The IT Revolution at the City Level: Testing a Model of Endogenous Biased Technology Adoption

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— Abstract —

This paper examines the process of technology adoption and its interaction with local labor market conditions. In particular, we examine cross-city differences in PC-adoption, relative wages, and changes in relative wages over the period 1980-2000 to evaluate whether the patterns conform to the predictions of a neo-classical model of technology choice. Our approach melds the literature on the effect of the relative supply of skilled labor on technology adoption to the often distinct literature on how technology may influence the relative demand for skilled labor. Our results support the idea that differences in technology use across cities and its effects on wages reflect an equilibrium response to local factor supply conditions. More specifically, our model and data suggest that cities initially endowed with relatively abundant and cheap skilled labor adopted PCs more aggressively than cities with relatively expensive skilled labor. Further, relative wages increased the most in cities that adopted PCs most intensively, leading the downward sloping relationship between relative wages and the supply of skilled labor that existed in 1970, 1980, and 1990 to lessen considerably by 2000. These findings contribute to the literature on changes in the returns to education by clarifying how to evaluate the role of technological change on wage changes when technology adoption is endogenous.

Key Words: Biased Technological Change, Wages, Education, Diffusion

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1 Introduction

The diffusion of a new technology is generally a slow and unequal process resulting in great variation in use of a new technology across regions, markets, and countries. One possible reason for these patterns is that new technologies are initially attractive only for particular configurations of factor prices; it may be optimal for one locality to adopt a new technology– if it has a comparative advantage in doing so– while in a different locality it is optimal to maintain an old technology. Over time, as the price of the new technology declines and its quality improves, the conditions for profitable adoptions likely eases, supporting a dynamic process with diffusion progressing both on the intensive (within localities) and the extensive margin (across localities). This view of technological adoption, which we will refer to as the neo-classical view, has a long tradition in the economic history literature. For example, Habakkuk (1962) argues that land abundance in the United states affected relative factor prices and thereby lead to different patterns of technological adoption compared to England. At a more regional level, Goldin and Sokoloff (1984) argue that factor prices differences in 1830 between the northern and southern US states (due to crop differences) help explain the differential patterns of industrialization.[1] More recently, Manuelli and Seshadri (2004) argue that the diffusion of the farm tractors across the US in the early 20th century also reflects neo-classical forces.

In this paper we explore whether a neoclassical model of endogenous technological adoption – similar in spirit to that suggested in the economic history literature – can help explain differences in wage and technology outcomes observed across US cities over the main period of diffusion of the personal computer (PC), that is, from 1980 to 2000. There are several reasons we pursue this line inquiry. First, as shown in Doms and Lewis (2006), there are large and systematic differences in the intensity of PC use across cities in the US that appear to be related to the relative supply of skilled labor, but it is unclear what the mechanism is that drives these differences. Second, the data available to evaluate our model of endogenous technology adoption during the IT revolution is much better than the data available to test such a model during other technological revolutions. Third, it is of interest to know whether a process of technological adoption driven by simple neo-classical principles of comparative advantage remains a relevant framework for describing diffusion in periods of major

[1] More recently, Beaudry and Green (2003) argues that differences in factor accumulation between the US and Germany may have caused differences in technological choices and thereby differences in wages and employment patterns.

technological change or if it is only relevant for rare or distant cases in history.

We find that cross-city patterns in PC-use, returns to education, and changes in returns to educational attainment conform well to the implications of our neo-classical model of endogenous technology adoption. Consistent with the model, it is in cities where high school educated workers are more costly (and scare) relative to college educated workers that PCs were adopted most intensely. It is also these cities that experience the greatest increase in the returns to education, that is, it is cities with a more abundant supply of college educated workers that adopted PCs most intensively and saw the returns to college increase fastest. However, even with greater use of PCs, the high adopting cities are not observed to have higher returns to education in 2000 than there slow-adopting counterparts. This later pattern contrasts with common intuition regarding the likely correlation between PC use and returns to education, but is implied by the endogenous technology adoption framework.[2]

Our approach to examining the relationships between technology and skilled labor melds much of the recent literature on these topics which usually takes one of two forms. The first examines to what extent technology adoption is affected by the relative supply of skilled labor.[3] The second, addressed in a voluminous literature, examines to what extent relative demand for skilled labor may be influenced by technology.[4] More rarely are both channels modeled simultaneously, though such an approach is, we believe, necessary to better understand and unify the dynamics of both technology adoption and changes in relative wages. As we shall show, it appears important to recognize the endoegeneity of technology choices for evaluating the role of PCs in recent increases in the returns to education.

This paper is also closely related to the recent literature on endogenous bias in technology which emphasizes two avenues by which factor supplies can affect the bias of technological change. First, market conditions may influence the direction of research and thereby favor innovations that are biased towards or against a particular factor. This avenue reflects the endogeneity of technology supply (see for example Acemoglu 1998, 2002). Alternatively, market forces may affect decisions regarding which technologies to adopt. In contrast with the innovation route, this second avenue reflects the potential endogeneity of the demand for biased technologies (see for example Caselli (1999), Beaudry and Green (1998, 2003)). Our

[2]An important byproduct of our analysis is the observation that city level wages do not behave as if there where fully integrated into an national aggregate. Instead we find that city level wages are determined locally in conjunction with PC use.

[3]For example, see Comin and Hobijn (2004) and Benhabib and Speigel (2005).

[4]For recent examples see Author, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006).

exploration focuses mainly on the relevance of this second channel.

The remaining sections of the paper are structured as follows. In section 2, we present a simple model of biased technology adoption and derive a set of implications regarding local level interactions between returns to education, changes in returns to education, and technology use. In the model, the labor market market is viewed as a local market while the market for technologies is a global market. Further, firms have a choice between a more and less skilled biased technology where the skilled biased technology is PC-intensive. In Section 3 we discuss the data. In Section 4 we explore a set of empirical patterns predicted by the theory. Finally Section 5 offers concluding comments.

2 A neo-classical model of technology adoption

Consider a environment where firms have access to a set of technologies to produce a final good denoted by Y_t. The production of Y_t requires inputs X_t, where these inputs can be organized in different ways to produce output, each of these alternative organizations corresponding to a different technology. If we parameterize the different technologies by $\theta \in \Theta$, then the production possibilities facing a firm can be represented by:

$$F(X_t, \theta), \qquad \theta \in \Theta_t$$

where for each $\theta \in \Theta$, the production function is assumed to satisfy constant returns to scale and concavity. In this case, a price taking firm will aim to maximize profits by solving the following problem

$$\max_{X_t, \theta_t} F(X_t, \theta_t) - w_t X_t$$

where w_t is the vector of factor prices. In such an environment, it is straightforward to extend the definition of a competitive equilibrium to include the choice of technologies, that is, a competitive equilibrium can be defined as a set of prices, allocations and technology choices, such that given prices, allocations and technology choices are optimal, and market clear. [5]

[5]Standard techniques can be used to prove the existence of a competitive equilibrium with technology choices as shown in Acemoglu (2005).

