B, some industries and years are simply characterized by more intensive computer use than others. Since there may also be certain unobserved features of cities that influence the propensity of workers to use computers, I further include time invariant city-specific terms.

[11] Occupations include executive, administrative, managerial; professional specialty; technicians and related support; sales; administrative support; protective services; other service; precision production, craft, repair; machine operators, assemblers, inspectors; transportation and material moving equipment; handlers, equipment cleaners, laborers. The calculation of potential experience is described in the Appendix.

Because y^j_{ict} is a binary variable, its expected value follows as

$$\mathrm{E}(y^j_{ict}|\mathbf{x}^j_{ict}, \mathbf{z}_{ct}, \log\,(\mathrm{Emp}_{ict}); \beta_t, \gamma, \theta, \mu) = \beta_t \mathbf{x}^j_{ict} + \gamma \mathbf{z}_{ct} + \theta \log\,(\mathrm{Emp}_{ict}) + \mu_i + \mu_c + \mu_t$$

hence,

$$y^j_{ict} = \beta_t \mathbf{x}^j_{ict} + \gamma \mathbf{z}_{ct} + \theta \log\,(\mathrm{Emp}_{ict}) + \mu_i + \mu_c + \mu_t + \epsilon^j_{ict}$$

where ϵ is a mean zero stochastic element. Estimation then proceeds by least squares where the standard errors are adjusted to account for the heteroskedasticity implied by the model.

With the probit model, the probability that this worker uses a computer at work is specified as

$$\begin{aligned} &\mathrm{Prob}(y^j_{ict} = 1|\mathbf{x}^j_{ict}, \mathbf{z}_{ct}, \log\,(\mathrm{Emp}_{ict}); \beta_t, \gamma, \theta, \mu) \\ &= \Phi(\beta_t \mathbf{x}^j_{ict} + \gamma \mathbf{z}_{ct} + \theta \log\,(\mathrm{Emp}_{ict}) + \mu_i + \mu_c + \mu_t) \quad \equiv \Phi^j_{ict} \end{aligned} \tag{2}$$

where all of the terms are the same as in (1), and $\Phi(\cdot)$ is the normal cumulative distribution function. The parameters are then chosen to maximize the sum of the log likelihoods over all observations, where the contribution from observation j, industry i, city c, time t is

$$y^j_{ict} \log(\Phi^j_{ict}) + (1 - y^j_{ict}) \log(1 - \Phi^j_{ict})$$

3 Results

3.1 Baseline Findings

I begin by estimating a version of equations (1) and (2) in which the vector of metropolitan area-level characteristics $\mathbf{z}_{ct}$ is omitted simply to focus on the association between own-industry local employment and the frequency of computer use. The resulting estimates appear in the columns labeled I in Table 2. Throughout, the probit results are reported in terms of their estimated marginal associations - calculated using the mean values of all covariates - rather than the raw coefficient estimates. Doing so allows for a direct comparison of the probit and LPM estimates.

Beginning with the individual level covariates, a number of the trends reported in Tables 1A and 1B emerge here too. Computer usage, for instance, tends to be higher among females, non-union members, and workers who are white. It also increases significantly with educational attainment: the probability that a college graduate uses a computer at work, for example, is between 14 and 17 percentage points higher than that for a high school graduate.[12]

With respect to localization, the estimated association between computer usage and a worker's log own-industry employment is significantly positive across both LPM and probit estimation techniques.[13] The LPM point estimate suggests that, all else held constant, a 1 standard deviation increase in a worker's log own-industry employment is associated with a 3 percentage point increase, roughly, in the probability of using a computer.[14] The probit result suggests that the marginal association is somewhat higher, approximately 4.5 percentage points. Hence, there seems to be some evidence that the nature of production in large industry clusters differs from that utilized in smaller markets.

To determine the robustness of this result, the next two specifications add the vector of time-varying city-level characteristics, $\mathbf{z}_{ct}$, back into the analysis. In particular, one potentially important determinant of computer usage is an aggregate human capital

[12]Since the high school indicator has been omitted, the education estimates represent probabilities relative to a high school graduate.

[13]I also performed all of the estimation measuring localization by the *share* of a metropolitan area's total employment accounted for by each industry rather than log city-industry employment. The results were qualitatively similar to what is reported here.

[14]The standard deviation of log own-industry employment is approximately 2 in these data.

measure. Acemoglu (2002), for example, has argued that a producer's decision to adopt skill-complementing technologies, such as computer equipment, may be related to the supply of skilled labor. Because markets with larger overall numbers of workers also tend to be populated by workers with higher levels of education (e.g. Glaeser (1999)), log own-industry employment may simply be picking up the influence of human capital on computer usage.

To address this matter, I add the fraction of a metropolitan area's adult population (age 25 or older) with a bachelor's degree to the specification labeled II in Table 2. Although the resulting estimates do suggest a positive association between the local college fraction and computer use - both estimates indicate that a 1 percentage point increase in the college fraction is associated with a 0.4 percentage point increase in the likelihood of using a computer - neither the LPM nor the probit estimate is significantly non-zero at conventional significance levels (i.e. at least 10 percent). The localization term, by contrast, remains positive and statistically important. Indeed, neither the LPM nor probit estimate changes noticeably from what results in the first specification.

