Information Technology Diffusion, Human Capital, and Spillovers: PC Diffusion in the 1990s and early 2000s

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I. Introduction

The literature on technology diffusion is immense, reflecting the importance of the adoption and implementation of new technologies in economic growth. One repeated and striking finding is that technology does not diffuse uniformly across cites, states, or countries. For instance, Griliches (1957) noted how hybrid seed corn adoption varied markedly across states. More recently, Comin and Hobijn (2004) have documented the large variance across countries in the adoption of a slew of technologies over the past several hundred years.[1]

The reasons that have been suggested for such differences across regions (whether they be cities, states, or countries) are many and varied, including theories about social networks, farm size, government barriers, and human capital.[2] The idea that human capital is important from a technology adoption perspective dates back to at least Gerschenkron (1962). One of the basic ideas is that countries/regions with high levels of human capital are able to learn and use new technologies more quickly than countries with lower levels of human capital.[3] Supporting this hypothesis, Benhabib and Spiegel (2002) find that countries with higher levels of human capital enjoy faster growth in total factor productivity growth.

In a nearly separate strand of literature, there have been several formal models developed that examine the interaction between human capital and technology adoption, including that of Beaudry and Green (2002) and Acemoglu (1998), and these model have been used to examine the purchases of computers (Nestoriak 2005) and advanced manufacturing technologies (Lewis 2005). The idea that information technology and skills are complements has been a tenet of those who argue that recent technological change (especially change in information technology) is skill biased (for example, Katz and Murphy 1992).

[1] Skinner and Staiger (2005) examine regional differences in the diffusion of beta blockers.
[2] See Skinner and Staiger for a brief summary of the debate that occurred between Griliches and several sociologists over the importance of social networks. For a careful examination of technology diffusion and social networks, see Conley and Udry (2004). Parente and Prescott (1994) suggest that countries vary by their barriers to technology adoption.
[3] Foster and Rosenzweig (1995) find evidence that technology adoption rises with experience using new technology.

Borrowing the above ideas, in addition to some others, in this paper we focus on the regional diffusion of the personal computer (PC), the epitome of the IT revolution. The PC and its complement, local area networks, came to the fore during the 1990s, in some cases replacing more centralized systems and in some cases providing computing to parts of the economy that previously had none. During the 1990s, more money was spent on PCs and they had higher nominal and real growth rates than other types of computers.

Using a rich dataset on information technology usage, we find there are large, persistent regional differences in PC diffusion and these differences are somewhat persistent. These differences do not arise because of industry composition effects; large differences remain across cities after controlling for the industry and establishment size make-up of cities. In this paper we ask why there are such large differences.

Our approach in answering this question is two fold. First, we examine inter-city differences in human capital. In dealing with human capital, it is important to address the potential endogeneity of the inter-city distribution of human capital and how that human capital evolves over time: a priori, there is ample reason to believe that factors that affect the level of human capital in an area also affect technology adoption. Therefore, we make use of instruments that are correlated with human capital supply in an area but are not directly related to the technology adoption decision, primarily historical differences in the local presence of degree-granting institutions (which tend to raise human capital levels locally). For similar reasons, we implement instruments that are related to changes over time in the human capital in cities, focussing on historical differences in the presence of Mexican immigrants, a group which has had a large and geographically differential impact on skill mix during the immigration boom of recent decades.

Our second approach to understanding persistant differences in PC diffusion is to investigate potential spillovers from a number of sources. We begin by examining whether there are local spillovers between the IT producing/service sector and the IT using sector; in cities with a large IT producing/service sector, there is the potential of spillovers as workers shift from the IT sector to other sectors or through social networks. The second spillover we examine is the from the finance industry, the most IT intensive industry. As with IT, workers changing industry and social networks could carry technologies from finance into other industries. For both the IT producing/service and financial sectors, we exploit the inter-city variation in the distribution of employment before the advent of the PC to measure the effect of the spillover. Finally, we examine corporate spillovers: the idea that the technology used at an establishment is provided by the corporation to which it belongs, permitting corporations to determine what technologies are adopted in regional offices regardless of local conditions. We find that while corporate effects do exist, they have little effect on the inter-city variation in PC intensity.

Overall, our results are very robust on the matter of human capital and technology adoption. We find that cities that have a high share of college graduates have much higher adoption rates of PCs. Additionally, we find that education is much more important than wages. These results are robust to the instruments that we employ. We also find that there do appear to be spillovers from the IT industry to technology adoption. Further, when examining the changes in technology use, we find that the level of education helps explain the rate of change, not just the level of technology. This finding is consistent with the point of view that a highly educated workforce is more adept at implementing new technologies.

An advantage of our U.S.-based approach over examining cross country data is that by looking within a country, we hold fixed a large number of factors that are potentially important but are difficult to quantify. Yet our comparisons are informative: as is the case with cross-country data, we find wide variation across cities in the U.S. in the use of technology. Perhaps more importantly, the robustness of our results to the use of a variety of different instruments for human capital and controls for spillovers allows us to more confidently state the causal role of human capital in technology adoption.

The following section discusses PCs and the data used in the paper, especially the measures of PC intensity by city. The third section discusses the form of the models we estimate, with special emphasis on the instruments we employ. The fourth section discusses our results, and a brief conclusion hints at what we may be up to next.

II. Computer investment in the 1990s and early 2000's: The personal computer era

II.1 Basic facts

"Information technology" is a nebulous and broad concept. In this paper we focus on one small, though important, part of information technology, the personal computers (PC). The diffusion of PCs is important for a number of reasons. On a heuristic level, the PC represents the epitome of changes in business computing over the past several decades, namely the migration from mainframe platforms to client/server platforms (see Bresnahan and Greenstein 1997). The PC has also increased its role: initially being mainly a stand-alone device used for office automation tasks such as spreadsheets and word processing, it has now become a communications device, a terminal, and in some cases, a server.

On an empirical level, nominal and real spending on PCs grew sharply during the 1990s and spending on PCs outstripped spending on other types of computers. As shown in table 1, real computer investment during the 1990s was propelled by strong gains in nominal spending (10 percent per year) and substantial drops in prices (18 percent). The segment within the computers and peripherals category that posted the largest increases was PCs; real spending on PCs averaged a phenomenal 50 percent growth, with prices falling an average of 25 percent and nominal spending increasing an average of 12 percent. Spending on other computers (including mainframes, midrandges, and workstations) grew more slowly in both nominal and real terms.[4]

Additionally, the amount of money spent of PCs is significant: in 1990, $10.6 billion was spent on personal computers compared to $9.6 billion for other computers. By 2000, the spending on PCs jumped to $34.0 billion compared to $25.5 billion for other computers. During the whole of the 1990s, businesses spent nearly 90 percent more on PCs than they did on other computers and PCs accounted for more than a third of all computer investment. Referring to the bottom panel of table 1, PC spending also held up better than other IT components during the IT downturn--nominal spending on PCs was flat between 2000 and 2003 whereas it declined for most other categories.

These numbers do not include other IT investments that are complementary to PCs, such as s printers and prepackaged software. For instance, prepackaged software experienced much higher growth real growth rates than other types of software (because prices actually fell for prepackaged software), and a disproportionate share of prepackaged software likely went to PCs. Another area of IT investment that is closely linked to PC investment is the investment in local area network (LAN) equipment. LAN investment exploded in the 1990s as prices fell and capabilities expanded.[5]

Official NIPA numbers do not say anything about the diffusion of PCs, or other types of IT goods for than matter. To complement the NIPA data, we use establishment level from 1990 to 2002 (even years only) from a private company, Harte-Hanks (HH). The HH data is an establishment-level survey that collects information about specific technologies, such as the number of IBM mainframes (and what type), the number of Pentium IV PCs, what software applications are used, and so forth. Nearly all of the Harte-Hanks data is based on counts of particular technologies; unfortunately, HH does not collect expenditure data on the different technologies. For this study, there are approximately 80,000 usable observations per year. Additionally, the HH data provides basic information on the

[4] The high rates of growth in real PC investment boosted the growth rate in the capital stock: according to BLS, between 1990 and 2001, the real PC stock grew an average of 42 percent annually whereas the growth rate in the stock of other computers chalked up a lower, but still respectable, 25 percent average rate.

[5] See Doms and Forman (2005).

establishment, such as the corporation to which it belongs, where the establishment is located, the size of the establishment (in terms of employment and revenue), and detailed industry codes of the establishment. In our analysis, we examine establishments with 5 or more employees and establishments in the private nonfarm sector.

Figure 1 shows the crude statistics for PCs and other types of computers relative to employment from 1990 to 2002. Perhaps the most striking series is PCs to employment: over the sample range, the density of personal computers increases 3 fold, from 16.7 PCs per 100 employees in 1990 to 52.3 PCs per 100 employees by 2002. The data for other types of computers (mainframes, midranges and workstations) vary from PCs in several ways. For instance, the number of workstations increased in the early 1990s has been roughly stable since. Conversely, the prevalence of midrange computers (an incredibly broad category) has steadily fallen. Mainframes are relatively scarce (and not shown on the graph), with only about 4 machines per 10,000 workers over our sample period.

The series in figure 1 make no adjustment for quality: a PC or midrange computer in 1990 is treated the same as a PC or midrange computer in 2002. The HH data has some information on the quality of computers. For PCs in each year HH presents the class of microprocessor. For workstations, midranges, and mainframes, HH occasionally reports the processing power as measured by millions of instructions per second (MIPS). Figure 2 shows the distribution of PCs per 100 employees by microprocessor type. This figure clearly shows how successive waves of PCs came to be adopted, from 8088/8086 based machines through the successive waves of Pentium chips. Throughout this paper we focus on PCs/100 employees; where the thrust of the results vary when PCs/100 employees is computed to control for type the type of microprocessor, they will be noted.[6]

[6] Additionally, we have also examined the use of email and the number of computers that are networked and found very similar results.

II.2 Examination of the variance across cities in technology use

Let $\gamma_{i,c,t}$ be the technology at establishment at time *t* for establishment *i* in city *c*. We estimate the following models,

$$(1) \qquad \gamma_{i,c,t} = \sum_{t=1990}^{2002} \left[\beta_{I,t} Ind_{i,t} * Size_{i,t} + \beta_{C,t} City_{i,t} + \beta_{Y,t} Year_{i,t} \right] + \varepsilon_{i,t}$$

where *Ind*, *Size*, and *City* are vectors of dummy variables of industry (3 digit SIC) of the establishment, size of the establishment (8 employment size classes), where the establishment resides (over 200 consolodated metropolitan areas (CMSAs)), and the year of the observation (even years including and between 1990 and 2002). We focus on the $\beta_{C,t}$ coefficients which vary over time and capture the mean differences in technology use across cities after controlling for over 950 industry/size interactions: we often refer to $\beta_{C,t}$ as the corrected PC concentration or PC intensity.