Let us now consider the situation with a set of distinct markets, indexed by i. Each of these markets is assumed to have access to the same set of technologies, but differ in terms of the supply of at least a subset of the factors X. The question we want to ask, is how do the different markets react to a a change in the set of choices, that is, a change in Θ_t. Obviously, the answer to this question depends on the nature of the change in Θ. In particular, given the time period that interests us, we want to examine the effects of having Θ extend to include a more skilled biased technology relative to the pre-existing choices. To this end, we will focus on the case where initially there is only one dominant technology used across all markets. This technology uses as inputs skilled labor S, unskilled labor U and traditional capital K. The market for skilled and unskilled labor is assumed to be a local market, with exogenously fixed local supplies. The market for K is assumed to be a common market, where firms from all localities can rent the capital at the rate r^k. Finally, for ease of presentation, the pre-existing technology is assumed to have the following functional form:

$$F^T(K,S,U) = K^{1-\alpha}[aS^\sigma + (1-a)U^\sigma]^{\frac{\alpha}{\sigma}}, \quad 0 < \alpha < 1, \quad 1 < a < 1, \quad -\infty < \sigma < 1$$

In this environment, the initial returns to skill will differ across markets. In particular, the ratio of the market specific skilled wage w_i^S to the unskilled wage w_i^U will be given by:

$$\frac{w_i^S}{w_i^U} = \frac{aS_i^{\sigma-1}}{(1-a)U_i^{\sigma-1}}$$

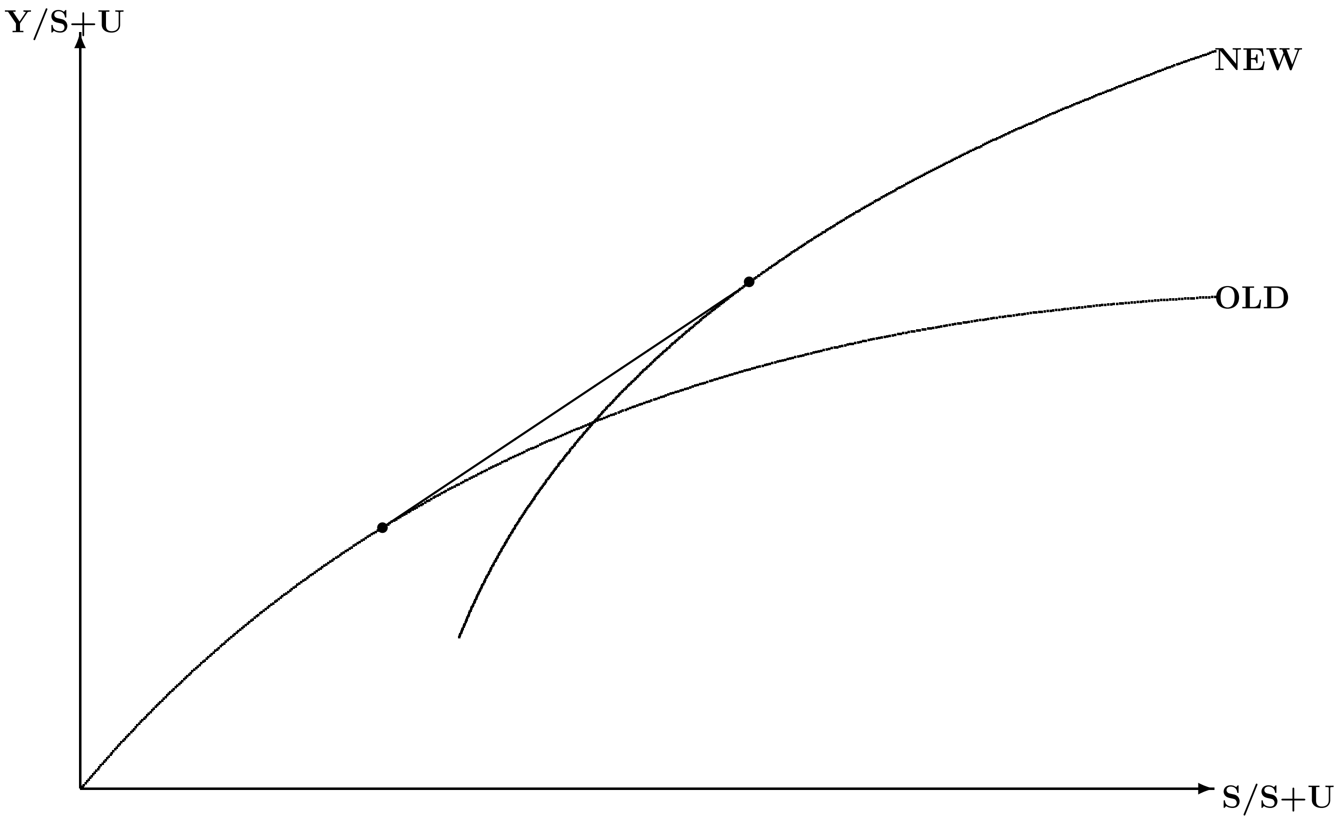
where S_i and U_i represent the quantities of skilled labor available market i.

Now suppose that at a point in time, say at $t = 0$, a new technology becomes available. This technology has two characteristics that differentiate it from the traditional technology. First, it uses a different form of capital, which we will denote as PC capital. This PC capital is assumed to be available on a common market at rental rate r^{PC}. Second, the new technology is assumed to be skilled biased relative to the old technology in the sense that a common factor prices, the new technology uses skilled labor more intensively (i.e., has a higher ratio of $\frac{S}{U}$). These features are captured in the following functional form for the new technology:

$$F^N(PC,S,U) = PC^{1-\alpha}[bS^\sigma + (1-b)U^\sigma]^{\frac{\alpha}{\sigma}}, \qquad a < b < 1$$

What is important to notice is that the new technology does not dominate the old technology in the sense of producing more output at any input combinations. In effect, for given rental rates of capital r^K and r^{PC}, the old technology is more productive than the new technology when used with a small fraction of skilled workers, while the new technology is more productive (higher output per worker) when used with a high fraction of skilled workers. This property is depicted in Figure 1.

Figure 1: Effects of Technological Choice



From Figure 1, it is easy to infer that localities with high ratios of skilled to unskilled workers will want to adopt the new technology, while those with low levels of skill may want to maintain the old technology. Actually, in such a situation, the adoption decision is characterized by three regions delimited by critical values of skill to unskilled ratios. In particular, it is easy to verify that there exist ϕ^L and ϕ^H $(0 < \phi^L < \phi^H)$ such that if a locality is characterized $\frac{S_i}{S_i+U_i} < \phi^L$, then it maintains the old technology. If $\frac{S_i}{S_i+U_i} > \phi^H > \phi^L$, then the locality switches completely to the new technology. Finally if $\phi^L < \frac{S_i}{S_i+U_i} < \phi^H$ then both technologies co-exist in a competitive equilibrium, with the fraction of production done using the new technology being an increasing function of $\frac{S_i}{S_i+U_i}$.[6] Since PC capital is used intensively in the new technology, it follows that the quantity of PCs per worker used in a locality is a monotonically increasing function of the ratio of skilled to unskilled workers. This forms the basis of Proposition 1.