Could a city's overall size or density explain these results? Recent work by Carlino et al. (2004), for example, shows that innovative activity in the form of patents is strongly tied to metropolitan density. Similarly, Harrison et al. (1996) find that, among metalworking establishments in the U.S., the adoption of new production technologies tends to be higher in large, diverse markets. City-industry employment may, therefore, be proxying for the effects of overall urban scale on the propensity of producers to use relatively sophisticated capital equipment.

The specification labeled III in Table 2 includes the logarithm of two variables: metropolitan area population and population density.[15] As it happens, neither of these variables en-

[15] Density is computed as a population-share weighted average of county-level densities, which may provide a more accurate depiction than overall average density (total city population/total city area) of the density faced by an average city dweller. It also mitigates somewhat the influence of extremely large, but sparsely

ters significantly in either set of results, and the coefficients on log own-industry employment maintain their values from the previous two specifications.

3.2 Robustness

This section considers three additional variations of equations (1) and (2) to assess further the robustness of the findings. First, because workers belonging to different education or occupation groups may have adopted computer equipment at different rates over time (e.g. computer adoption may have been more rapid among college graduates than high school dropouts between 1984 and 1997), I interact all of the personal covariates with the three year dummies to allow these variables to carry year-specific coefficients.[16] Second, since the influence of economic diversity may be inadequately captured by resident population or density, I include a more direct measure. Following Ades and Glaeser (1999), I use CBP data on four-digit city-industry employment to compute a 'Dixit-Stiglitz' index (DS) which, for city c in year t is

$$\mathrm{DS}_{ct} = \left(\sum_{i=1}^{N_{ct}} \left(\frac{\mathrm{Emp}_{ict}}{\mathrm{Emp}_{ct}} \right)^{\frac{1}{2}} \right)^{2}$$

The terms Emp_{ict} and Emp_{ct} represent city-industry and aggregate city employment, and N_{ct} is the number of industries in city c, all in year t.[17] By construction, larger values of this index represent greater diversity.[18] Third, because the broad industrial base of a city may also influence the propensity of workers within any particular industry to adopt a certain technology, I add 17 contemporaneous industry shares.[19]

populated, counties on the density calculations.

[16]This includes education, experience, race, gender, marital status, union status, and occupation.

[17]Summary statistics for this variable appear in Table A1 of the Appendix.

[18]For example, a city economy with two industries, each of which accounts for one half of total employment, will have a Dixit-Stiglitz index of 2. An economy with four equally sized industries will have a value of 4.

[19]Industries include mining; construction; nondurable manufacturing; durable manufacturing; transportation; communications; utilities and sanitary services; wholesale trade; retail trade; finance, insurance, real

The results appear in Table 3 as specifications IV, V, and VI. Overwhelmingly, they reveal little change from the findings described above. In fact, none of the LPM or probit estimates of the association between log own-industry employment and computer usage change noticeably when any of these alterations are made. All remain statistically significant and take on the same magnitudes as before.

The Dixit-Stiglitz index, interestingly, does *not* enter significantly in any of the specifications considered. Given the lack of significant coefficients for population and population density, of course, such a finding is not all that surprising since the diversity index is strongly correlated with both of these variables.[20] Although not reported, there is also a general lack of significant coefficients across the 17 broad industry shares. Collectively, these results suggest that, after accounting for the scale of a worker's own industry, the overall diversity and industrial makeup of a metropolitan area are not important determinants of individual-level computer usage. Interpreting computer adoption as an indicator of technological change, such a result stands in contrast to the literature stressing the importance of diversity (i.e. 'Jacob's' externalities) over localization (see, for example, Harrison et al. (1996)). After having accounted for the local scale of an industry, the size and diversity of the surrounding market are not important correlates of computer usage.

3.3 Education-Group Estimates

As demonstrated by the results thus far, computer use increases significantly with education, both in absolute terms (Table 1A) and conditional on a variety of personal characteristics (Table 2). This feature of the data suggests that the relationship between city-industry employment and computer usage may vary by educational attainment. In such an instance, the models estimated above would be misspecified.

estate; business and repair services; personal services; entertainment and recreation services; medical services; educational services; social services; other professional services.

[20]The correlation of the Dixit-Stiglitz index with log population is 0.77; with log density, 0.72.

Indeed, it could very well be the case that workers with low levels of education exhibit little variation with respect to their use of computer technology while workers with high levels of education show large increases in computer use as industry scale rises. When pooled, the resulting coefficient on log own-industry employment may very well be positive, but the relationship would be driven entirely by highly educated workers.

To examine this possibility, I interact the logarithm of own-industry employment with each of the education group indicators - no high school, some high school, high school, some college, college - which are entered in place of log (Emp_{ict}) in equations (1) and (2). LPM and probit estimates from the specification in which all of the city-level variables considered so far (i.e. specification VI from Table 3) appear in Table 4.

What they show, however, is a lack of any substantial difference between the localization coefficients across education categories within either estimation technique. Only the probit coefficient for the no high school category seems to diverge from the other coefficients in any significant way. Still, formal tests fail to reject (at conventional significance levels) the hypothesis that all education groups carry the same coefficient on log own-industry employment. These results are summarized in the bottom two rows of Table 4. The localization-computer usage relationship, therefore, seems to hold uniformly across workers of differing 'skill' levels.