Equation (1) is estimated using OLS and using sample weights derived by comparing the HH data with County Business Patterns.[7, 8] Figure 3 shows the results for $\beta_{C,t}$ for 1990 and 2002 (the 1990 results are shown along the horizontal axis and the 2002 results are shown on the vertical axis). Detailed results are also contained in appendix table 1 for the 160 CMSAs that we were also able to labor market information and make up the bulk of our analysis in later sections.[9]

The axes in figure 3 are scaled to the San Francisco Bay area, the CMSA that consistently ranks very highly in nearly all measures of technology that we have examined. For instance, in 1990 (the X-axis), the mean establishment in San Francisco had 15.9 more PCs per 100 employees than the mean establishment in Hickory North Carolina (the CMSA that frequently ranks the lowest amongst our

[7] The dependent variable in (1) are often truncated at 0 and at an upper bound dictated by employment. To address this distributional issue, two sided Tobit models were also estimated and the results generated are nearly identical.
[8] County Business Patterns provides the employment size distribution of establishments by industry by state and county: the HH data provide information on size, industry, and county as well, so by comparing the two datasets we can ascertain the appropriate sample weights.
[9] We restrict the sample to establishments that reside in metropolitan statistical areas. We do this primarily for data reasons: one of our objectives is to see how local labor market conditions are related to technology choice, and local labor market data is pretty thin for rural areas. With that said, we find that rural areas are much less PC intensive than urban areas, a finding that has been documented elsewhere with other technologies.

CMSAs) after controlling for industry differences across the two cities (Hickory North Carolina is famous for its furniture manufacturing industry though it now is a major producer of fiber optic cable). In 2002, the difference in PC intensity between the Bay Area and Hickory increased to 28.8.[10]

There are several items to note in figure 3. First are the very large differences between the CMSAs, as noted in the Bay Area/Hickory example above.[11] Second, the differences are persistent over time: one crude measure of persistence is the correlation in $\beta_{C,t}$ between 1990 and 2002 is 0.74, almost identical to the Spearman rank correlation. The dashed line on figure 3 is the regression line between the 1990 and 2002 points, and it has a statistically significant upward slope.

A third item to note is that although there is persistence, some cities moved closer to San Francisco, while others moved further away. Looking at figure 3, cities whose points lie above the solid line moved closer to SF; the distance in PC intensity increased for cities that lie below the line. For instance, Hickory moved further away and Boston moved closer. In our sample, 65 cities moved closer to SF while 94 others moved further away. With that said, there was some increased bunching at the top of the PC intensity distribution: in 1990, only 5 were within 3 PCs/employees of SF, whereas by 2002 that number increased to 10.

Equation (1) only controls for industry and size. Further controls were also added to reflect other aspects of technology used at the establishment, especially in 1990. We are interested in knowing whether the results shown in figure 3 are influenced by differences across cities in other aspects of technology that are employed. For instance, do firms in the Boston area disproportionately use Digital Equipment Corporation (DEC) systems, and hence have a lower PC propensity than establishments in the SF Bay area?

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[10] It is important to emphasize that the differences between the $\beta_{C,t}$'s are not directly attributable to industry composition differences across cities: the $\beta_{C,t}$'s strip out the effects of industry, and San Francisco's high $\beta_{C,t}$ does not occur just because San Francisco has proportionately more employment in industries that are relatively IT intensive.

[11] Figure 3 does not show the standard errors of the estimate for each CMSA. We have not yet constructed the standard errors but will do so. However, each point in the figure is based upon at least 200 establishment level observations, and in the case of the larger CMSAs, based on several thousand observations, implying that the standard errors will be relatively small. For the San Francisco Bay area, over 4,000 observations are used.

The short answer to the question of whether the inter-city differences in PC propensity in 1990 are correlated with inter-city differences in other computer platforms appears to be largely no. The HH data provide information on the major system and the vendor of the major system used at the establishment. The HH data also provide information on whether mini, mainframe, and workstation computers are at the site. We modify (1) to control for the presence of mainframes, minis, and workstations, along with controls for the major vendors (IBM, HP, DEC, Wang, Unisys, or other), and controls for whether the major IBM system was a System 36 or AS/400.[12] Although these variables are related to the PC intensity of an establishment, they do very little in explaining the differences across cities in PC intensity. The differences between $\beta_{C,t}$ from (1) and from (1) modified to include major system controls tend to be less than 1 PC per 100 employees for most cities, and a regression between the two measures yields a coefficient extremely close to 1 and an R-square of .94.

In summary, there is tremendous heterogeneity across cities in their propensity to use PCs, and this propensity is somewhat persistent over time. However, by 2002, some cities had closed some of the gap with the Bay Area while others lagged even further behind. The question arises, why did some areas have a greater PC propensity than others and why did some cities catch up?

III. Models of Technology Diffusion

In this paper we examine several factors that may lie behind the geographic patterns of IT diffusion that were shown in the previous section. The factors we examine fall into two categories, human capital and spillovers. In terms of human capital, we basically examine the inter-city patterns of skills and wages and see how those are correlated with the level of technology use and the change in technology use. For spillovers, we examine three specific forms, including spillovers from the IT

[12] We chose these categories because they were the most abundant. In our data, there are literally hundreds of different types of major systems. An establishment with a particular type of DEC mainframe would have the dummy variables for DEC and MAINFRAME set equal to 1, but we do not distinguish between the different types of DEC mainframes.

producing sector, the finance sector, and spillovers at the corporate level. In all of the analysis we are acutely aware of identification/endogeneity problems and devote much of our efforts in trying to minimize these to the greatest degree possible.

III.1 Human Capital

The relationship between labor and technology is complex and has been written on extensively. To simplify matters somewhat, the existing literature can be decomposed into two parts: how technology affects labor demand (e.g., Autor et al., 2003), and how labor affects technology adoption (e.g., Benhabib and Spiegel 2002 for a review). In this paper we focus on the later.

All else equal, it would not be surprising that a city with a highly skilled work force would use some technologies more intensively than cities with lower skilled work forces. One reason might be that human capital and technology are complements, and, indeed, that is what basically lies behind several models, notably the models developed by Beaudry and Green (2000) and Acemoglu (1988).[13] The implications from both these models is relatively straight forward: areas that have a relative abundance of skilled workers are also areas that are likely to have relatively high levels of technology. In the case of Acemoglu's model this is because high relative employment of skilled workers induces innovation directed towards raising the relative output of skilled workers; in the case of Beaudry and Green's model, it is that areas with more skilled labor have a comparative advantage in producing with a technologically-intensive technique.

In a regression framework, an estimable equation could have the following form:

(2) $$\beta_{c,t} = \alpha_0 + \alpha_1 HC_{c,t-1} + \alpha_2 X_{c,t-1} + \varepsilon_{c,t} + \eta_{c,t}$$

where $\beta_{c,t}$ is the adjusted city-level technology use in city *c* at time *t* estimated from equation (1) in the previous section, $HC_{c,t-1}$ is a measure of human capital in the city, $X_{c,t-1}$ is a vector of other

[13] Two papers recently have conducted empirical work examining technology use and local labor market conditions based on the Beaudry and Greene and Acemoglu models. Lewis (2005) examines the use of a set of manufacturing technologies while Nestoriak (2005) examines computer investment.

characteristics of the city, $\varepsilon_{c,t}$ are unobserved characteristics of the city that are related to technology adoption, and $\eta_{c,t}$ is a standard error term. The problem with interpreting estimates of α_1 in (2) as the impact of human capital supply on technology use, as we would like to do, is that there may be determinants of technology adoption omitted from (2) (captured by $\varepsilon_{c,t}$) which are correlated with $HC_{c,t-1}$; if so estimates of α_1 will be biased. For example, many localities use tax incentives to induce high tech enterprises to locate in their market, which may simultaneously attract a skilled workforce to the market.[14] Our approach to this problem is to develop instruments for $HC_{c,t-1}$, that is, variables which are correlated with the human capital in a city but not, we will argue, correlated with any of the unobserved determinants of technology adoption. We discuss our instruments later in this section.

However, there one reason why the variance in HC to be at least partly exogenous. As Gyourko et al. (2004) point out, there are some cities that have amenities that some people value and also have limited capacity in terms of geography (Boston, San Francisco, and Manhattan are prime examples). Gyourko et al. show that over time relatively high skilled/wealthy people tend to congregate in such places. As a consequence, property values escalate in these cities faster than the national average and the share of high wage people living in these cities increase. These cities are referred to as "superstar" cities.[15]

The Gyourko model brings to fore of what we mean by "human capital". Human capital is often proxied by education, in part because education is observed in many datasets. Additionally, it is sometimes argued that education proxies for the ability to copy and to learn, and therefore is an appropriate concept when examining technology diffusion. On average, people who went to college

[14] Another example if there are economies of scale in adoption of new technologies then denser urban markets may be more likely to adopt first. If higher skill workers have a higher willingness-to-pay to live in dense urban markets, as seems to be true empirically, then one would observe (at least partially) spurious correlation between skill mix and technology use driven (in part) by market density. This is just an example, though: in fact, the relationship between city size and technology adoption is quite weak in our sample.

[15] Another mechanism that can cause sorting is if there are spillovers or agglomeration economies. For instance, Moretti (2005) finds that there appear to be spillovers in urban areas between high-skilled workers; all else equal, wages are higher for workers in areas for which there are a lot of other high-skilled workers.

are more likely to successfully adapt to a new technology because they have a demonstrable ability to learn, so the argument goes.