Proposition 1: Adoption of the new technology will be greater in localities with a greater ratio of skill to unskilled workers, leading the ratio of PCs per worker to be an increasing function of a locality's sill supply.

Proposition 1 indicates that skill biased technologies are adopted most aggressively by localities in which skill is relatively abundant, and therefore the observable aspects of the technology – such as here PC capital — are most prevalent in localities with more skill. This implication is the focus of the Doms & Lewis (2006) paper. Here, we want to go further and derive a set of additional implications in order to examine more closely the relevance of a biased technology adoption model for understanding differences in outcomes across localities. To this end, we first extend slightly Proposition 1 and derive a corollary that captures the incentive mechanism that lead to the different adoption decisions. Note that from an individual firm's perspective, the differential adoption decisions across localities must reflect different incentives induced by factor prices. In effect, in localities with initially high ratios of skilled to unskilled labor, the relative price of skilled labor is initially low (prior to the availability of the new technology), favoring the adoption of a technology which uses skill intensively. This implication is expressed in Corollary 1.

Corollary 1: The ratio of PCs per worker is an increasing function of a localities initial ratio of skill to unskilled wages.

Proposition 1 and Corollary 1 focus on the effects of local market condition on adoption decisions. We now want to change perspective and examine instead how the arrival of the new technology affects relative wages. In particular, we first want to emphasize how changes

[6] The values of ϕ^L and ϕ^H are defined by

$$(\frac{\alpha}{r^K})^{\frac{\alpha}{1-\alpha}} a[a + (1-a)(\frac{1}{\phi^L})^{\sigma}]^{\frac{1-\sigma}{\sigma}} = (\frac{\alpha}{r^{PC}})^{\frac{\alpha}{1-\alpha}} b[b + (1-b)(\frac{1}{\phi^H})^{\sigma}]^{\frac{1-\sigma}{\sigma}}$$

and

$$(\frac{\alpha}{r^K})^{\frac{\alpha}{1-\alpha}} (1-a)[a(\phi^L)^{\sigma} + (1-a)]^{\frac{1-\sigma}{\sigma}} = (\frac{\alpha}{r^{PC}})^{\frac{\alpha}{1-\alpha}} (1-b)[b(\phi^H)^{\sigma} + (1-b)]^{\frac{1-\sigma}{\sigma}}$$

in the return to skill, as expressed by the change in the (log) ratio $\frac{w_i^S}{w_i^U}$, vary across localities faced with similar new options. This is captured in Proposition 2 and Corollary 2.

Proposition 2: The arrival of the skilled biased technology causes the returns to skill to increase most in localities where skill is most abundant.

The content of Proposition 2 can be obtained by deriving the relationship between the return to skill and the supply of skill before and after the arrival of the new technology, and taking the difference between the two. This relationship is expressed analytically below and graphically in Figure 2. As can be seen, for localities with very low initial supply of skilled workers, relative wages don't change since the new technology is not adopted. For localities, with $\phi^H < \frac{S_i}{S_i+U_i}$, they experience the largest increase in the returns to skill since they switch entirely to the new technology which acts as an increase in the demand for skill. Finally, for localities in partial adoption region $\phi^L < \frac{S_i}{S_i+U_i} < \phi^H$, the increase in the returns to skill in strictly increasing in the supply of skill since the endogenously induced demand for skill is increasing with skill.

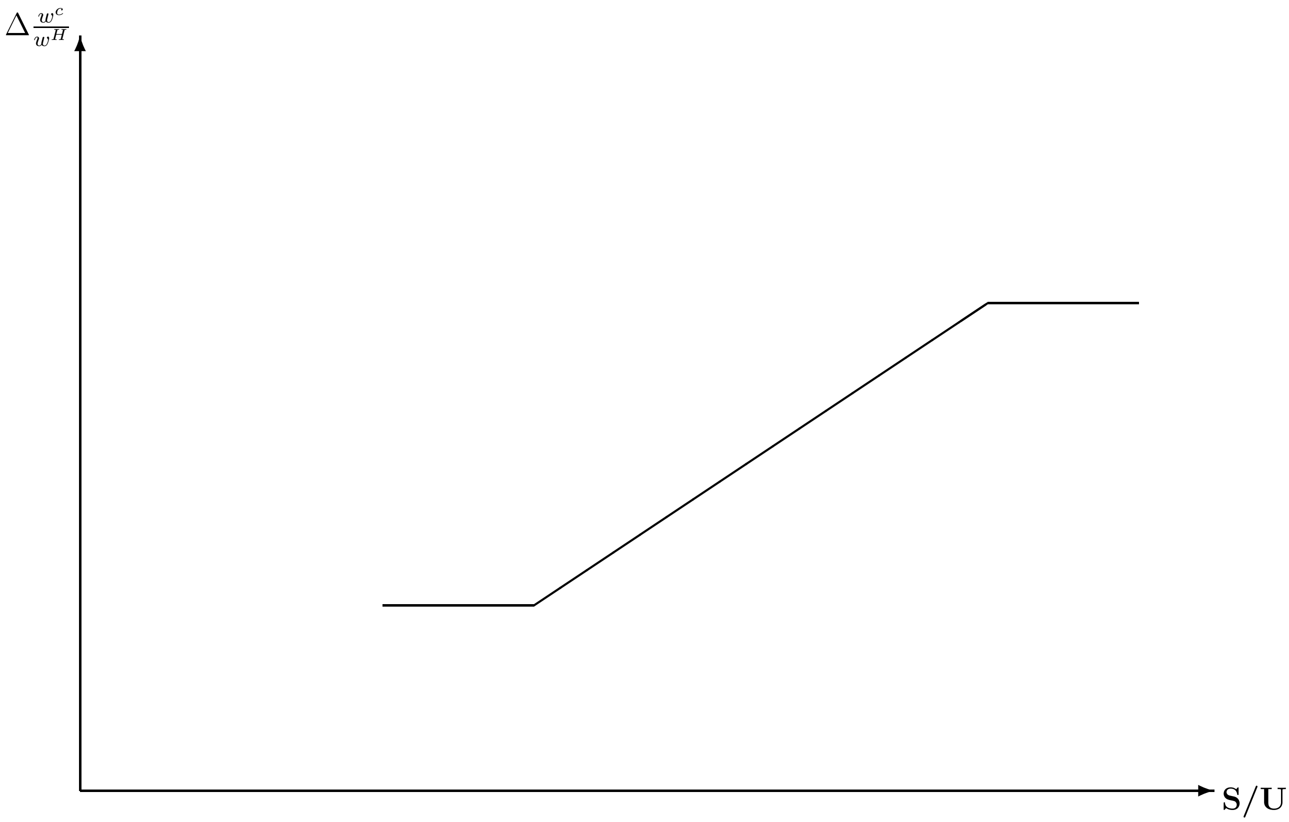
$$
\begin{aligned}
\Delta \ln \frac{w_i^s}{w_i^U} &= & 0 \quad & if & \frac{S_i}{S_i+U_i} \leq \phi^L \\
\Delta \ln \frac{w_i^s}{w_i^U} &= & (1-\sigma)[\log \frac{S_i}{U_i} - \log \phi^L] \quad & if & \phi^L < \frac{S_i}{S_i+U_i} \leq \phi^H \\
\Delta \ln \frac{w_i^s}{w_i^U} &= & (1-\sigma)[\log \phi^H - \log \phi^L] \quad & if & \phi^H < \frac{S_i}{S_i+U_i}
\end{aligned}
$$

Proposition 2 expresses how the arrival of the new technology induces a positive association between the supply of skill and changes in returns to skills. However, the proposition bypasses the channel through which this arise and, in this sense, it represents a reduced form relationship. Corollary 2 addresses this issue by combining Propositions 1 and 2 to highlight how it is the adoption of the PC-intensive technology that leads to increases in returns to skill.