3.4 Controlling for Computers at Home

As pointed out by Krueger (1993), there may be a variety of unobserved worker characteristics that lead some individuals to take jobs that require the use of a computer while others do not. If these characteristics are correlated with localization (e.g. workers with propensities to self-select into jobs that make use of computer equipment may choose to live in large labor markets), the estimated coefficients on log industry employment would be biased.

In an effort to address this matter, I follow Krueger's (1993) strategy of conditioning on whether a worker reports having a computer at home.[21] Although only a rough proxy for unobserved heterogeneity, this variable should at least capture some of the characteristics by which workers sort into computer- and non-computer-related jobs.

The results, which have been suppressed in the interest of saving space, reveal a significantly positive association between computers at home and computers at work. The LPM and probit estimates both suggest that the presence of a computer at home increases the likelihood that a worker will use a computer at work by roughly 8 to 10 percentage points. More importantly, the results also reveal virtually no change in any of the localization coefficients. The LPM and probit coefficients in the pooled specifications average, respectively, 0.015 and 0.023 just as in Tables 2 and 3. The education-group specific results are similarly close to what is reported in Table 4.

3.5 Industry-Specific Estimates

While the analysis above accounts for industry-specific fixed effects in computer usage, it does not consider inter-industry differences in the relationship between computer usage and city-industry employment. In light of the differences in mean computer usage (Table 1B) across different sectors, it is reasonable to expect such slope differences too.

Just for the sake of showing some broad industry differences, Table 5 reports the estimated coefficients for 18 relatively aggregated sectors. Given the similarities between the LPM and probit model results, I focus only on the estimation of the linear probability model in this instance.[22] Interestingly, while there is some heterogeneity across industries (e.g. the coefficient for educational services is 0.013 while that for mining is 0.06), the results show an

[21] This variable is created from the responses to the question in the CPS that asks if there is a computer in the household.

[22] Since the LPM estimates are easier to compute than the probit coefficients, this greatly facilitates the estimation, particular when considering 200 individual slope parameters below.

impressive degree of uniformity. All are positive and significantly non-zero at conventional confidence levels.

Results from the more detailed set of industries are summarized in Table 6. To save space, I have limited the results to the 20 largest and 20 smallest coefficients from the 201 estimated. As can be seen, the localization parameters range from a maximum of 0.14 (Leather Tanning and Finishing) to a minimum of -0.1 (Mobile Home Dealers and Coal Mining), indicating that, at this level of disaggregation, not all industries exhibit increased computer usage as city-level employment grows. However, for the majority of sectors, the association is positive. Of the 201 industries in the sample, 160 produce positive coefficients on log own-industry employment, 85 of which are significant at 10 percent. Of the remaining 41, only 3 are statistically non-zero at conventional significance levels (Office and Accounting Machines (321), Logging (230), and Metalworking Machinery (320)).

3.6 Wages, Localization, and Computer Usage

Although the primary intent of this paper is to explore technology differences as a function of localization, the evidence reported thus far leads naturally to the following question: given that workers employed in cities with a large own-industry presence are more likely to use relatively advanced technologies at the workplace, do localization economies disappear after we account for these technological differences? To provide an answer, I consider the following straightforward characterization of hourly labor earnings:

$$w_{ict}^{j} = \mu_i + \mu_c + \mu_t + \beta_t \mathbf{x}_{ict}^{j} + \gamma \mathbf{z}_{ct} + \epsilon_{ict}^{j} \tag{3}$$

where w_{ict}^{j} is the log hourly wage of worker j, employed in industry i of city c in year t; μ_i, μ_c, and μ_t are industry-, city-, and time-specific fixed effects; $\mathbf{x}_{ict}^{j}$ and $\mathbf{z}_{ct}$ are the same vectors of personal and city-level variables specified in equations (1) and (2); and ϵ_{ict}^{j} is a residual. To this baseline specification, I add two variables: the logarithm of a worker's city-industry employment and a dummy variable describing his or her computer usage at work. The basic intent here is to compare the estimated coefficient on log city-industry employment before conditioning on a worker's computer usage to the coefficient after doing so. If localization effects are driven by the use of more sophisticated capital equipment, controlling for individual computer usage should substantially reduce the magnitude of the coefficient on log own-industry employment.

Hourly wages are calculated by dividing a worker's weekly wage and salary income by usual hours worked per week.[23] Because the CPS only collects wage and salary information for a subset of the respondents, the sample size that can be used to estimate equation (3) is only about one quarter of the sample available for the study of computer use. In forming the sample, however, I also restrict the analysis to individuals with a calculated hourly wage between 1 and 100 dollars (in real 2000 dollars) in an effort to minimize the effects of outliers. Doing so produces a sample of 22794 observations.[24]

Results appear in Table 7. For the sake of brevity, I have limited the output reported to the coefficients on log own-industry employment and computer usage. The first column, labeled I, demonstrates the standard localization result: after conditioning on a host of individual-specific observable characteristics, including education, experience, occupation, and industry, as well as a variety of city-level features, there is a significantly positive association between the scale of a worker's own industry and his or her hourly earnings. Based on the point estimate, the implied elasticity is 0.028 which is similar to what previous work has documented, at least for manufacturing (e.g. Henderson (1986, 2003), Wheeler (2004)).

Does this estimated localization effect change once we condition on an individual's com-

[23]Additional details about the computation of hourly wages appear in the Appendix.