However, it is also popularly known that not all college graduates are created and behave alike, and that ability can vary substantially within observationally identical individuals; in fact, education explains only about 20 percent of the variance in wages in standard regressions. Therefore, examining the wages of the workforce may provide additional information as to the skill of the workforce. In addition, if new technologies are skill intensive (e.g. Autor et al., 2003) then the relative wages of skilled and unskilled workers will affect the choice of technology. An estimable equation then becomes,

(3) $$\beta_{c,t} = \alpha_0 + \alpha_1 HC_{c,t-1} + \alpha_2 X_{c,t-1} + \alpha_3 w_{c,t-1} + \varepsilon_{c,t} + \eta_{c,t}$$

where $w_{c,t-1}$ is a vector of mean log wages in city *c*. Finally, in light of the falling price of information technology over the 1990s, the relationship between human capital and technology use may have changed over time. Therefore, we allow the coefficients to be time-varying

(4) $$\beta_{c,t} = \alpha_{0,t} + \alpha_{1,t} HC_{c,t-1} + \alpha_{2,t} X_{c,t-1} + \alpha_{3,t} w_{c,t-1} + \varepsilon_{c,t} + \eta_{c,t}$$

Another strategy we pursue is to examine the determinants of changes in technology use over the 1990s. This approach allows us to evaluate the view, mentioned above, that highly skilled/educated workers are better able to learn about the new technology and employ the technology profitably, a result that is consistent with the findings of several applied papers.[16] In the case of computers, for instance, having a college degree (an often used measure of human capital for which there is relatively ample data) may act as a signal that a worker has a comparative advantage in learning a new technology; if someone got through college, they can probably learn how to use a PC. An implication from this line of thinking is that areas that have relatively high levels of human capital can catch-up more quickly to the technology frontier than areas with lower levels of education; that is, the change in

[16] See Bartel and Lichtenberg (1987), Benhabib and Spiegel (1994), and Foster and Rosenzweig (1995).

technology in a city is related to the level of human capital. Our estimation equation is a first difference version of (4):[17]

$$(5)\qquad \Delta\beta_{c,t} = \tilde{\alpha}_0 + \tilde{\alpha}_1 HC_{c,t-1} + \tilde{\alpha}_2 \Delta HC_{c,t-1} + \tilde{\alpha}_3 X_{c,t-1} + \tilde{\alpha}_4 \Delta X_{c,t-1} + \Delta\varepsilon_{c,t} + \Delta\eta_{c,t}$$

$\tilde{\alpha}_1$ tells us whether a skilled workforce is advantageous for the adoption of new technologies. In addition, since (5) is a first difference of (4) $\tilde{\alpha}_2$ has a similar interpretation to $\alpha_{1,t}$ of (4), representing the influence cross-city differences in human capital supplies on cross-city differences in the use of technology. A distinction from (4), though, is that estimates of $\tilde{\alpha}_2$ are identified from changes alone which may reduce bias coming from any persistent (and time-invariant) city-level variables we do not observe.[18] Still, as $\Delta HC_{c,t-1}$ and $HC_{c,t-1}$ are not necessarily exogenous to unobserved factors affecting the <u>change</u> in technology over time, we instrument for them in (5) as well.

III.2 Discussion of instruments for human capital

Our main measure of human capital supply in area will be the college "equivalent" fraction, (which we will sometimes abbreviate as CESH) defined to be the fraction of an area's of workers who have a least a four year college degree plus one-half of the fraction with at least some college education. Measures similar to this one are often used in research examining the impact of skill-biased technological change (Katz and Murphy, 1994; Autor et. al., 2003; Card and DiNardo, 2002). To

[17] Wages were removed from (5) only to save space. Both levels and lags of the independent variables appear in a first difference of (4) because of the time-varying coefficients. To see this, take the first difference of (4) (ignoring wages):

$$\begin{aligned}\Delta\beta_{c,t} &= \Delta\alpha_{0,t} + \Delta\left(\alpha_{1,t} HC_{c,t-1}\right) + \Delta\left(\alpha_{2,t} X_{c,t-1}\right) + \Delta\varepsilon_{c,t} + \Delta\eta_{c,t}\\ &= \Delta\alpha_{0,t} + \Delta\alpha_{1,t}\cdot HC_{c,t-1} + \alpha_{1,t-1}\Delta HC_{c,t-1} + \Delta\alpha_{2,t}\cdot X_{c,t-1} + \alpha_{2,t-1}\Delta X_{c,t-1} + \Delta\varepsilon_{c,t} + \Delta\eta_{c,t}\\ &= \tilde{\alpha}_0 + \tilde{\alpha}_1 HC_{c,t-1} + \tilde{\alpha}_2\Delta HC_{c,t-1} + \tilde{\alpha}_3 X_{c,t-1} + \tilde{\alpha}_4\Delta X_{c,t-1} + \Delta\varepsilon_{c,t} + \Delta\eta_{c,t}\end{aligned}$$

In estimation we actually enter the level variables in two lags, e.g. $HC_{c,t-2}$, which can also be justified from a first difference of (4). The reason for this is that "t-2" in practice will be 1980 ("periods" are 10 years in this analysis). The hope is that city characteristics before PCs were available (1981) are credibly exogenous to 1990s PC adoption decisions.

[18] First difference estimates can be biased by <u>time-varying</u> city unobservables and because the impact of unobservables may vary over time. The required assumption for first difference estimates to suffer from less bias than cross-sectional estimates is that $Cov\left(\Delta HC_{c,t-1}, \Delta\varepsilon_{c,t}\right)/Var\left(\Delta HC_{c,t-1}\right) < Cov\left(HC_{c,t-1}, \varepsilon_{c,t}\right)/Var\left(HC_{c,t-1}\right)$

address potential endogeneity in the local college equivalent share, we turn to an instrumental variables strategy. The goal is to find variables that affect the relative supply of educated labor in an area but that arguably have no other direct impact on adoption of new IT technologies. We have two sets of instruments: one for the share of educated workers, $HC_{c,t-1}$, and another for changes in that share $\Delta HC_{c,t-1}$.

Our instruments for $HC_{c,t-1}$ are based on the historical density of colleges in an area. The general idea behind these instruments is that the presence of colleges in an area reduces the cost of obtaining higher education for an area's residents. As a result, human capital theory predicts otherwise similar individuals will have higher college attainment (Card, 1999). At an individual level, for example, several studies have showed that the distance a person lives from a college when they are growing up predicts their college attainment (e.g. Kane and Rouse, 1995; Card, 1995).[19]

One instrument we use, following Moretti (2004), is a dummy for whether or not the metropolitan area has a land-grant college. Land-grant colleges came into existence after Congress in 1862 passed the Morrill Act, which gave states land to fund the creation of university-level agricultural schools. As Nervis's (1962) history describes, after these land-grant colleges were founded they moved away from being strictly agricultural schools, and many developed into large universities (for example, University of Minnesota, University of California, University of Maryland). These schools dramatically increased access to higher education: Moretti (2004) showed areas with land-grant colleges even today tend to have a significantly higher college-educated share. Given the long lag from the founding of these schools until now and their original purpose of providing support for agriculture, it is not incredible to think that the location of these schools is unrelated to unobserved determinants of regional differences in technology and skill mix today. Owing to the fact that all 50

[19] At an aggregate level, another channel through which college density may raise attainment is that people who go away to college may be more likely to search for a job in the labor market where they attended college.

states received at least one land-grant college, the metropolitan areas that have land-grant colleges are quite regionally diverse. Our sample contains 35 such locations, which are listed in Table 2.

To give a preliminary indication of the effectiveness of this instrument, Figure 4 plots kernel density estimates of education mix of metropolitan areas with and without land-grant colleges. The distribution of college share across metropolitan areas, shown in the upper panel of the figure, is distinctively shifted to the right in areas with a land-grant college compared to areas without in both 1980 and 1990. To demonstrate that college towns are not simply more educated for some other reason, the lower panel of the table shows similar density estimates for the share of workers who are high school dropouts.   The fact that the dropout distribution is not shifted for areas with land grant colleges while the college distribution is shifted is is consistent with the view that where land grant colleges happen to be located, they raise college attainment.

In addition to the land-grant colleges, we also use lagged information on local college density generally. Among other things, there has been a dramatic growth in two-year colleges since World War II (documented in Kane and Rouse, 1999) which may have raised educational attainment in areas which received new schools. To capture the effect other colleges may have on local college share, we construct additional instruments using information on enrollment at two- and four-year colleges in 1971 in each metropolitan area.[20]

We make two adjustments to the raw enrollment numbers in order to construct the instruments. First, we remove enrollment at any land grant colleges: we are aiming to capture the college capacity beyond land grant colleges. Second, we residualize the enrollment in the size of the adult population. The purpose of this adjustment is that it is higher education capacity relative to the size of the population, not raw size, which one expects raise the <u>share</u> of the population which is college educated.[21] (For example, New York City had a large number of people enrolled in college in 1971, but that appears to

[20] Data are from the 1971 HEGIS Institutional Characteristics file.

[21] Raw enrollment numbers are also correlated with later college equivalent share. An additional advantage of the residualized numbers is that they are by construction orthogonal to city population, something we do not believe would be a valid instrument for education shares.

be because it is a big city; its college enrollment was not unusually high compared to its size.) The residuals were constructed by regressing total college enrollment (excluding land grant colleges) at two- and four-year colleges on fourth-order polynomials in the size of the 1971 population aged 15-64. Separate regressions were run for two- and four-year college enrollment. Estimated residuals from these regressions serve as our additional instruments.

Table 3 shows the first-stage regression results for 1980 and 1990 CESH with and without additional control variables used in the regressions. The F-statistics indicate that instruments are able to predict regional differences in college equivalent share, with most of the power coming from the land-grant college dummy.

While the college capacity of an area can help predict the long run average college completion rates of an area, we also need instruments for decadal changes in college equivalent share $\Delta HC_{c,t-1}$. Our strategy in this case makes use of the fact that the U.S. has experienced an immigration boom which rapidly altered the skill mix of the workforce in the markets where immigrants cluster. In the past 35 years, the percent of U.S. workers who are foreign-born has risen from 5 (at its low point in 1970) to almost 15. Along with the growth in volume of immigration has been a shift in the origins of immigrants to Latin America and Asia, resulting a mix of immigrants that is less educated, on average, than U.S.-born workers. Chief among these new immigrants are Mexicans, who make up one-third of recent arrivals. Mexican workers have very low levels of four-year college completion rates, on the order of 3 percent, with an additional 8 percent completing at least "some college" education (Lewis, 2004). In contrast, one-quarter of native-born workers have completed a four-year degree, and another one-third complete at least some college. Thus where Mexicans settle, they tend to drive down the proportion of workers who are college educated.

However, we do not use the actual arrivals of Mexican immigrants in different metropolitan areas, which may be endogenous, to generate our instrument. Instead, we rely on another feature of immigration, that newly arriving immigrants have a very strong tendency to cluster into markets where earlier waves of immigrants from the same part of the world settled previously (documented in many studies including Bartel, 1989). As such, places that happened to have settlements of immigrants from Mexico in 1980 tend to have persistently slower growth in share of the population with college attainment during the subsequent decades. The location of such immigrant "enclaves" has been used as instruments for changes in local skill mix in a long labor economics literature examining the impact of immigration on native-born wages and employment (Altonji and Card 1991 is an early example), as well as more recent work examining the impact of local skill mix on on-the-job computer use and the adoption of advanced manufacturing technologies (Lewis, 2004, 2005).

To be more specific, we use as an instrument the share of an area's (working-age) residents who are from Mexico in 1980. Figure 5 and Table 4 show that, as expected, areas with a greater Mexican presence in 1980 saw significantly slower growth in college share between 1980 and 1990: there is a "first stage." Once again the idea is that the initial presence of Mexican settlement acts like a "magnet" for future Mexican immigrants, which in turn drives down the proportion who are college educated. This is demonstrated in Figure 6. The left-hand panel plots the change in the proportion of the population which is Mexican-born in different areas between 1980 and 1990 against the initial proportion (which is the instrument). There is a strong upward sloping relationship between the two; Mexican migration patterns are geographically persistent.[22] In support of the validity of this instrument, we argue that the persistence of Mexican migration derives from non-economic (and non-technologically related) forces like family reunification and the desire to be in a culturally familiar environment. (Note that the instrument is calculated using all Mexicans, not exclusively those who are in the labor force or employed.) Card and Lewis (2005) show that this instrument has little correlation with measures of local economic conditions including employment growth and the wages and employment rates of Mexicans in an area. The right hand panel of Figure 6 shows that areas where

[22] Card and Lewis (2005) find that 75 percent of the cross-metro variation in the volume of Mexican immigration during the 1990s is explained by the location of previous waves of Mexican migrants in 1980 and 1990.