Corollary 2: Returns to skill increase most in localities which choose to use PCs most intensively.

Any approach taken to evaluate Corollary 2 must acknowledge the endogeneity between PCs and returns to skill. Corollary 2 implies that its is the adoption of PCs induced by differences in initial supply of skill (or initial returns to skill) that causes increases in returns to skill. Viewed in this light, Corollary 2 can be evaluated by employing an IV strategy where either initial (pre-PC-adoption) levels of skill or returns to skill are used as instruments for PC-adoption in a regression of changes in the returns to skill on PC-adoption.

Figure 2: Effect of Initial Supply on Change in Relative Wage



At first pass, Proposition 2 may possibly appear to contradict the law of supply and demand because it predicts an increase in return to skill where supply is most abundant. However, this is not the case since the model does not allow the level of the return to skill to be positively related to supply. In fact, as stated in Proposition 3, even after the introduction of the skill-biased technology, the returns to skill must remain a weakly decreasing function of the supply of skill. Note that it is possible for the arrival of the skill biased technology to cause the disappearance of a negative relation between return and supply if localities are concentrated in the technology-mixing zone ($\phi^L < \frac{S_i}{S_i+U_i} < \phi^H$), since in this region there is factor price equalization. However, in the absence of any externalities in adoption, the model implies that the relationship between returns to skill and supply of skill cannot be positive even after the introduction of the skilled-biased technology.

Proposition 3: The arrival of the skill biased technology cannot induce a positive association between the return to skill and the supply of skill.

The content of Propositions 2 and 3 can be easily inferred from Figure 1. Because the returns to skill in this figure are captured by the slope of the production function, we can note that the slope of the outer envelop is weakly decreasing in the fraction of skilled workers. This is the content of Proposition 3. In contrast, if we consider the change in the return to skill induced by the new technology for an initial supply in the region ($\phi^L < \frac{S_i}{S_i+U_i} < \phi^H$), we see that the increase in the slope is larger for initial higher levels of supply. The reason is that the return to skill was initially more depressed in the higher supply localities and therefore the new technology allows for greater induced demand for skill in such areas. The content of Proposition 3 is depicted in Figure 3. In this figure we see that the availability of the new technology alters the relationship between returns to skill and supply. However, the slope of the new relationship is nowhere positive. Note that in the region $\phi^L < \frac{S_i}{S_i+U_i} < \phi^H$, the slope of the relationship is zero. This arises since the technological choice allows the reallocation of additional skill between the two technologies without affecting the returns.[7]

Now that we have examined the effects of supply on both adoption and wage change, we can therefore combine the two to obtain Corollary 3.

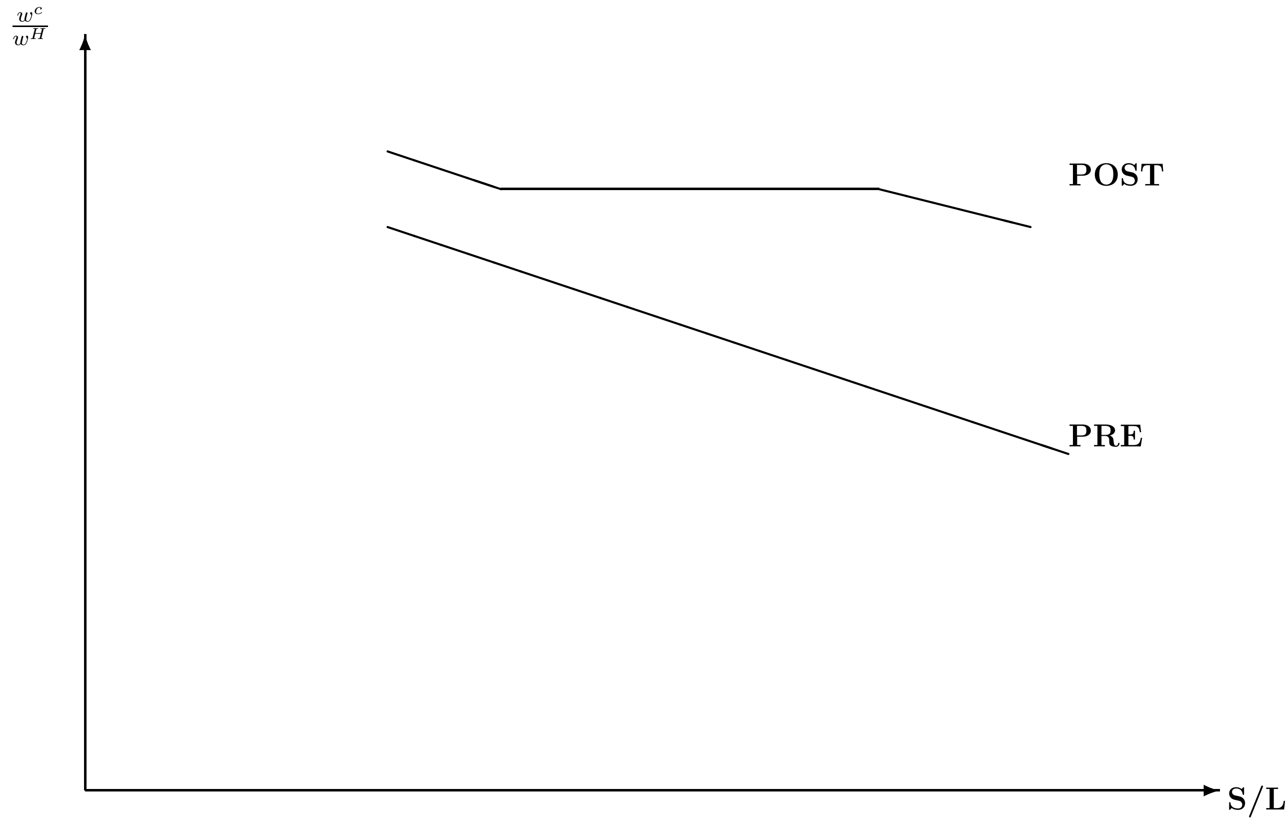
Corollary 3: The return to skill will not be larger in localities with more intensive use of PCs.