[24]The estimates of interest, as it turns out, were not sensitive to this trimming.

puter usage? What we can see from the second specification in the table (labeled II) is that, while the use of a computer at work is positively associated with a worker's wage – the coefficient suggests that, all else equal, computer usage is associated with 12 percent higher hourly earnings[25] – the estimated magnitude of the localization coefficient changes only slightly between the two specifications. In particular, the elasticity only drops from 0.028 to 0.026, leading to the conclusion that only a very small fraction (less than 10 percent) of the estimated boost to wages associated with the geographic concentration of industry can be linked to the use of computer equipment.[26]

Because the majority of localization studies focus on manufacturing, I repeated the analysis just using those workers employed in one of the 77 manufacturing industries identified in the sample.[27] Although the estimated localization coefficient turns out to be somewhat smaller than what is reported above for all 201 industries, 0.018 (t-statistic = 3.33), it is still significantly positive and suggestive of an important shift in labor earnings. When I control for computer usage, I find very much the same computer premium, 0.12 (t-statistic = 7.46) as previously. What is more, I also find nearly the same localization term, 0.016 (t-statisic = 2.97).

Might there be differences across education groups? In particular, while the use of computer equipment might not explain localization effects across all individuals as a whole, could the extent to which this particular technology influences the localization-wage connection differ by education group? Localization effects on wages might, for instance, stem from the use of more advanced technologies among one type of worker but not another. The

[25]As noted in the Introduction, this result is very similar to what Krueger (1993) estimates with the 1984 and 1989 CPS data.

[26]Quantifying localization by employment shares rather than log employment produces a similar result: the coefficient on a city-industry's share of employment drops from 2.18 to 1.86 once individual computer usage is added to the regression.

[27]This leaves 4606 observations over the four years.

third and fourth columns of results in Table 7 report education-group-specific estimates, beginning with the inclusion of log own-industry employment only in specification III, and then after controlling for individual computer usage in specification IV.

On the whole, the coefficients show remarkable consistency across the returns to both city-industry scale and computer use across workers of different educational attainment levels. Although formal tests reject the hypotheses that all five localization coefficients are equal and all five computer use coefficients are equal, the point estimates show relatively little variation. Localization elasticities range between 0.013 for workers with 0 to 8 years of education to 0.036 for workers with a bachelor's degree or more. Computer usage coefficients fall between 0.1 for workers with some college and 0.15 for college graduates.

Moreover, while the magnitudes of the log own-industry employment coefficients do decline between specifications III and IV, the size of the decline is small and approximately the same for workers of all five groups: 0.013 to 0.011 for no high school, 0.029 to 0.026 for some high school, 0.021 to 0.019 for high school, 0.029 to 0.027 for some college, 0.036 to 0.034 for college. Hence, the extent to which localization economies are accounted for by computer usage appears to be small for workers at all points of the educational attainment distribution.

3.7 Industry-Specific Wage Results

Because previous work has shown the localization-wage association to differ across industries, I have also estimated (3) allowing the coefficient on log own-industry employment to differ across the 201 sectors identified the sample. To summarize briefly, the resulting estimates show that, for a majority of industries, geographic concentration is associated with higher average wages. Without conditioning on computer use, 148 of the 201 coefficients are positive; 60 of which differ statistically from zero. Furthermore, the average value across these 201 estimates, 0.031 (standard deviation = 0.1), is very close to what is reported in

Table 7 just as one would expect.

When I condition on individual-level computer usage, I find essentially the same results. In particular, when a single computer-use indicator is added to the regression, the average change in the log own-industry employment coefficients - relative to the first regression in which it does not appear - is only -0.001 (standard deviation = 0.009).[28] When the computer use coefficients are also permitted to differ by industry, the average change of the employment coefficients is somewhat larger in magnitude: -0.003 (standard deviation = 0.04).[29] Nevertheless, these figures are small when compared to a mean of 0.031 for the unconditional localization estimates, suggesting once again that computer use does not seem to account for much of localization-wage association.

A closer look at this result is given by the following simple exercise. Suppose that we take the estimated industry-specific log industry employment coefficients from the linear probability model (1) - summarized in Table 6 - and correlate them with the industry-specific log industry employment coefficients from the wage equation (3).[30] Doing so should provide an indication of extent to which industries which experience large localization-wage 'effects' also experience large localization-computer use 'effects.'

The resulting correlation, 0.14 (p-value = 0.05), indicates that the two sets of coefficients are, in fact, positively related.[31] Thus, industries which experience large localization-wage

[28] The average log own-industry employment coefficient is 0.03 (standard deviation = 0.1). 147 are positive, 62 of which are significant.

[29] The average log own-industry employment coefficient is 0.029 (standard deviation = 0.1). 143 are positive, 63 of which are significant.

[30] For this exercise, I use the coefficients from the specification of (3) in which I have not conditioned on computer use. As suggested by the results above, however, it makes little difference if, instead, I use the coefficients from either specification in which computer use is included. The correlations among the three sets of coefficients all exceed 0.9.

[31] This is an unweighted correlation. Because the estimated coefficients have non-zero variances, I also calculated a weighted correlation where the weights are given by the inverse of the sum of the two coefficient standard errors (i.e. the localization-wage standard error and the localization-computer use standard error).

effects also tend to show larger increases in computer usage with local market scale than do industries experiencing only small localization-wage effects. This result helps to explain the fact that the estimated localization-wage associations diminish somewhat when computer use is included in the regression.