Mexicans arrived during the 1980s, the share of the work force that were college equivalents increased more slowly.

In order for the instrument to be valid, Mexican enclave areas should also not be systematically different from other markets in some way which affects the rate of PC adoption during the 1990s. Figure 6 shows, unsurprisingly, cities in California and Texas are at the top of the list of Mexican enclaves, revealing that the closeness to the Mexican border (as well as historical opportunities for agricultural employment) is an important determinant of the location of Mexican settlements.[23] It is hard to see how closeness to the Mexican border per se would affect technology adoption, though there may be legitimate concerns that instruments may pick up differences in policy in California or Texas, or unmeasured attributes of their economies. However, we have not found that dummies for California or Texas enter significantly in our regressions (nor are our estimates diminished by their inclusion). There is substantial variation in skill mix even within California and Texas. Our argument for this instrument is also aided by the fact that PCs were not available when these enclaves were being established in 1980 and earlier.

III.3 Spillovers and network externalities

When examining information technology diffusion, spillovers and network externalities are phenomena that have received much attention.[24] Network externalities imply that the benefit of a technology increases with the number of others who use that technology (the size of the network). Spillovers, on the other hand, imply that the use of technology by one party could help others in using that technology. For instance, spillovers could occur at a geographic level because of labor markets:

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[23] The locations of Mexicans partly trace its roots to agricultural employment patterns established under the guest worker program of 1942-64, the so-called “Bracero” program. Note the presence of Chicago in the list of top 20 cities, where Mexicans arrived via Midwestern agricultural jobs. (Chicago is in fact the second largest destination for Mexicans after Los Angeles.) Even before that, Mexicans were settling in the what is now the southwestern U.S. when it was Spanish territory, and under the 1848 treaty of Guadeloupe-Hidalgo, which ceded territory to the U.S., the Mexicans were allowed to remain in the U.S. (Daniels, 2004)

[24] See Shapiro and Varian (1999) for an overview of the importance of spillovers and network externalities. Additionally, see Klenow and Goolsbee (2002) for a paper that examines spillovers and provides a more recent review of the spillover literature

the greater the number of workers in an area that know how to use a technology, the easier it becomes for firms to hire workers with those skills. Additionally, local spillovers could occur through social and professional networks: a dentist hears how great a new billing system is from another dentist in her community. Several recent papers have specifically addressed the importance of social networks, including Conley and Udry (2004). This paper also makes clear the econometric hurdles facing research in this area.

One conclusion that has been reached is that separately identifying spillovers from network externalities is extremely difficult (except in special cases, such as with ATM networks). Additionally, differentiating a "spillover" effect from other, often unobserved, characteristics proves challenging. To see why so, examine the following equation of technology use of an establishment that contains a spillover term:

(6) $$\gamma_{i,c,t} = \alpha_0 + \alpha_1 \Gamma_{t-1}^{c} + \alpha_2 X_{i,c,t-1} + \varepsilon_{c,t} + \varepsilon_{i,t}$$

As in section II, $\gamma_{i,c,t}$ is the technology of establishment i in city c at time t. Also, $\Gamma_{c,t-1}$ is a measure of the technology used in the city at time t-1, and the coefficient, α_1, measures the "spillover". From the econometrician's point of view, there are several pieces of information that we do not observe, including some characteristics of the city ($\varepsilon_{c,t}$) and characteristics of the establishment ($\varepsilon_{i,t}$). If there is any correlation between $\varepsilon_{c,t}$ and technology adoption (the common unobservables problem), and if the $\varepsilon_{c,t}$ are serially correlated, then α_1 will be biased upwards. An example would be if we did not observe the educational distribution of a city. Cities with relatively high levels of education would have relatively high levels of $\Gamma_{c,t-1}$.

With the concerns of identification in mind, we attempt several measures of spillovers that hopefully alleviate biasedness in α_1. The three measures we examine are spillovers from the IT producing industry, spillovers from the finance industry, and corporate spillovers.

III.3.1 Spillovers from the IT industry

In examining the results in the various figures and the appendix tables, several cities that are well known for being high-tech centers also appear to have high technology measures, such as San Francisco, Seattle, Boston, and Austin. One possibility is that the high-tech centers provide spillovers to non-high-tech industries, such as workers moving from the high-tech industry to non-high-tech industries, taking with them the knowledge of knowing how to use IT effectively.[25] Additionally, the knowledge of using IT can be transmitted through more informal social networks.

These stories have intuitive appeal, but, econometrically, we face an identification problem: the emergence of the high-tech industry can be correlated with the same factors that affect technology adoption of establishments in that city. In our case, it is likely no coincidence that high-tech centers are in cities with highly educated workforces. To partially address this concern, we develop two measures that hopefully reduce the endogeneity.

One high-tech industry is communication services. In fact, we find there to be a strong, contemporaneous relationship between the share of the workforce employed in this sector and PC propensity. In order to reduce concerns about endogeneity, we use employment distribution of the communications service industry in 1980, several years before divestiture and several years before there was massive entry into the market. The logic behind this instrument is that AT&T's employment distribution in 1980 was the result of decisions made during previous decades before PCs were introduced. For the remainder of the IT sector (IT hardware and software), we similarly use the 1980 employment share.

III.3.2 Spillovers from the finance industry

One of the most IT intensive sectors of the economy is finance. For our sample of establishments, finance establishments have an average of 10 more PCs per 100 employees than other

[25] We have pursued how to obtain information on worker flows across industries but have yet done so to more accurately measure this type of spillover.

industries and are also the most PC intensive of all industries.[26] Therefore, cities with relatively large finance sectors are also cities that will likely benefit from having many people that know how to use and deploy IT effectively. From an estimation strategy point of view, we need a measure of the finance industry that is not correlated with $\varepsilon_{c,t}$. In our regressions, we use the share of employment in the finance industry from 1980. Like several of our other measures, 1980 was before the PC was marketed and well before penetration rates took off.[27]

III.3.3 Corporate spillovers

Our final "spillover" variable derives from the observation that establishments that the technology of an establishment is not independent of the technology of the corporation that it belongs. There are several reasons for establishments within a corporation to share common technology, including costs. One area where intra-corporate transfers of technology have been considered important is in the foreign direct investment (FDI) literature (see Keller 2004 for a review). The basic story is that when companies expand overseas, they take some of their technology with them, and the host country benefits because of the high productivity of the foreign entrant and the spillovers that entail.

In our analysis, a similar story holds. For example, a Wal-Mart store in Hickory N.C. is likely to have technology based on its corporation and not just on the conditions in Hickory (an area that has relatively low levels of education). One way then for technology to diffuse through the country is by the corporate structure; areas that contain many branches of corporations that are relatively IT intensive may themselves become IT intensive. To derive information on the corporate structure across cities, we use the corporate identification information provided in the HH data. A corporate

[26] IT capital is also very high according to the BLS productivity statistics.
[27] We are looking into getting the importance of the finance industry by city for earlier time periods to make it a better instrument, much like the logic used in constructing the land grant college instrument. Glaeser (2005) argues that New York City's prominence as a financial center is a legacy of it being an ideal port much earlier.

identifier is provided for establishments that belong to large corporations, and basic information about the corporation is provided (such as employment and revenue).

Specifically, for each establishment, we measure the PC intensity of other establishments that belong to the firm outside of the city:

$$(7) \qquad f_{i,t} = \frac{\sum_{j \notin C, j \in F_i} PC_{j,t}}{\sum_{j \notin C, j \in F_i} Employment_{j,t}}$$

where F_i is the firm to which establishment i belongs. For instance, if we are examining a GM dealership in Baltimore, we compute the average PC intensity of all GM establishments outside of Baltimore.

We re-estimate (1) with the inclusion of $f_{i,t}$.

$$(8) \quad \gamma_{i,c,t} = \sum_{t=1990}^{2002} \left[\beta_{I,t} Ind_{i,t} * Size_{i,t} + \beta_{C,t} City_{i,t} + \beta_{Y,t} Year_{i,t} + \beta_{f,t} f_{i,t} \right] + \varepsilon_{i,t}$$

Unlike our regressions conducted at the city-level, we examine this corporate spillover effect at an establishment level because we can exploit the variation within a city. In each of the three years we examine (1990, 1996, and 2002), we find the $\beta_{f,t}$ coefficients to be positive and significantly different from 0; that is, establishments that belong to PC intensive firms themselves are more PC intensive even after controlling for the city in which they belong and detailed industry and size class. Therefore, the corporation that the establishment belongs to is an important determinant of the technology that that establishment employs.

However, the main thrust of this paper is in understanding inter-city dispersion in $\beta_{C,t}$. How important are these corporation effects in understanding the dispersion in $\beta_{C,t}$? One way to address this question is to compare the estimates of $\beta_{C,t}$ from (1) with the estimates from (8). In equation (1), the mean corporate effects by city are folded into $\beta_{C,t}$ whereas the estimates of $\beta_{C,t}$ from (8) are computed while simultaneously controlling for corporate effects. We estimate (8) for 1990, 1996, and

2002. We find that corporate effects, although very important at the establishment level, do relatively little in explaining cross city differences: for most cities, corporate spillovers alter $\beta_{C,t}$ by fewer than 2 PCs/100 employees and often by less than 1. That is, in reference to figure 3, the San Francisco Bay area does not have a high PC intensity because it has branches of corporations that are PC intensive, and Hickory NC does not rank low on the PC intensity scale because it lacks branches of PC intensive firms. Further, the results presented throughout this paper (especially the regression results in the next section) are largely unaffected by controlling for corporate effects.

IV. City regression results

Several variants of model (4) are estimated in cross sections for 1990, 1996, and 2002, and for the change in PC intensity from 1990-2002. The results of the regression for these four time periods are summarized in tables 5-8. The variance for each $\beta_{C,t}$ is proportional to the sample size used to construct this measure. Therefore, each regression uses weights equal to the square root of the number of observations (a generalized least squares approach).[28]

The columns in tables 5-8 vary in two dimensions: the first is which sets of independent variables are included and the second is whether college equivalent share (abbreviated as CESH) is instrumented. As discussed in the previous section, the level regressions (1990, 1996, 2002) use land grant colleges and population-adjusted 1971 college enrollment as instruments. In the change regression, the instruments are Mexican immigrant shares. We begin with a broad overview of the results followed by a more detailed numerical analysis.