Corollary 3 indicates that although PC adoption and increases in the returns to skill should go hand-in-hand (as stated in Corollary 2), such positive co-movement cannot induce an outcome where the returns to skill are higher in a locality with a higher PC-intensity. The reason for this result comes directly from the fact that PC adoption is endogenous in the framework. To be more precise, PCs are adopted more aggressively in one locality versus another only because the cost of skill is lower. Hence PC capital cannot be more intensely used in a locality with a higher cost of skill. If instead of viewing the adoption and subsequent use of PCs as an endogenous phenomena as an exogenous phenomena, then it would be natural to expect PC use to be positively associated with returns to skill (since we are assuming

[7]This mechanism is identical to that underlying factor price equalization zones in international trade theory.

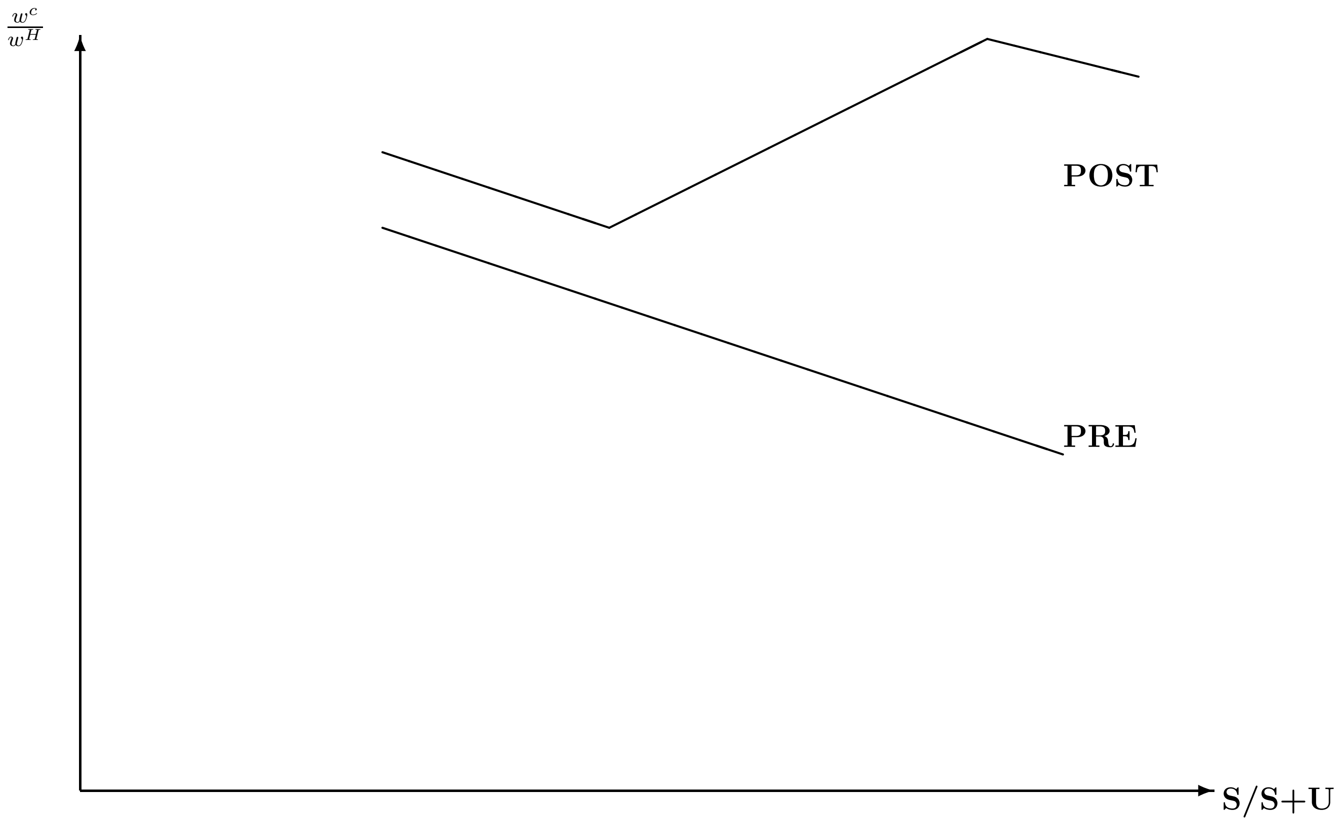
that PCs are associated with more skill intensive technology). Hence, this prediction nicely illustrates how a model of endogenous technology adoption differs from more conventional models with exogenous technological change.

Figure 3: Effect of Supply on Relative Prices



It is useful to point out that the implication of endogenous adoption stated in the previous propositions and corollaries could be overturned if the adoption process involved externalities. For example, suppose there existed a network type externality associated with the adoption of the new technology, that is, suppose that as more local production was done with the new technology, the productive performance of the new technology increased. In such case, we would be possible to have returns to skill being positive correlated to PC-intensity. It would also be the case that – as illustrated in Figure 4– the returns to skill should be, at least over a range, an increasing function of the supply of skill.

Figure 4: With Externality



So far we have focused on the implications of the process of technology adoption on the returns to skill, but we have not examined implications for each component, that is, implications for changes in the the wage of skilled workers and wages of unskilled workers taken individually. Proposition 4 addresses this point.

Proposition 4: After the arrival of the skill biased technology, the wage paid to skilled workers should **increase** most in localities which adopt PCs most intensively, or alternatively in localities with either an initially low return to skill or a high supply of skill. Conversely, the wage paid to unskilled workers should **decrease** most in localities which adopt PCs most intensively, or alternatively in localities with either an initially low return to skill or a high supply of skill.

Proposition 4 indicates that the model of endogenous technology adoption predicts opposite responses for high skilled wages versus low skilled wages to local supply conditions. In particular, as in the case of Proposition 2, Proposition 4 predicts positive relationships between changes in wages for a skill group and its relative supply. The intuition is again simple. If a locality has an abundance of skilled workers, then it should adopt the new technology aggressively which induces an increased demand for skill and a substitution away from less skilled workers. If instead the locality has mostly unskilled workers, then it does not adopt the new technology intensely and hence such a locality should not experience a strong reduction in the demand for less skilled workers. As we shall discuss later, the prediction that the adoption of PCs leads to a decrease in the wage of less skilled workers is a feature that helps differentiate the current model relative to a standard capital-skills complementarity view based on a nested CES specification.