However, the correlation is also relatively small, suggesting a fair amount of 'independence' between the two. That is, industries exhibiting large wage gains with city-industry employment only experience *modestly* higher rates of computer adoption as city-industry employment increases than industries exhibiting small wage gains. Put differently, the localization-wage effects in the pooled results (Table 7) seem to be driven primarily by industries for which there is only a moderate increase in the frequency of computer use with local market scale. At the same time, the localization-computer use associations in Tables 2 and 3 appear to be driven by industries which experience only moderate increases in wage earnings with local market scale. This result, of course, helps to explain why the localization-wage coefficients drop only very little once computer use is added to (3).

4 Conclusion

A large literature has shown that the geographic concentration of industry is associated with significantly higher productivity, measured either at the plant or worker level. While often interpreted as evidence of positive externalities, this paper has explored the hypothesis that localization economies may be related to the use of more advanced technologies.

Evidence taken from the Current Population Survey on individual computer usage indicates that the frequency of computer use is positively associated with the magnitude of an industry's presence within a metropolitan area. These results hold with striking consistency across a wide array of relatively detailed industries and are robust to the inclusion

This procedure gives greater weight to those observations which are estimated more precisely. The resulting correlation turned out to be quite similar to the unweighted statistic, 0.12 (p-value = 0.08).

of a variety of city-specific characteristics, both time-varying and fixed. In spite of this finding, however, I also find that the association between a worker's hourly wage and the size of his or her own city-industry is not strongly influenced by computer use. Hence, although technology appears to differ across industrial clusters of varying sizes, technological differences (at least as quantified by computer usage) account for very little of the observed shift in productivity that accompanies localization.

Such findings raise two issues for future work. First, since the CPS computer usage data is rather limited in terms of describing technological differences across workers and producers, exploration of more detailed plant-level data on the types of capital equipment used would provide a more definitive conclusion regarding the extent to which observed technological differences explain localization effects. This paper has merely taken a first step in answering this research question.

Second, while this paper has reported some empirical evidence on technological use, it has not offered any theoretical insights that may help to understand why workplace technology may vary with city-industry scale. One possibility is that, with localization comes a thick market externality in which producers find it easier to locate skilled employees. Following the hypothesis advanced by Acemoglu (2002), this search externality may encourage producers to adopt more sophisticated technologies. Of course, similar stories could be told with respect to Marshall's (1920) two additional explanations for localization. Knowledge spillovers or the increased use of specialized input providers may, for some reason, change the nature of the technology that producers adopt.[32] Theoretical work studying this issue would be useful in further assessing the plausibility of these ideas.

[32] Knowledge spillovers across large numbers of workers, for instance, may allow workers to acquire skills at a faster rate (e.g. Glaeser (1999)). This, in turn, may give producers the incentive to adopt advanced (i.e. skill-complementing) technologies.

Table 1A: Computer Usage Statistics

Category	Mean Computer Usage (St. Dev.)	Obs.
Year 1984	0.3 (0.46)	18689
Year 1989	0.39 (0.49)	35502
Year 1993	0.49 (0.5)	32895
Year 1997	0.53 (0.5)	36785
No High School	0.04 (0.2)	4303
Some High School	0.14 (0.34)	9050
High School	0.34 (0.47)	42951
Some College	0.52 (0.5)	32507
College	0.67 (0.47)	35060
Female	0.53 (0.5)	57380
Male	0.39 (0.49)	66491
White	0.47 (0.5)	105195
Non-White	0.37 (0.48)	18676
Union	0.33 (0.47)	4321
Non-Union	0.46 (0.5)	119550
Executive, Admin., Managerial	0.7 (0.46)	17808
Professional Specialty	0.63 (0.48)	19413
Technicians	0.7 (0.46)	4456
Sales	0.46 (0.5)	16166
Administrative Support	0.73 (0.45)	19695
Protective Services	0.25 (0.43)	920
Other Service	0.11 (0.31)	12715
Precision Production, Craft, Repair	0.2 (0.4)	14499
Machine Operators, Assemblers, Inspectors	0.16 (0.4)	7785
Transportation and Material Moving Equip.	0.11 (0.32)	4860
Handlers, Equip. Cleaners, Helpers, Laborers	0.12 (0.32)	4388
Farming, Forestry, Fishing	0.06 (0.23)	1166

Note: 123871 observations. Weighted averages of computer use by category.