In terms of the level regressions (1990, 1996, and 2002), the most robust result we have found is that college equivalent share is frequently significantly related to our PC intensity measure.[29,30] The

[28] The results do not change substantially when weights are not used.
[29] We found this result as well when we examined local area networks and email.

coefficients are nearly always significantly greater than 0 and are generally robust to the inclusion of other sets of variables. Also, this variable accounts for a good deal of the variation in PC intensity; examining column 1 of tables 5, 6 and 7, the regression with only CESH and a constant accounts for over half of the variation in $\beta_{C,t}$. Another interesting feature of our CESH results is that the instrumenting using land grant colleges (column 2) generates very similar results; adding additional instruments based on 1971 college enrollment does not affect the results.

The next variables in tables 5-7 are the log of the average wages of the city for high school graduates and graduates from 4 year colleges. These variables were included to capture differences in the quality of college educated and high-school educated workers across cities. Generally speaking, the wages of college graduates are positively associated with PC intensity in 1990 and 1996. However, as more controls are added, the coefficients on the wages tend to diminish, though they do not disappear. The coefficients on the wages for high-school graduates tend to be smaller than those of college graduates and are also rarely insignificantly different from 0.

We also examined several different moments of the wage distribution in addition to the mean of the wage distribution. In nearly all cases, these measures did not influence other coefficients in the model and were statistically insignificant from 0. For instance, we used measures that capture the share of the workforce that is in the top and bottom tails of the national income distribution. The thinking was that cities with large left tails (lots of low wage workers) would be less PC intensive, ceteris paribus. Likewise, cities with fat right tails might be more likely to be PC intensive, especially in 1990 when PC penetration rates were still relatively low. Our rationale was for pursuing this strategy stems from the model of Borghans and Weel (2004). However, we found little relationship so did not include the results in the table.

[30] We also experimented extensively with other definitions of skill in a city, including the share of the population with more than 4 years of college. We repeatedly could not reject the hypothesis that the coefficients on this more highly educated group differed from the 4 year college group.

In other results not reported in any of these tables, we also examined whether the effect of college share differed by age of worker. Recently Goldfarb (2005) finds that cohorts of college graduates from the mid-1990s were more likely to adopt the internet at home which he argues to derive from their learning about the internet while in school. To assess whether a similar type of young cohort effect occurred for PC adoption, we asked where the share of CMSAs workers who were under-30 year old college graduates had a differential impact on PC use compared to over-30 college graduates. We found that it did not; if anything, in fact, it appeared to be the case that older college graduates had a larger impact on PC use. This is consistent with other work showing young workers are slightly less likely to use computers than mid-career workers (Card and DiNardo, 2002)

In terms of the spillover variables, the most significant result cities that had large communication service employment back in 1980 before divestiture are also cities that consistently had higher PC intensity. This could reflect a number of phenomena, including the potential spillover from communication services to other industries, the presence of above average IT infrastructure (such as the wiring for high capacity data connections), and possibly that these cities were relatively IT intensive in earlier years.[31]

The other IT spillover variable was the IT manufacturing and software share, a variable intended to capture the potential spillovers to businesses that are close to the large IT centers. The coefficients are positive and occasionally significantly greater than 0. Finally, the share of employment in finance rarely enters the models in a meaningful way.

To better understand how the coefficients in tables 5-7 are related to the fitted and observed differences in PC intensity across cities, table 9 shows how the fitted values change when an independent variable changes between two points in their distribution, the two points being the 25th and 75th percentiles, the 10th and 90th percentiles, or the 5th and 95th percentiles. Table 9 shows the results for 1990 and 2002.

[31] The earliest year for our HH data is 1990, and we do not have any information on the IT employed across cities before then.

The results in table 9 echo a previous theme; the education level of the workforce appears to matter most. For instance, in 1990, when CESH moves up from the 25th to 75th percentile, the model predicts an increase of 2.5 PCs per 100 employees (compared to an actual difference of 5.0 PCs per 100 employees between the 25th and 75th percentile of the PC use distribution). When CESH moves from the 5th to the 95th percentiles, the difference is 6.3. The second most important variable appears to be communications service employment; cities that had high employment in communications services were also cities with high PC penetration rates. By contrast, the spillover effects from the IT manufacturing and software industries are more muted. Taken together, when running a horse race between education and spillovers from the IT sector, education appears to be more important. Recall that the San Francisco Bay area ranked highly in both IT employment and in education; our results suggest that PC intensity in the Bay Area is driven more by the education of the population than by the presence of its IT sector.

The predicted effects of wages of college graduates fade over time: cities with high wages had higher PC penetration rates by sizeable margins in 1990 (the 10th/90th percentile difference was 1.8 PCs per 100 employees). In 2002, wages for college graduates no longer mattered as much, but wages for high school graduates did. Perhaps these results indicate that during initial periods of adoption, high productivity college-educated workers were more likely to get PCs than other workers. By 2002, the college wage affect had lessened significantly, whereas the high-school wage effect increased as computer use among college graduates had increased significantly while computer use among high school graduates is still increasing. As shown in figure 7, the share of college graduates that report using a computer on the job increased significantly over our sample period, reaching over 80 percent by 2001.[32] By contrast, the share of high-school graduates using a computer remains fairly low.

To provide further flavor of what the coefficients in the tables 5-7 mean, table 9 also contains the contribution of each variable to the difference between PC intensity of San Francisco to several

[32] Robert Valletta kindly provided these data and who tabulated them from various computer use supplements to the Current Population Survey.

other cities (Boston, Fresno, Hickory, and NY). Recall that the results presented in figure 3 (and provided in appendix table A), showed the corrected PC intensity relative to San Francisco, the city that ranked highest in PC use. Hickory, the area that ranked lowest in PC use in 1990 with roughly 16 fewer PCs per employee than San Francisco, is predicted from its lower supply of college-educated workers alone to have 7.7 fewer PCs per employee than San Francisco. Similarly for Boston, New York and Fresno, roughly half the gap from San Francisco appears to be explained by human capital alone. Fresno is an interesting case because of its slow growth in CESH over the 1990s, due, it appears, to inflows of Mexican workers. Figure 3 showed that Fresno fell further behind San Francisco over the 1990s; results in the middle panel of Table 9 indicate that this is partly explained by their slow growth in the local supply of skilled labor.

To look further at the forces affecting the changes in PC use over the 1990s in these areas, we turn to our estimates of (5). Table 8 presents the results for the change in PC intensity regressions. As outlined in the previous section, the models estimated vary by the right hand side variables included as well as whether the CESH variables are instrumented. As outlined in section III, there are reasons to include levels in the regressions as well as changes.

Several results are robust. First, the change in the CESH is often statistically greater than 0 at traditional significance levels (1 and 5 percent). Further, this result is robust when instrumented (in fact, the coefficients increase in magnitude). Second, the level of education also matters: the higher the education level, the greater the change in PC intensity. Finally, there exists a negative relationship between the growth in technology and the initial level. This result could have two interpretations. The first is a reversion to the mean argument: cities with higher than expected technology initially revert back to the average, and this could happen because of measurement error. The second argument is one of saturation: growth in PC intensity will slow as a greater share of the workforce has PCs.

These three variables appear to affect the change in PC intensity substantially, as shown on the bottom panel of table 9. The initial PC intensity has perhaps the largest effect; going to the 95th

percentile from the 5th percentile, the predicted change in PC intensity falls by 5.3 PCs per 100 employees. For the initial college equivalent share, the change in PC intensity is nearly as large; cities at the 95th percentile enjoyed a 4.2 PC per 100 employee advantage over cities at the 5th percentile. The change in the college equivalent share is also important.

In terms of the selected cities at the bottom of table 9, all were held back relative to San Francisco because they had lower initial levels of college equivalent shares. However, Boston and New York, NY enjoyed faster growth in college equivalent shares, helping those two cities close the gap with San Francisco. By contrast, Fresno California (a city with a very large Mexican population), suffered from low levels of college graduates and below average increases in college graduates. Hickory had a similar experience with educated workers to Fresno, though Hickory did not have a large Mexican population.

V. Conclusions

This paper has set out to, first, document the large disparities in PC intensity across cities, and, second, to provide some explanation for those differences. To accomplish these goals, we employed data on detailed technology use for a large number of establishments coupled with detailed data on labor forces. The primary statistical challenge facing us was identifying how various variables are related to technology adoption. To overcome this challenge, we employed a number of instruments, which we argue are correlated with variables of interest (such as the education level of a city or of the change in the education level in a city) but not correlated with unobserved factors that affect technology adoption. An additional challenge facing us is that many factors affect technology adoption, and we simultaneously attempt to control for these additional factors, especially factors related to potential spillovers.

Our results are as straight forward as they are robust: cities with highly educated work forces, and cities where the education level increases, are much more intensive than their less educated counterparts. Additionally, cities that are IT and financial centers are also likely to be more technologically intensive. However, we do not find much of a role in inter-city variation in wages in explaining the differences.

Going forward, we will extend our analysis to other technologies. As we mentioned in a footnote earlier, initial analysis suggest that our results hold for local area networks and for email.

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Table 1: Information Technology Investment, 1990-2000 & 2000-2003

	Average annual percent change, 1990-2000:			Nominal spending ($ billions)		
	Nominal investment	Prices	Real investment	1990	2000	1990 through 2000
IT	11.8	-7.0	20.2	131.5	401.7	2,371.7
Computers and peripherals	10.1	-17.7	33.9	38.6	101.4	725.6
Personal Computers	12.3	-25.1	50.0	10.6	34.0	267.3
Other computers	10.5	-20.2	38.4	9.4	25.5	141.6

	Average annual percent change, 2000-2003:			Nominal spending ($ billions)		
	Nominal investment	Prices	Real investment	2000	2003	2000 through 2003
IT	-4.4	-6.5	0.8	401.7	350.8	1,454.3
Computers and peripherals	-2.1	-14.7	14.8	101.4	95.3	363.5
Personal Computers	0.3	-21.5	27.8	34.0	34.3	123.8
Other computers	-3.2	-21.8	23.7	25.5	23.1	86.9

Source: Kindly provided by BEA.