3 Empirical Implementation and Data

Section 2 highlighted several implications of viewing technological adoption as driven by principles of comparative advantage. Our goal now is to examine whether city-level outcomes observed over the 1980-2000 period exhibit the patterns implied by such a model. We choose to focus on this period for several reasons. First, this is a period often referred to as one of technological revolution due to astounding technical progress and diffusion of information technology. Hence it is a perfect candidate period to see whether a neo-classical model technological adoption is relevant. Second, it is a period in which returns to education have increased substantially and where the main culprit is thought to be skill biased technological change. Therefore, it is particularly relevant to examine whether this period is best characterized as reflecting the effects of exogenous technological change (in contrast to much of this literature which treats the extent and bias of technological change as an exogenous driving force) or whether instead it reflects a process of endogenous choice of techniques.[8]

The city-level data we use can roughly be divided into two sources; technology and demographic. The technology data is derived from establishment-level information on technology use and is described in more detail in Doms and Lewis (2006). Basically, about 80,000 observations per year are used to compute the PC intensity (PCs per employee) of each city in our sample (230 cities).[9] In computing the PC intensity, we control for the industry and size of the establishment. Our resulting measure is therefore a industry-adjusted measure. We focus on PCs instead of other IT technologies for several reasons. First and foremost,

[8]Note that it could be possible that the extent of bias of technical change is endogenous at the national level, but not at the city level since markets across cities are well integrated. In such a case, our approach of focusing on city level outcomes would not identify elements of endogenous technological change. In other words, our empirical work evaluates the joint hypothesis that technological adoption is a phenomena that reacts to market conditions and that the labor market in cities across the US are not perfectly integrated.

[9]Doms and Lewis (2006) define "city" primarily as consolidated metropolitan statistical areas (CMSAs). The logic was to derive city definitions that corresponded to the idea of a local labor markets. In some cases CMSAs were combined.

businesses spent about 90 percent more money on PCs during the 1990s than on other types of computers. Also, spending on PCs is likely correlated with other information technology spending, such as spending on software, computer networking equipment, printers, et cetera. Finally, we were able to obtain consistent measures of PCs over this period.[10]

Figure 5 shows a scatter plot of the city-level PC measures for 1990 and 2002 (the 1990 results are shown along the horizontal axis and the 2002 results are shown on the vertical axis). The axes in figure 5 are scaled to the San Francisco Bay area, the city that consistently ranked very highly in nearly all measures of technology that we have examined. For instance, in 1990, the mean establishment in San Francisco had 15.9 more PCs per 100 employees than the mean establishment in Hickory North Carolina (the city that frequently ranked among the lowest of our sample of cities) after controlling for industry differences across the two cities. In 2002, the difference in PC intensity between the Bay Area and Hickory increased to 28.8. One item to note about figure 5 is that the differences in PC intensity are persistent over time: one crude measure of persistence is the correlation in between 1990 and 2002 is 0.74, almost identical to the Spearman rank correlation.

Most of the city-demographic information we use comes from the decennial censuses, specifically the 5 percent public-use micro-data files for 1980, 1990, or 2000. The thrust of our analysis is to examine how the technology measures discussed above correspond to relative supplies of skilled labor and to relative wages. Our measure of skilled labor is defined as workers who have a least a four year college degree plus one-half of those with at least some college education.[11]

Our measure of relative wages is computed by examining wages of people who report exactly a high-school degree or GED and by people with exactly a four years of post high school education. We adjusted wages for both groups by controlling for a fourth-degree polynomial in potential work experience, a female dummy, an immigrant dummy, and a dummy for people born after 1950. Although the results presented in subsequent tables use theses adjusted relative wages, the results are robust to using non-adjusted wages as well.

[10]Other measures of information technology were examined in Doms and Lewis (2006), including more refined measures of "PC". The results in Doms and Lewis (2006) were very robust to choice of technology measure.

[11]Measures similar to this one are often used in research examining the impact of skill-biased technological change, such as Katz and Murphy(1992), Autor et. al.(2003), and Card and DiNardo(2002). Further, our sample of workers includes employed 16-65 year-olds with at least one year of potential work experience and not living in "group quarters".

We also construct several city-level measures that we label as city controls. These measures include the log of the size of the labor force, and percent of the workforce in a city are African American, female, Hispanic, and U.S. citizens. Additionally, we construct 9 industry controls which reflect the employment distribution across major industry groups within each city.

In the empirical work that follows, it is necessary for us to use instruments that are correlated with the human capital in a city but not correlated with any of the unobserved determinants of technology adoption. Instruments used in Doms and Lewis (2006) relied on the historical density of colleges in an area. There are three reasons why the presence of colleges in an area may increase the general skill level of that area. The first is that the presence of colleges in an area reduces the cost of obtaining higher education for an area's residents. Second, college graduates may more likely settle in areas where they went to school as a result of low search costs. Finally, areas that have an abundance of colleges may also have amenities that college graduates place relatively high values on.[12] 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. Doms and Lewis (2006) show areas with land-grant colleges tend to have a significantly higher college-educated share. In addition to the land-grant colleges, we also use lagged information on local college density generally. 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 non-land-grant may have on the local college share, we also construct additional instruments using information on enrollment at two- and four-year colleges in 1971 in each metropolitan area.

4 Empirical Results

Our presentation of empirical results closely follows the order of the Propositions and Corollaries presented in Section 2. We begin by examining the determinants of technology adoption as measured by diffusion of PCs (Proposition 1). The first results will echo those presented in Doms & Lewis (2006). However, we go a step further by examining whether returns to

[12]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).

skill in 1980, at the beginning of the diffusion process for PCs, are negatively associated with the intensity of PC use in 2000 (Corollary 1). We then turn to examining implications of the model for changes in the returns to skill, as measured by the ratio of college wages to high school wages. In particular, we explore whether the data exhibit both a positive co-movement between PC-adoption and changes in the returns to skill as implied by Corollary 2, but do not reveal a positive association between the level of returns to skill and PC use as implied by Corollary 3. We also report the reduced form implications of the model regarding the changes in the returns to skill and the supply of skill (Proposition 2), in addition to examining changes in the relationship between the level of return and the supply of skill (Proposition 3). Finally, we examine the relationship between PC-adoption and changes in the wages paid to high school workers and college workers separately (Proposition 4).

4.1 PC adoption and local market conditions

To begin and to illustrate the strength of the relationship between PC adoption and skills, Figure 6 shows a scatter plot of PC intensity against the log ratio of skilled versus unskilled labor for 2000. To examine the relationship between these variables more rigorously, Table 1.1 reports a series of regression results. The first column of Table 1.1 reports the results obtained by regressing our city-level measure of PCs-per-worker on the log ratio of college to high school educated workers. As can be seen from the table, cities with a high fraction of college educated workers in 2000 also had adopted PCs more intensively by the year 2000. The data in Figure 6 demonstrate that the relationship is not driven by outliers. Since cities that use information technology more intensively may attract higher educated workers, this observation does not imply that the local supply of college educated workers caused a greater adoption of PCs. In order to address the possibility of reverse causation, Column 4 reports an estimate obtained by instrumental variables, where the instruments, which are described more fully in the previous section, correspond to measures of local college accessibility and attendance as of 1971, which is well before the availably of PCs.[13] The IV estimate is almost identical to the OLS estimate, suggesting that the endogeneity of worker migration cross cities to take advantage of more IT intensive cities may not be very strong.