Table 1B: Computer Usage by Industry

CPS Code	Industry	Usage Rate
740	Computer and Data Processing Services	0.95
701	Savings and Loan Associations	0.9
702	Credit Agencies, n.e.c.	0.87
322	Electronic Computing Equipment	0.85
700	Banking	0.84
890	Accounting, Auditing, Bookkeeping Services	0.84
730	Commercial Research, Development, Testing Labs	0.81
711	Insurance	0.81
441	Telephone Communications	0.8
710	Security, Commodity Brokerage, Investment Companies	0.79
732	Business Management and Consulting Services	0.78
362	Guided Missiles, Space Vehicles and Parts	0.77
852	Libraries	0.76
432	Services Incidental to Transportation	0.73
440	Radio and Television Broadcasting	0.72
882	Engineering, Architectural, and Surveying Services	0.72
841	Legal Services	0.7
371	Scientific and Controlling Instruments	0.7
380	Photographic Equipment and Supplies	0.69
512	Electrical Goods	0.69
100	Meat Products	0.18
60	Construction	0.17
650	Liquor Stores	0.17
252	Structural Clay Products	0.16
641	Eating and Drinking Places	0.16
832	Nursing and Personal Care Facilities	0.16
771	Laundry, Cleaning, and Garment Services	0.15
151	Apparel and Accessories	0.15
602	Dairy Products Stores	0.14
21	Horticultural Services	0.12
772	Beauty Shops	0.11
770	Lodging Places	0.1
722	Services to Dwellings and Other Buildings	0.1
132	Knitting Mills	0.08
402	Taxicab Services	0.08
230	Logging	0.07
610	Retail Bakeries	0.07
220	Leather Tanning and Finishing	0.06
780	Barber Shops	0.01
782	Shoe Repair Shops	0

Note: Weighted averages of computer use by industry.

Table 2: Computer Usage and Localization

Baseline Specifications

Variable	LPM I	LPM II	LPM III	Probit Model I	Probit Model II	Probit Model III
No High School	-0.075	-0.075	-0.074	-0.24	-0.24	-0.24
	(8.4)	(8.4)	(8.4)	(15.1)	(15.2)	(15.1)
Some High School	-0.06	-0.06	-0.06	-0.12	-0.12	-0.12
	(13.8)	(13.8)	(13.7)	(14.9)	(14.9)	(14.9)
Some College	0.07	0.07	0.07	0.1	0.1	0.1
	(17.6)	(17.6)	(17.7)	(17.6)	(17.6)	(17.6)
College	0.14	0.14	0.14	0.17	0.17	0.17
	(23.1)	(23.1)	(23.1)	(22.9)	(22.9)	(22.9)
Experience	0.015	0.015	0.015	0.03	0.03	0.03
	(11.2)	(11.2)	(11.2)	(12)	(12)	(12)
Experience^2	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2
	(8.3)	(8.3)	(8.3)	(9.6)	(9.6)	(9.6)
Experience^3	0.02	0.02	0.02	0.05	0.05	0.05
	(5.9)	(5.9)	(5.9)	(7.6)	(7.6)	(7.6)
Experience^4	-0.002	-0.002	-0.002	-0.005	-0.005	-0.005
	(4.8)	(4.8)	(4.8)	(6.8)	(6.8)	(6.8)
Non-White	-0.04	-0.04	-0.04	-0.07	-0.07	-0.07
	(5.8)	(5.8)	(5.8)	(6)	(6)	(6)
Female	0.04	0.04	0.04	0.06	0.06	0.06
	(12.1)	(12.1)	(12.1)	(11.4)	(11.4)	(11.4)
Female*Non-white	-0.006	-0.006	-0.006	0.003	0.003	0.003
	(0.9)	(0.9)	(0.9)	(0.2)	(0.2)	(0.2)
Union	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02
	(2.4)	(2.4)	(2.4)	(2.3)	(2.3)	(2.3)
Married	0.01	0.01	0.01	0.01	0.01	0.01
	(4.7)	(4.7)	(4.7)	(4.4)	(4.4)	(4.4)
Log Own-Industry	0.015	0.015	0.015	0.023	0.023	0.023
Employment	(6.1)	(6.1)	(6.4)	(6.7)	(6.7)	(7.1)
College Fraction	–	0.38	0.17	–	0.39	0.12
		(1.4)	(0.6)		(0.95)	(0.3)
Log Population	–	–	-0.07	–	–	-0.15
			(1.2)			(1.5)
Log Population	–	–	-0.04	–	–	-0.04
Density			(0.9)			(0.6)
R^2	0.37	0.37	0.37	–	–	–
Log-likelihood	–	–	–	-57944.8	-57944	-57935.2

Note: 123871 observations used in LPM. 123851 observations used in probit model (20 observations from industry 782 - for which all $y^j_{ict} = 0$ - are dropped). The probit coefficients represent estimated marginal associations, computed by estimating the cumulative distribution function at mean regressor values. Coefficients on experience^2 have been multiplied by 100, experience^3 by 1000, experience^4 by 10000. Absolute values of heteroskedasticity-consistent t-statistics (z-statistics), with respect to a null of zero, are reported in parentheses for the LPM (probit) results. All specifications include time-, industry-, and city-specific fixed effects.