Table 2: CMSAs with Land-Grant Colleges

Albany-Schenectady-Troy, NY	Knoxville, TN	Providence, RI
Baton Rouge, LA	Lansing-East Lansing, MI	Raleigh-Durham, NC
Boston, MA	Lexington-Fayette, KY	Reno, NV
Columbus, OH	Lincoln, NE	Richmond-Petersburg, VA
Fayetteville-Springdale, AR	Los Angeles-Long Beach, CA	Sacramento, CA
Fort Collins-Loveland, CO	Macon-Warner Robins, GA	San Diego, CA
Gainesville, FL	Madison, WI	San Francisco Bay Area, CA
Greensboro--Winston-Salem--High Point, NC	Minneapolis-St. Paul, MN-WI	Springfield, MA
Greenville-Spartanburg, SC	Nashville, TN	Tallahassee, FL
Hartford, CT	New York, NY	Tucson, AZ
Houston, TX	Oklahoma City, OK	Washington, DC-MD-VA
Huntsville, AL	Philadelphia, PA-NJ	

Table 3: College Equivalent Share, Basic Models

	(1)	(2)	(3)	(4)	(5)	(6)
		1980			1990	
CMSA has land-grant college	0.044	0.039	0.015	0.043	0.041	0.010
	(0.006)**	(0.006)**	(0.004)**	(0.008)**	(0.008)**	(0.005)*
Population-Adjusted 1971 Enrollment in 2-Year Colleges, Millions		0.467	0.340		0.303	0.152
		(0.111)**	(0.067)**		(0.135)*	(0.073)*
Population-Adjusted 1971 Enrollment in 4-Year Colleges, Millions		0.177	0.270		0.334	0.468
		(0.142)	(0.100)**		(0.176)+	(0.108)**
Constant	0.285	0.279	0.393	0.394	0.385	0.476
	(0.004)**	(0.006)**	(0.078)**	(0.005)**	(0.007)**	(0.081)**
Other Controls	No	No	Yes	No	No	Yes
Observations	160	160	160	160	160	160
R-squared	0.23	0.31	0.77	0.17	0.21	0.79
F-Statistics, Instruments	47.22**	23.38**	15.47**	33.07**	14.02**	8.39**

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

Table 4: College Equivalent Share, First Difference Models

	(1)	(2)	(3)
	1980-90 Change		1980
Share from Mexico, 1980	-0.197	-0.087	0.115
	(0.047)**	(0.043)*	(0.082)
Population-Adjusted 1971 Enrollment in 2-Year Colleges, Millions		-0.221	0.254
		(0.112)+	(0.211)
Population-Adjusted 1971 Enrollment in 4-Year Colleges, Millions		0.021	0.458
		(0.117)	(0.219)*
CMSA has land-grant institution		-0.002	0.031
		(0.004)	(0.007)**
Constant	0.107	0.030	0.568
	(0.001)**	(0.047)	(0.089)**
Other Controls	No	Yes	Yes
Observations	160	160	160
R-squared	0.10	0.34	0.73
F-Stat, Instruments	17.9**	2.40+	7.45**

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

Table 5: Corrected PC Intensity Models, 1990

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	IV, LGC	IV, LGC, 1971 colleges	OLS	IV, LGC, 1971 colleges	OLS	IV, LGC, 1971 colleges	OLS	IV, LGC, 1971 colleges
College equivalent share	0.509	0.533	0.533	0.520	0.486	0.357	0.373	0.320	0.338
	(0.038)**	(0.087)**	(0.076)**	(0.036)**	(0.069)**	(0.049)**	(0.113)**	(0.053)**	(0.131)*
Average log wage, high school graduates				-0.094	-0.083	-0.021	-0.027	-0.013	-0.019
				(0.034)**	(0.039)*	(0.035)	(0.053)	(0.036)	(0.056)
Average log wage, college graduates				0.211	0.204	0.109	0.115	0.087	0.095
				(0.035)**	(0.038)**	(0.040)**	(0.058)*	(0.042)*	(0.068)
IT software and manufacturing industry employment share (1980						0.194	0.180	0.156	0.145
						(0.144)	(0.170)	(0.145)	(0.160)
Communications services industry employment share (1980)						4.540	4.326	4.630	4.420
						(1.067)**	(1.712)*	(1.061)**	(1.729)*
Finance services industry employment share (1980)								0.569	0.523
								(0.329)+	(0.444)
Constant	0.015	0.007	0.008	-0.352	-0.348	-0.218	-0.225	-0.181	-0.191
	(0.011)	(0.025)	(0.022)	(0.059)**	(0.059)**	(0.063)**	(0.077)**	(0.066)**	(0.092)*
Observations	160	160	160	160	160	160	160	160	160
R-squared	0.53	0.53	0.53	0.64	0.64	0.68	0.68	0.69	0.69

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

IV, LGC=College equivalent share instrumented with land grant colleges

IV, LGC, pop-adj #colls, 1971=College equivalent share instrumented with land grant colleges and 1971 colleges

Table 6: Corrected PC Intensity Models, 1996

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	IV, LGC	IV, LGC, 1971 colleges	OLS	IV, LGC, 1971 colleges	OLS	IV, LGC, 1971 colleges	OLS	IV, LGC, 1971 colleges
College equivalent share	0.739	0.827	0.792	0.707	0.718	0.508	0.611	0.461	0.575
	(0.057)**	(0.130)**	(0.113)**	(0.053)**	(0.102)**	(0.073)**	(0.171)**	(0.079)**	(0.198)**
Average log wage, high school graduates				-0.010	-0.013	0.078	0.038	0.089	0.048
				(0.049)	(0.056)	(0.053)	(0.079)	(0.053)+	(0.084)
Average log wage, college graduates				0.227	0.230	0.108	0.150	0.080	0.130
				(0.052)**	(0.055)**	(0.060)+	(0.088)+	(0.062)	(0.102)
IT software and manufacturing industry employment share (1980						0.370	0.277	0.320	0.254
						(0.216)+	(0.258)	(0.218)	(0.244)
Communications services industry employment share (1980)						5.000	3.641	5.099	3.804
						(1.602)**	(2.593)	(1.598)**	(2.615)
Finance services industry employment share (1980)								0.732	0.448
								(0.496)	(0.675)
Constant	0.152	0.127	0.137	-0.458	-0.459	-0.309	-0.355	-0.263	-0.323
	(0.017)**	(0.038)**	(0.033)**	(0.087)**	(0.087)**	(0.095)**	(0.117)**	(0.100)**	(0.139)*
Observations	160	160	160	160	160	160	160	160	160
R-squared	0.52	0.51	0.52	0.64	0.64	0.67	0.66	0.67	0.67

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

IV, LGC=College equivalent share instrumented with land grant colleges

IV, LGC, pop-adj #colls, 1971=College equivalent share instrumented with land grant colleges and 1971 colleges

Table 7: Corrected PC Intensity Models, 2002

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	IV, LGC	IV, LGC, 1971 colleges	OLS	IV, LGC, 1971 colleges	OLS	IV, LGC, 1971 colleges	OLS	IV, LGC, 1971 colleges
College equivalent share	0.689	0.606	0.587	0.637	0.540	0.469	0.396	0.395	0.309
	(0.052)**	(0.127)**	(0.114)**	(0.052)**	(0.111)**	(0.079)**	(0.211)+	(0.084)**	(0.242)
Average log wage, high school graduates				0.057	0.089	0.135	0.165	0.153	0.186
				(0.054)	(0.063)	(0.060)*	(0.100)	(0.060)*	(0.106)+
Average log wage, college graduates				0.124	0.106	0.027	-0.004	-0.017	-0.056
				(0.057)*	(0.060)+	(0.067)	(0.107)	(0.068)	(0.123)
IT software and manufacturing industry employment share (1980						0.452	0.538	0.376	0.450
						(0.251)+	(0.341)	(0.250)	(0.318)
Communications services industry employment share (1980)						3.931	5.060	4.175	5.360
						(1.899)*	(3.583)	(1.875)*	(3.650)
Finance services industry employment share (1980)								1.300	1.514
								(0.555)*	(0.794)+
Constant	0.186	0.219	0.226	-0.286	-0.276	-0.171	-0.135	-0.091	-0.042
	(0.021)**	(0.050)**	(0.045)**	(0.096)**	(0.097)**	(0.108)	(0.145)	(0.111)	(0.171)
Observations	160	160	160	160	160	160	160	160	160
R-squared	0.52	0.52	0.51	0.59	0.58	0.61	0.61	0.63	0.62

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

IV, LGC=College equivalent share instrumented with land grant colleges

IV, LGC, pop-adj #colls, 1971=College equivalent share instrumented with land grant colleges and 1971 colleges

Table 8: 1990-2002 Difference Regressions on 1980-1990 Changes in City Characteristics

	(1) OLS	(2) IV, Imm	(3) OLS	(4) IV, Imm	(5) OLS	(6) IV, Imm	(7) OLS	(8) IV, Imm	(9) OLS	(10) IV, Imm
Change in College Equivalent Share										
(1980-1990)	0.900	1.993	0.865	2.049	0.706	2.162	0.616	1.748	0.627	1.585
	(0.160)**	(0.571)**	(0.168)**	(0.746)**	(0.182)**	(0.958)*	(0.185)**	(0.622)**	(0.177)**	(0.570)**
College equivalent share, 1980							0.136	0.264	0.241	0.387
							(0.078)+	(0.209)	(0.080)**	(0.222)+
Adjusted PCs per 100 employees, 1990									-0.469	-0.545
									(0.127)**	(0.180)**
Constant	0.202	0.087	0.215	0.079	0.224	0.070	0.057	0.006	-0.002	-0.060
	(0.017)**	(0.060)	(0.020)**	(0.086)	(0.021)**	(0.102)	(0.120)	(0.144)	(0.117)	(0.141)
Other Controls:										
Wage Growth (1980-1990)	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Change in IT Share (1980-1990)	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Change in Finance Share (1980-1990)	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Wages, 1980	No	No	No	No	No	No	Yes	Yes	Yes	Yes
IT Share, 1980	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Finance Share, 1980	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Observations	160	160	160	160	160	160	160	160	160	160
R-squared	0.17	.	0.19	.	0.21	.	0.31	0.13	0.37	0.24

Standard errors in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

IV, Imm=College equivalent share instrumented with immigrant shares

Table 9: Changes in Predicted Values of Corrected PC Intensity

1990

Differenced percentiles	Change in PC Intensity	estimated change in PC intensity from: College Equivalent Share	Wages of High School graduates	Wages of College Graduates	IT Manufacturing and Software	Communications Service Employment, 1980	Financial Service Employment, 1980
75th/25th	5.0	2.5	-0.6	1.0	0.2	1.5	0.4
10th/90th	9.5	4.9	-1.1	1.8	0.4	3.0	0.8
95th/5th	11.3	6.3	-1.5	2.6	0.6	3.6	1.1
Fitted values for selected cities relative to San Francisco							
Boston, MA	-5.7	-2.4	0.0	-0.4	0.1	-0.7	-0.6
Fresno, CA	-7.0	-3.1	0.3	-1.2	-0.5	-2.7	-0.8
Hickory-Morganton, NC	-15.9	-7.7	0.4	-1.2	-0.6	-3.1	-1.4
New York, NY	-5.4	-2.6	0.0	0.5	-0.2	-0.8	0.5