Columns 2,3,5 and 6 follow up on this conjecture by breaking down the local skill measure into its level as of 1980 (which is just before the introduction of the IBM PC) and its change

[13] The first stage had an r^2 of .32.

between 1980 and 2000. The only difference between columns 2 and 3, and between columns 5 and 6, is the addition of a set of city level controls.[14] The estimates in columns 2 and 3 are obtained by OLS, while those in column 5 and 6 are obtained by IV. The results reported in Column 5 and 6 are based on the same 1971 variables to instrument both the the level and the change in skill supply. Note that if the supply of skills is exogenous to the process of technology adoption, then the coefficients on both the 1980 level of skill and the change in skill between 1980 and 2000 should have the same size coefficient, and this is what is observed in all four columns.[15] Furthermore, the estimates obtained by OLS and IV are very similar adding support to the notion that it is the local supply of skill that favored differential adoption patterns across US cities and not the reverse.[16] While there are many models or mechanisms of technological change that could potentially explain the observations presented in Table 1.1, our goal here is to examine whether the mechanism outlined in the theory section is a relevant.

The estimates presented in Table 1.1 indicate that cities who had a more educated labor force as of 1980 adopted PCs more aggressively between 1980 and 2000. The neo-classical model presented in Section 2 suggests that such an outcome arises due to the price incentive by firms in cities with initially expensive low skilled workers (relative to high skilled workers) to adopt skill-biased technologies.[17] In Table 1.2 we examine whether the data support such a mechanism by regressing PC intensity as of 2000 on the relative cost of skilled versus unskilled labor in 1980. As can be seen in Column 1, cities with low relative cost of skills in 1980 are observed to be using PCs more intensively as of 2000. In the second column, we add the change in the ratio of college and high-school educated workers, and in column 3 we also control for share of employment at the industry level (in two digit industries). In the fourth column, we instrument the change in the ratio of college to high school educated workers using again 1971 college attainment and access variables as instruments. In all cases, we find that the return to skill as of 1980 has a significant negative effect on subsequent PC-adoption. We also find that after controlling for initial returns to skill, an increase in the college population favors more PC-adoption. Once again we find only minor differences between treating changes in the college population as exogenous to the adoption process as

[14]The city level controls correspond the size of the labor force, unemployment rate, the fraction of population which is female, percent African-American, and U.S. citizens.

[15]We tested the equality of these coefficients. For column 2, the p-value of this test is .39. For column 5 it is .48.

[16]Recall that the measure of city-level PC-use we use controls for a cities industrial composition.

[17]A clear negative trend between relative wages and the supply of skilled labor for 1980 and 1990 is shown by the scatter-plots in figures 8a and 8b.

compared with estimating by IV, further suggesting that the endogeneity of skill supply to PC-adoption process is likely minor.

4.2 Returns to skill and PC adoption

We now turn to the relationship between the adoption of PCs and changes in the returns to skill. Recall that our model implies a positive association between these two endogenous variables. In Table 1.3 we report results obtained by regressing the change in the return to skill over the period 1980-2000 on the extent of PC-adoption in 2000. In the first 3 columns we estimate the relationship by OLS, which likely provides a downward biased estimate due to the endogeneity of PC-use. In particular, given our theoretical framework, we expect that unobserved variables which lead to higher returns to skill would result in lower PC adoption. As can be seen, our OLS results find a positive association between these two variables, but this association is fragile to the inclusion of city-level controls. In columns 4 to 6, we report IV estimates where we instrument the PC-adoption variable by the 1980 ratio of college educated workers to high school educated workers. As shown in Table 1.1, the first stage of this regression works well. The IV results indicate a strong positive association between PC-adoption and changes in returns to skill. In contrast to the OLS results, using IV we find the estimates of this relationship to be very robust to the inclusion of city controls. We also estimated (but not reported here) the relationship using as an instrument the 1980 value of the returns to skill (as suggested by Table 1.2). In this case, we also found a very significant and robust positive relationship between changes in returns to skill and PC-adoption. The estimates are even bigger than the ones report in Column 4-6, but are less precise.

In addition to predicting that localities that adopt PCs intensively should witness greater increases in returns to skill, the model also predicts that the adoption process should not lead to a situation where returns to skill are higher in cities that adopted PCs most intensively. To examine this implication of the model, Table 1.4 reports estimates of the relationship between returns to skill in 2000 and the use of PCs in 2000. The first 3 columns report results based on estimating the relationship by OLS, and in the last three columns the relationship is estimated by IV, where the ratio of college to high school equivalent workers in 1980 is the instrument. In none of these cases do we observe a positive relationship between PC-use and returns to skill. In the absence of controlling for the ratio of college to high-school educated workers, we actually find a significant negative relationship. When we control for a city's educational composition, we still find a negative relationship though it is imprecisely estimated. Taken together, the results in Tables 1.3 and 1.4 provide considerable support for the view that PC-adoption and changes in returns to skill should be viewed as jointly determined, and that the process appears to conform to the neo-classical principles outlined in Section 2.

4.3 Reduced form relationship between returns and skill supply

Tables 1.3 and 1.4 report results associated with examining the implications of the model as stated in Corollaries 2 and 4. For completeness, it is also of interest to directly examine the reduced for relationship emphasized by Proposition 2 and 3. To this end, we begin by showing a plot, Figure 7, of the changes in the returns to skill and the initial supply of skill. As can be seen, there is a clear positive relationship with a regression slope coefficient of .06 and standard error of .01. Turning to a fuller set of regressions, the first three columns Table 1.5 reports the results of regressing change in the returns to skill over the period 1980 to 2000 on the 1980 ratio of college to high school educated workers and the change in skill supply over the period 1980-2000.

In order to better interpret the coefficients on the initial supply of skill and the coefficient on the change in the supply of skill, it is helpful to recall that the theory implies that the arrival of a skilled biased technology will cause a flattening of the relationship between the returns to skill and the local supply of skill (as depicted in Figure 3). If we approximate this prediction by a change in the linear relationship between return and relative supply, then we can see that theory predicts the change in the returns to skill to be positively related to the initial level of skill and negatively related to the change in skill. In order to see this more clearly, let us express the initial relationship between return and supply by:

$$\frac{w_{i,0}^S}{w_{i,0}^U} = \alpha_1 + \alpha_2 \frac{S_{i,0}}{U_{i,0}}$$

and denote the relationship after the arrival of the technological option by

$$\frac{w_{i,1}^S}{w_{i,1}^U} = \beta_1 + \beta_2 \frac{S_{i,1}}{U_{i,1}}$$

where $\alpha_2 < \beta_2 \leq 0$.

Then the change in the returns to skill is then given by

$$\Delta \frac{w_i^S}{w_i^U} = (\beta_1 - \alpha_1) + (\beta_2 - \alpha_2)\frac{S_{i,0}}{U_{i,0}} + \beta_2 \Delta \frac{S_i}{U_i}$$

with the prediction that $\beta_2 - \alpha_2 > 0$ and $\beta_2 \leq 0$. In words, the coefficient on the initial supply should capture the change in the slope of the relationship between return and relative supply of skill–which the theory predicts in positive – and the coefficient on the change in supply should capture the final slope– which according to the theory could be either negative or zero.