Table 3: Computer Usage and Localization

Robustness Checks

Variable	*LPM*			*Probit Model*		
	IV	V	VI	IV	V	VI
Log Own-Industry Employment	0.015	0.015	0.015	0.023	0.023	0.023
	(6.4)	(6.3)	(6.3)	(7)	(7)	(7)
College Fraction	-0.11	-0.11	-0.25	-0.05	-0.04	-0.15
	(0.4)	(0.4)	(0.8)	(0.1)	(0.1)	(0.3)
Log Population	-0.09	-0.09	-0.05	-0.13	-0.11	-0.05
	(1.4)	(1.3)	(0.6)	(1.4)	(1.1)	(0.4)
Log Population Density	-0.03	-0.03	-0.06	-0.04	-0.05	-0.1
	(0.5)	(0.4)	(0.9)	(0.5)	(0.6)	(1.1)
Time Varying Personal Coefficients	Yes	Yes	Yes	Yes	Yes	Yes
Dixit-Stiglitz Diversity Index	–	0.08	-0.3	–	-0.4	-1.1
		(0.1)	(0.4)		(0.4)	(0.9)
Industrial Composition	No	No	Yes	No	No	Yes

Note: 123871 observations used in LPM. 123851 observations used in probit model. The probit coefficients represent estimated marginal associations, computed by estimating the cumulative distribution function at mean regressor values. All personal covariates including education, experience, marital status, race, gender, and occupational indicators are given year-specific coefficients. Absolute values of heteroskedasticity-consistent t-statistics (z-statistics), with respect to a null of zero, are reported in parentheses for the LPM (probit) results. Coefficients on the diversity-index have been multiplied by 10000. All specifications include time-, industry-, and city-specific fixed effects.

Table 4: Computer Usage and Localization

By Educational Level

Category	LPM	Probit Model
No High School	0.017	0.007
	(5.8)	(0.7)
Some High School	0.017	0.02
	(6.7)	(4)
High School	0.016	0.023
	(8.4)	(8.1)
Some College	0.016	0.025
	(5.6)	(6.5)
College	0.014	0.022
	(4)	(5.2)
Test Statistic	0.44	6.1
p-value	0.78	0.19

Note: 123871 observations used in LPM. 123851 observations used in probit model. Coefficients on interactions between education indicators and log own-industry employment. The probit coefficients represent estimated marginal associations, computed by estimating the cumulative distribution function at mean regressor values. Heteroskedasticity-consistent t-statistics (z-statistics), with respect to a null of zero, are reported in parentheses for the LPM (probit) results. "Test Statistic" represents test of null that all five coefficients are equal. Specification includes all variables listed in specification VI of Table 3. All specifications include time-, industry-, and city-specific fixed effects.

Table 5: Computer Usage and Localization

Major Industry-Specific Results

Industry	Coefficient (t-stat.)
Agriculture, Forestry, Fisheries	0.025 (2.4)
Mining	0.06 (6.8)
Construction	0.035 (6.1)
Nondurable Manufacturing	0.022 (4.1)
Durable Manufacturing	0.037 (6)
Transportation	0.035 (5.8)
Communications	0.018 (2.2)
Utilities and Sanitary Services	0.029 (3.3)
Wholesale Trade	0.033 (5.5)
Retail Trade	0.029 (5.4)
Finance, Insurance, Real Estate	0.025 (5.3)
Business and Repair Services	0.037 (7)
Personal Services	0.031 (5)
Entertainment and Recreation Services	0.024 (4.3)
Medical Services	0.022 (4.3)
Educational Services	0.013 (1.8)
Social Services	0.048 (4)
Other Professional Services	0.033 (5.3)

Note: LPM estimates. 123871 observations. Regressions include all variables from specification *IV* of Table 3.

Table 6: Computer Usage and Localization

Detailed Industry-Specific Results

CPS Code	Industry	Estimate (t-stat.)
	Panel A: 20 Largest Coefficients	
220	Leather Tanning and Finishing	0.14 (6)
311	Farm Machinery and Equipment	0.1 (2.7)
150	Misc. Textile Mill Products	0.09 (2.3)
190	Paints, Varnishes, and Related Products	0.085 (2.9)
600	Misc. General Merchandise Stores	0.078 (2.6)
101	Diary Products	0.077 (2.5)
661	Sewing, Needlework, and Piece Goods Stores	0.073 (2.4)
40	Metal Mining	0.071 (2.8)
191	Agricultural Chemicals	0.07 (1.6)
361	Railroad Locomotives and Equipment	0.069 (2.4)
141	Floor Coverings	0.068 (1.9)
781	Funeral Service and Crematories	0.067 (1.4)
551	Farm Products - Raw Materials	0.062 (1.2)
621	Gasoline Service Stations	0.061 (3.2)
500	Motor Vehicles and Equipment	0.06 (2.3)
540	Paper and Paper Products	0.06 (2)
262	Misc. Nonmetallic Mineral and Stone Products	0.058 (2.1)
312	Construction and Material Handling Machines	0.057 (3.4)
530	Machinery, Equipment and Supplies	0.056 (5.3)
201	Misc. Petroleum and Coal Products	0.056 (1.9)
	Panel B: 20 Smallest Coefficients	
590	Mobile Home Dealers	-0.1 (1.6)
41	Coal Mining	-0.1 (1.3)
422	Pipe Lines	-0.066 (1.3)
321	Office and Accounting Machines	-0.062 (2.4)
622	Misc. Vehicle Dealers	-0.062 (1.1)
30	Forestry	-0.053 (1.6)
230	Logging	-0.047 (1.6)
160	Pulp, Paper, Paperboard Mills	-0.045 (1.7)
801	Bowling Alleys, Billiard and Pool Parlors	-0.042 (1.1)
821	Offices of Chiropractors	-0.042 (1.2)
681	Retail Florists	-0.03 (0.9)
232	Wood Buildings and Mobile Homes	-0.022 (0.5)
830	Offices of Health Practitioners, n.e.c.	-0.022 (0.7)
210	Tires and Innertubes	-0.022 (1)
161	Misc. Paper and Pulp Products	-0.021 (0.8)
140	Dyeing and Finishing Textiles	-0.02 (0.7)
670	Vending Machine Operators	-0.02 (0.4)
320	Metalworking Machinery	-0.02 (1.7)
110	Grain Mill Products	-0.019 (0.5)
370	Cycles and Misc. Transportation Equipment	-0.019 (0.6)

Note: LPM estimates. 123871 observations. Regressions include all variables from specification *IV* of Table 3.