2002

	Change in PC Intensity	estimated change in PC intensity from: College Equivalent Share	Wages of High School graduates	Wages of College Graduates	IT Manufacturing and Software	Communications Service Employment, 1980	Financial Service Employment, 1980
75th/25th	9.2	4.4	1.1	-0.3	0.4	1.3	0.7
10th/90th	17.2	8.7	2.0	-0.5	0.8	2.6	1.5
95th/5th	22.5	11.1	2.8	-0.7	1.0	3.1	2.0
Fitted values for selected cities relative to San Francisco							
Boston, MA	-1.0	-1.9	-0.3	0.1	0.2	-0.6	-1.4
Fresno, CA	-19.9	-5.8	-3.2	0.2	-1.1	-2.5	-1.8
Hickory-Morganton, NC	-28.9	-10.7	-4.3	0.2	-1.5	-2.8	-3.2
New York, NY	-3.4	-2.9	0.4	-0.1	-0.4	-0.7	1.2

2002/1990 Change

	Change in College Equivalent Share	Initial College Equivalent Share	Initial (1990) Corrected PC Intensity
75th/25th	1.4	1.7	-2.4
10th/90th	2.9	3.3	-4.5
95th/5th	3.7	4.2	-5.3
Fitted values for selected cities relative to San Francisco			
Boston, MA	1.6	-1.8	2.7
Fresno, CA	-3.2	-2.3	3.3
Hickory-Morganton, NC	-1.8	-5.8	7.5
New York, NY	0.3	-1.9	2.6

Figure 1: Aggregate Statistics from the Harte-Hanks Sample

(technology per 100 employees)

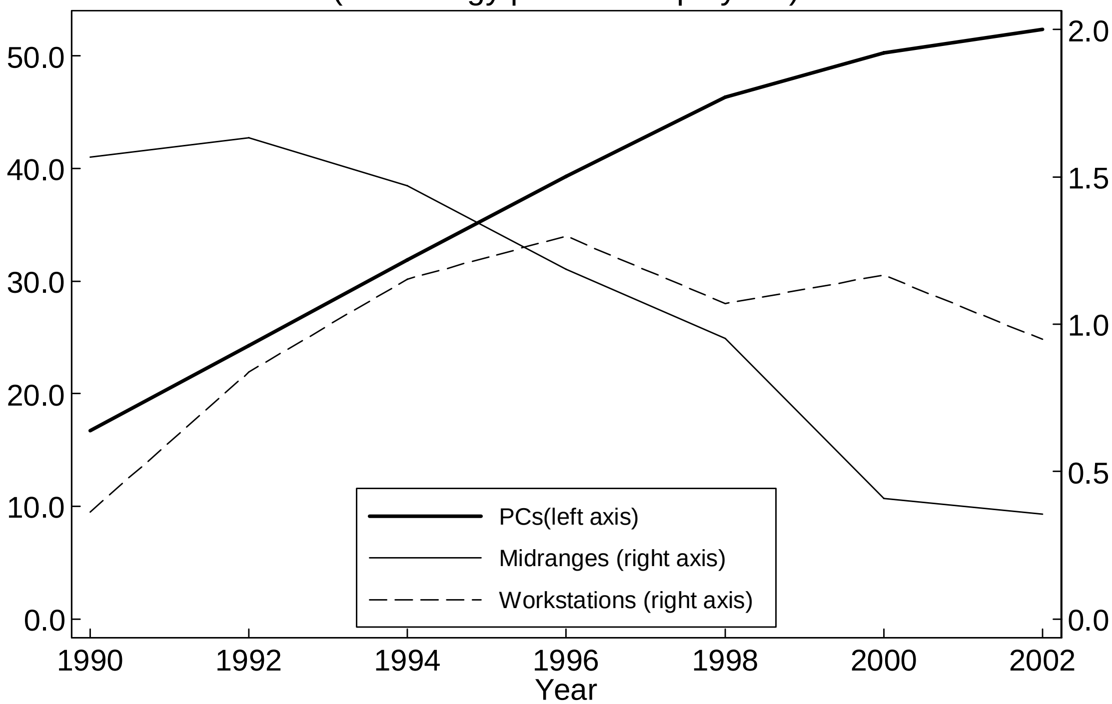


Figure 2: Average PCs per 100 Employees by CPU Type

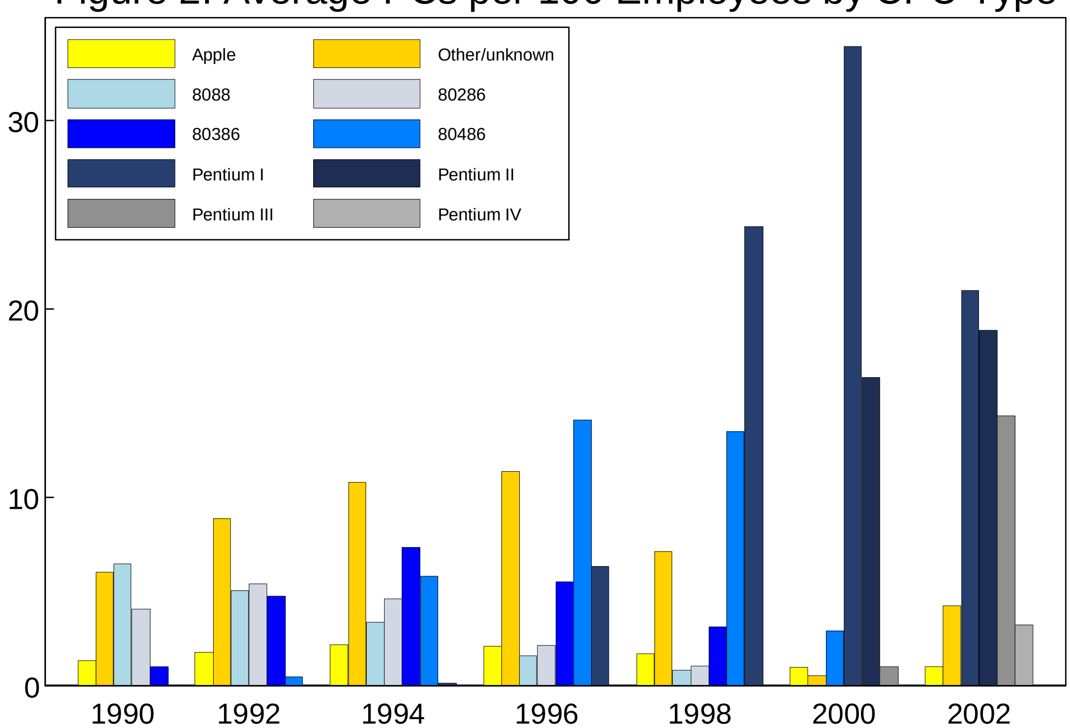


Figure 3: PCs per 100 Employees by City
Difference from San Francisco Bay Area Total

(after controlling for industry and establishment size)

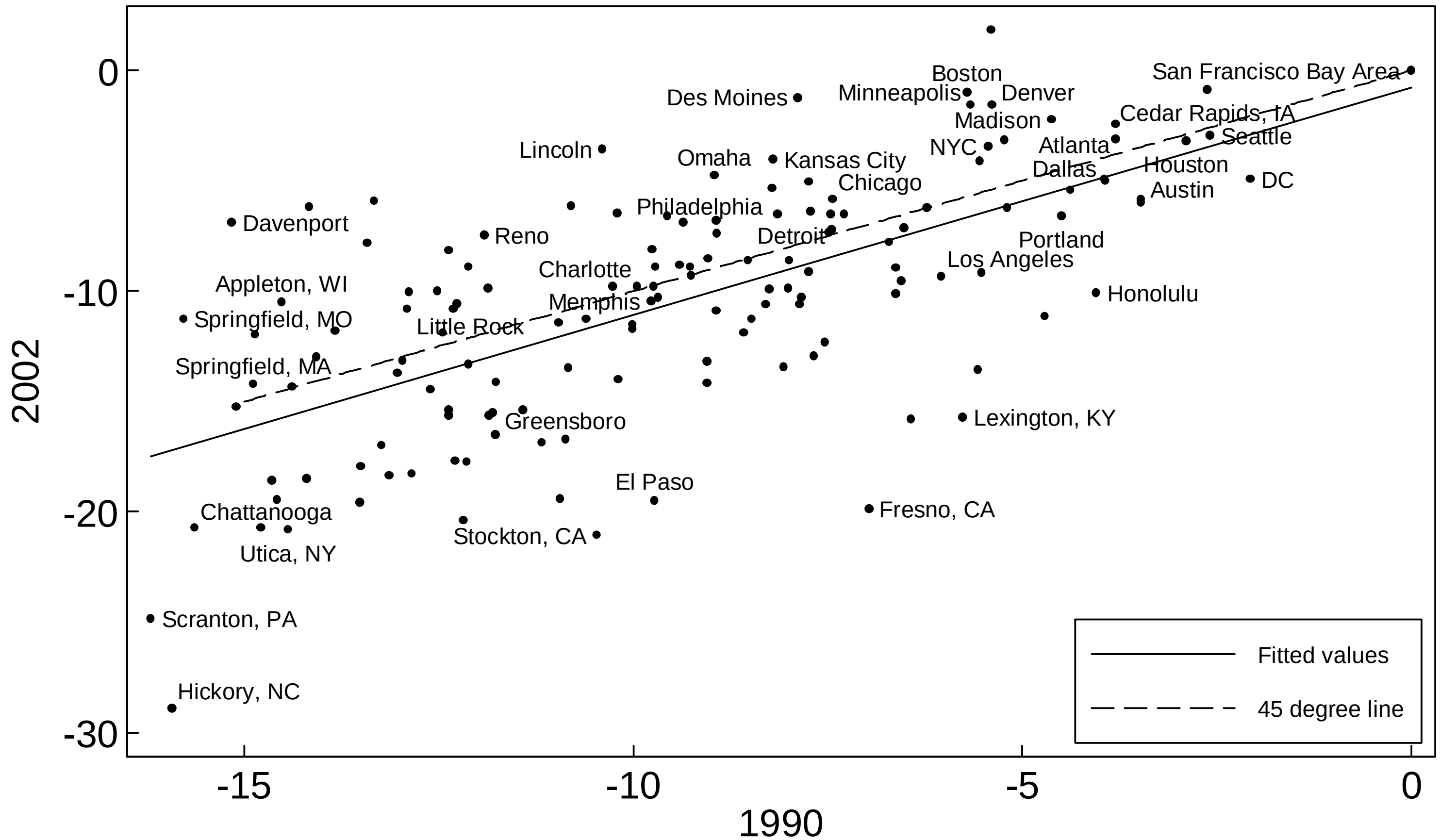


Figure 4: Kernel Densities of Education Across CMSAs With and Without Land Grant Colleges (LCGs)