Table 7: Wage Regression Results

	Specification			
	I	*II*	*III*	*IV*
Log Own-Industry	0.028	0.026	–	–
Employment	(7.1)	(6.8)		
Computer Use	–	0.12	–	–
		(15.6)		
Log Own-Industry	–	–	0.013	0.011
Employment*No High School			(1.55)	(1.36)
Log Own-Industry	–	–	0.029	0.026
Employment*Some High School			(4.75)	(4.42)
Log Own-Industry	–	–	0.021	0.019
Employment*High School			(4.82)	(4.43)
Log Own-Industry	–	–	0.029	0.027
Employment*Some College			(6.12)	(5.72)
Log Own-Industry	–	–	0.036	0.034
Employment*College			(7.17)	(6.87)
Computer Use*	–	–	–	0.13
No High School				(2.02)
Computer Use*	–	–	–	0.11
Some High School				(4)
Computer Use*	–	–	–	0.12
High School				(10.82)
Computer Use*	–	–	–	0.1
Some College				(8.2)
Computer Use*	–	–	–	0.15
College				(9.91)
R^2	0.52	0.52	0.52	0.52

Note: 22794 observations. Dependent variable is log hourly wage. Regressions also include education, experience, occupation, race, gender, marital status, and union membership (all of which carry time-varying coefficients); industry-, city-, and time-specific intercepts; log resident population, log population density, and the college rate. Heteroskedasticity-consistent t-statistics, with respect to a null of zero, are reported in parentheses.

A Appendix

A.1 Current Population Survey Data

The October supplements of the CPS included questions about computer usage. Workplace usage is quantified from the responses to the question "Do you directly use a computer at work?" All calculations in the 1984, 1989, and 1993 samples are weighted by the CPS 'supplement' weight. Calculations using the 1997 data are weighted with the CPS 'final' weight. A worker's potential experience is computed as the maximum of (age-years of education-6) and 0. Since the CPS in 1993 and 1997 does not code educational attainment in years of schooling completed for all individuals, years of education are imputed from Table 5 of Park (1994) for these two years of data.

In the wage analysis, I calculate hourly wages by dividing an individual's weekly wage by usual hours worked per week. These are converted to real terms using the Personal Consumption Expenditure Chain-Type Price Index of the National Income and Product Accounts. Topcoded weekly wages (999 dollars for 1984, 1923 dollars for 1989, 1993, 1997) are multiplied by 1.5 to approximate the mean of the upper tail of the wage distribution. This procedure is similar to those used in other studies of CPS wage data (e.g. Katz and Murphy (1992), Juhn et al. (1993), Card and DiNardo (2002)). To remove the influence of outlier observations, I restrict the sample to individuals with a calculated hourly wage between 1 and 100 dollars (in year 2000 dollars). The resulting sample of 22794 observations on hourly wage earnings has a mean of 14.27 dollars (standard deviation = 9.46).

A.2 Industry Coverage

A total of 201 industries at various levels of aggregation (two-, three-, and four-digit standard industrial classification) appear in final sample. These industries cover most of the private sector with the exception of agricultural production (i.e. 1984 CPS industry codes 20 through 890). Since the CPS industry codes changed slightly between 1992 and 1993, a consistent set of codes have been implemented based on the crosswalks provided by the U.S. Bureau of the Census. These are described by Barry Hirsch at his website www.trinity.edu/bhirsch. After matching these consistent industry codes to their SIC counterparts, total city-level employment for these industries is constructed from County Business Patterns files for each of the years by aggregating county-level data to the metropolitan area level. Due to disclosure constraints, employment figures in the CBP are occasionally reported as ranges for certain county-industries: 0-19, 20-99, 100-249, 250-499, 500-999, 1000-2499, 2500-4999, 5000-9999, 10000-24999, 25000-49999, 50000-99999, 100000 or more. The two largest ranges were not reported for any of the county-industries used in this paper. Where ranges are given, I impute employment by taking midpoints.

Table A1: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Uses Computer at Work	0.45	0.5	0	1
No High School	0.04	0.16	0	1
Some High School	0.07	0.26	0	1
High School	0.35	0.48	0	1
Some College	0.26	0.44	0	1
College	0.28	0.45	0	1
Experience	18.4	11.9	0	59
Non-White	0.15	0.36	0	1
Female	0.46	0.5	0	1
Female*Non-White	0.08	0.27	0	1
Union	0.035	0.18	0	1
Married	0.6	0.49	0	1
Own-Industry Employment	33180	58268	2	448578
College Fraction	0.23	0.05	0.1	0.39
Resident Population	4544019	5195918	100327	18282477
Population Density	2300.4	3429.6	14.4	14433.3
Dixit-Stiglitz Diversity Index	453.9	408.9	43.9	1682.9

Note: Unweighted summary statistics. 123871 observations over 207 metropolitan areas.

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