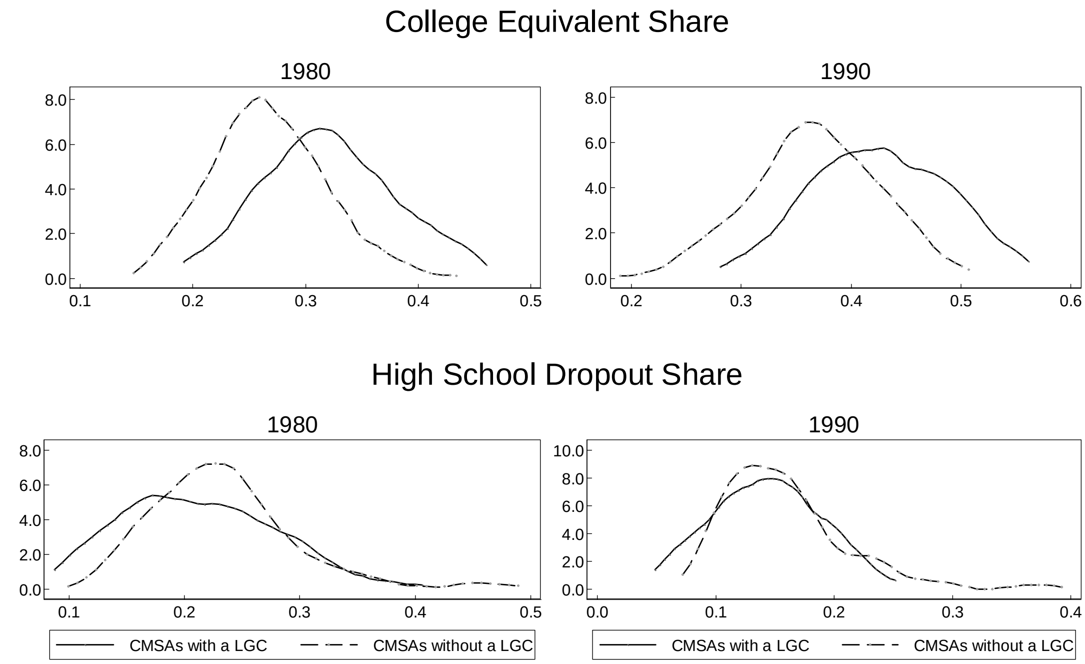


Figure 5: Mexican Share and College Equivalent Share

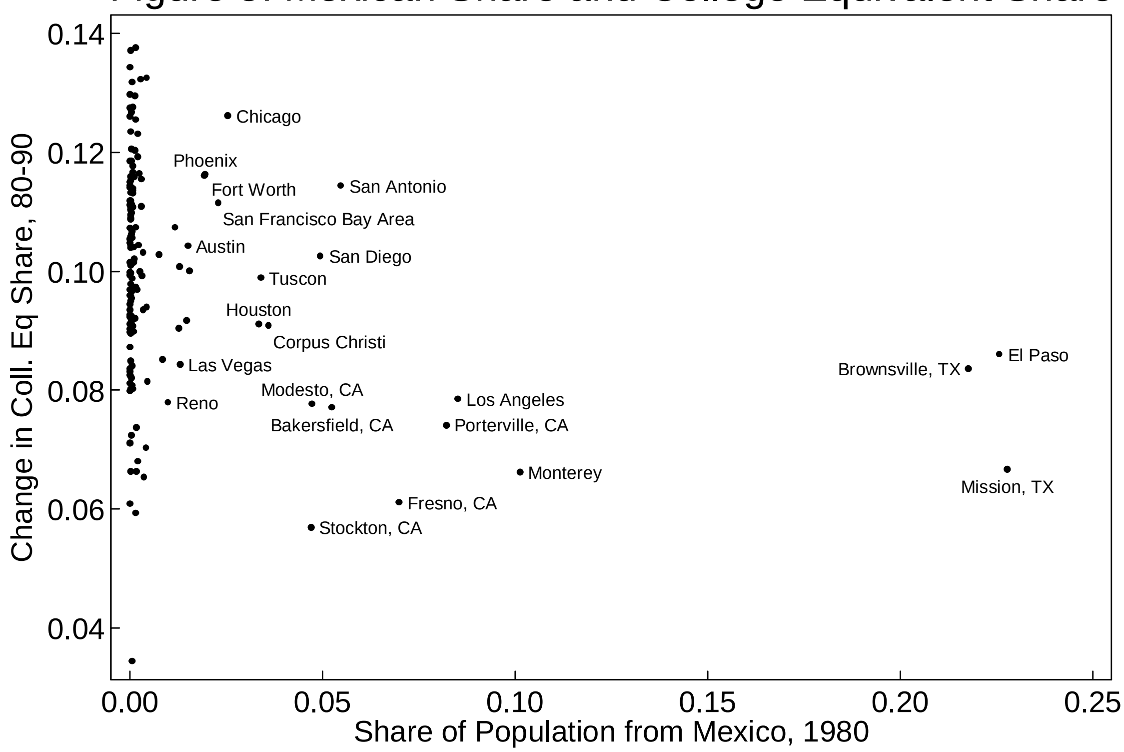


Figure 6: 1980 Mexican Share and Change in College Equivalent Share

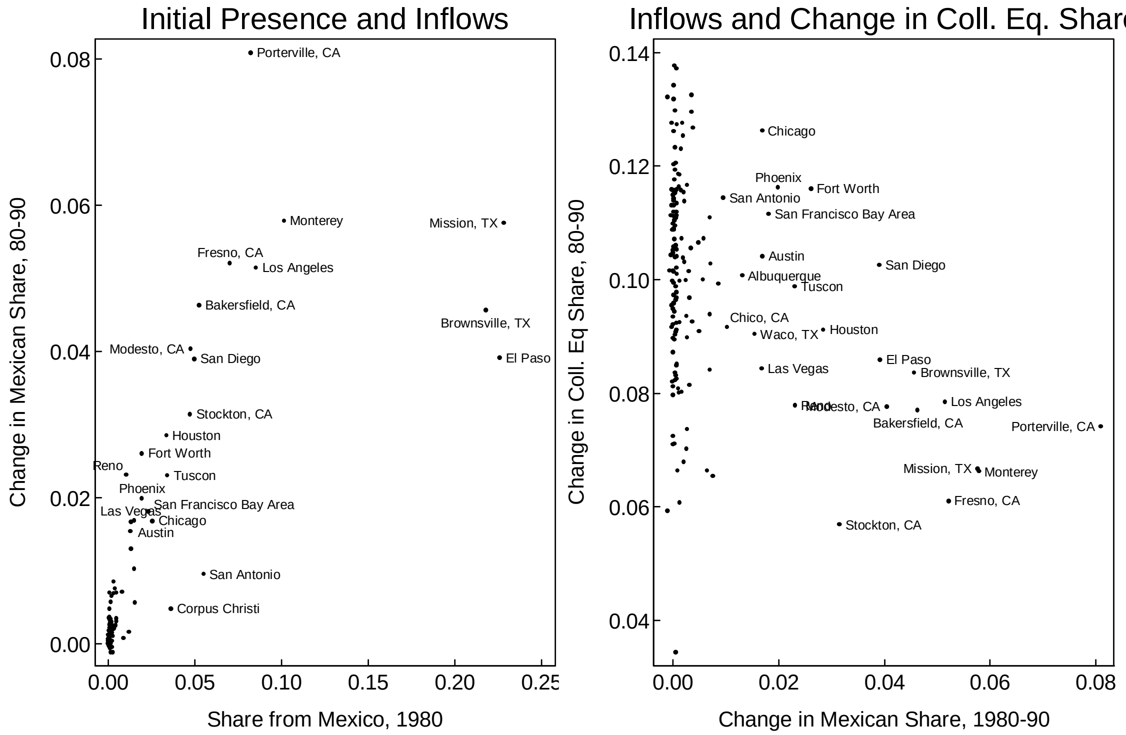
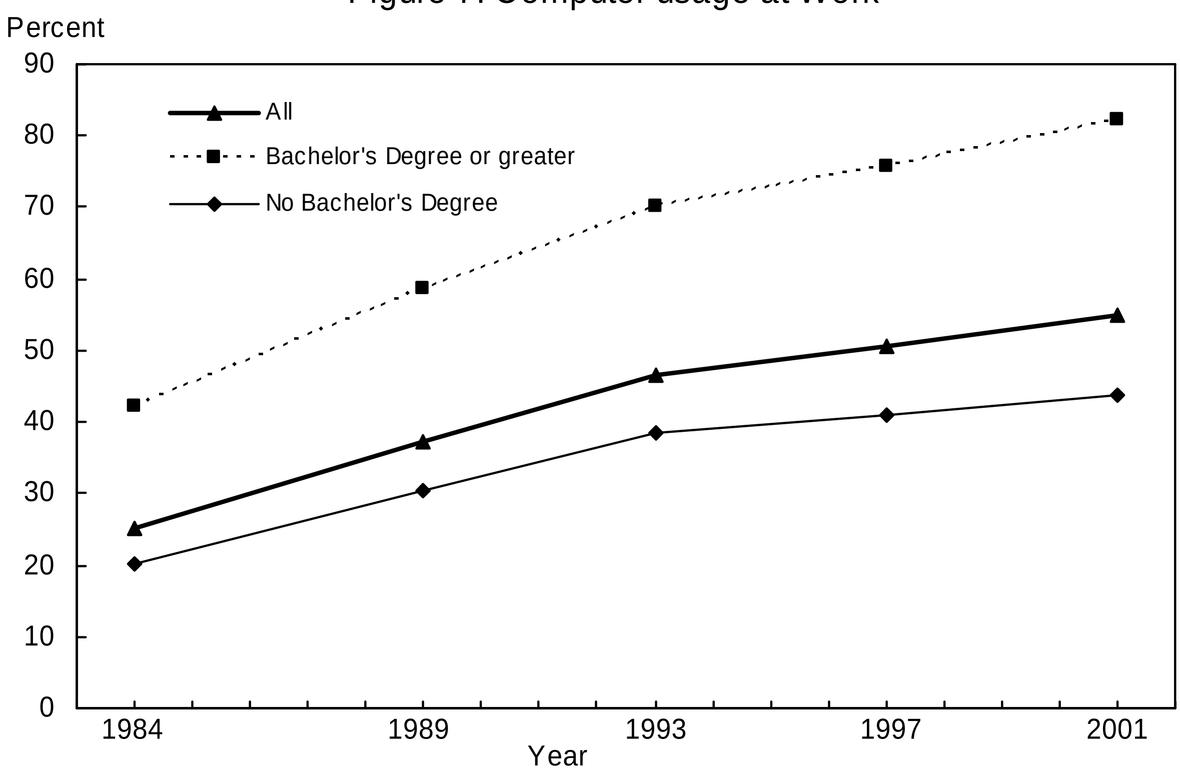


Figure 7: Computer usage at Work



Source: Tabulations of CPS computer use supplement data by Robert Valletta