Interestingly, the results in Columns 1-3 of Table 1.5 indicate a positive relationship between the change in returns and the initial supply of skill, while simultaneously observing a negative or zero relationship between the change in returns and the supply of skill. In fact, the latter relationship is sufficiently week to suggest it may be a zero relationship. The last three columns examine the effect of replacing the initial skill ratio with the initial value of the returns to skill, as also suggested by Proposition 2. Here we see, consistent with the theory, that returns to skills increased most in cities where the returns where initially low.

The results presented in Table 1.5 were aimed at evaluating the implications of Proposition 2. The goal of Figure 8 and Table 1.6 is to examine more directly the local flattening of the relationship between returns to skill and supply of skill implied by the theory. To this end, Figure 8 plots the relative wages and the supply of skill for 1980, 1990 and 2000 and Table 1.5 reports the associated regression estimates. From the figure or the table, we can that the slope of the relationship between returns to skill and the supply of skill is significantly negative in both 1980 and 1990.[18] By contrast, in 2000 there is essentially the decreasing returns to skill evaporates at the local level. This finding is consistent with Proposition 3 if cities are finding it optimal to simultaneously use both old and new technologies. Note that these observation are also consistent with those presented in Table 1.5, which can be viewed as providing first difference estimates of both the slope in 2000 (through the coefficient on the change in supply of skill) and the change in the slope between 1980 and 2000.[19]

[18] We also examined data from the 1970 decennial census and found a stronger downward sloping relationship than we found for 1980 or 1990. However, because of data issues, we could only focus only on 140 of our 230 sample of our cities.

[19] An alternative explanation for such convergence is that the supplies of skills convergence across cities. However, there was actually only minimal convergence in the fraction of college equivalent workers across cities over this period, with the variance of the fraction college equivalents per city being almost the same in 2000 as in 1980. This contrasts with Glaser (2005) that reports a divergence in the concentration of

4.4 Changes in wages and PC adoption

In order to complete our exploration of the implications derived in Section 2, namely Proposition 4, Table 1.7 displays results of changes in college and high school wages separately. In this table we see that the growth in wages of high school educated workers (in columns 1,3 and 5) was negatively associated with the extent of PC adoption within cities, and this pattern is observed for both the case where the relationship is estimated by OLS or by IV using the city level market conditions in 1980 as instruments for PC adoption. Note that this result is not implied by the previous results since high school educated workers could have been gaining in cities that adopted PCs aggressively while simultaneously having college educated workers doing even better. However, this is not what is observed. Instead, consistent with the theory, we see that high school educated workers were negatively affected by the adoption of PC in an absolute sense, not just a relative sense.

For college educated workers, the OLS results do not uncover much of a relationship between their wage change and the adoption of PCs. However, since both variables are endogenous, the coefficient can be expected to be biased. Accordingly we also report results where we instrument the extent of PC-adoption by the ratio of college and high school educated workers in 1980 and the return to college in 1980 (using only one of these instruments gives similar, but slightly less precise, estimates). The IV results indicate that college educated workers had faster wage gains in cities that adopted PCs most intensely. [20]

5 Exploring Some Alternative Explanations

The evidence presented in Tables 1.1 to 1.7 provide considerable support for the model of endogenous technological adoption we presented in Section 2. However, such evidence does not imply that this model is right since the data are certainly consistent with alternative interpretations. For this reason, it is interesting to examine which alternative explanations are consistent with the data and which are not. In particular, we want to ask here whether

college educated over this period. His result relies on looking precisely at the fraction of workers with 4 years of college or more. If instead we look at the fraction of college equivalents, where workers with post secondary education are allocated equally between high skill and low skill, then there is no indication of either convergence or divergence. Finally, if we look at the log of the ratio of college equivalents to high school equivalents, there is evidence of convergence but the coefficient is nowhere near -1.

[20] When breaking down effects by sex, we find that it is college educated women who gained most by the introduction of PCs, and it is high school educated men that lost most. For college educated men and high school educated women, the effects are very small.

the observed patterns can be easy explained by alternative formulation suggested by the literature. One class of explanations we want to examine remains in the neo-classical tradition but des not rely on our endogenous choice of technology story, but instead focuses upon the effects of a fall in the price of equipment – which PCs are one incarnation – within a stable production function framework. To be more precise, let us continue to consider an environment with four factors: traditional capital (K), PC/equipment (PC), skilled labor (S)and unskilled labor (U). However, instead of considering two production functions, let us postulate a unique production function denoted by $f(K_t, PC_t, S_t, U_t)$, with wages for skilled and unskilled labor given by the marginal products. The issue we want to address is whether the cross-city patterns we have document can be explained within this alternative framework as the result of a common fall in the price of PC/equipment. If we impose no restrictions on the function $f(\cdot)$, the answer to this question is a trivial yes since the stable production need simply to be chosen as the outer envelop of our two productions function setup.[21] Hence, to make this question relevant, we need to ask whether the observed patterns could be explained by commonly use parameterization for such a function. To this end, we will focus on three nested CES specifications.

The first parameterization we will consider, denoted by f^I, is in the spirit of the work by Katz Murphy (1992). In this case, the two types of capital form a sub-aggregate and the two types of labor form a sub-aggregate. The function $f^I(\cdot)$ can therefore be represented by

$$f^I(K_t, PC_t, S_t, U_t) = [K_t^\sigma + PC_t^\sigma]^{\frac{\alpha}{\sigma}}[S_t^\gamma + U_t^\gamma]^{\frac{1-\alpha}{\gamma}}$$

In the second case (F^{II}), motivated by the capital skill-complementarity hypothesis, we allow PC capital to be a complement to skilled labor. This case is represented by the following production function

$$f^{II}(K_t, PC_t, S_t, U_t) = K_t^\alpha[[S_t^\sigma + PC_t^\sigma]^{\frac{\gamma}{\sigma}} + U_t^\gamma]^{\frac{1-\alpha}{\gamma}} \qquad \sigma < 0$$

[21]Given that there is a fundamental observational equivalence between a choice of technique framework and a stable production function framework, one may ask what gain is there to focus on the multiple production function framework. Our answer is that the endogenous choice of technique framework leads one to consider parametrizations of the aggregate production function which otherwise would appear bizarre, un-intuitive and would therefore likely be overlooked. In contrast, when such parametrizations are presented through the lens of the endogenous technological adoption framework, they are become intuitive and credible contenders as explanations to observations.

The third possibility is motivated by Autor, Levy and Murnane (2003) which emphasizes the substitution between PCs and unskilled workers. In this case, the production function takes the form

$$f^{III}(K_t, PC_t, S_t, U_t) = K_t^{\alpha}[[U_t + PC]^{\gamma} + S_t^{\gamma}]^{\frac{1-\alpha}{\gamma}}$$

Now given that we want to consider the situation where firms at the city level can rent both types of capital on a common market, it is useful to define a reduced form production function $\tilde{f}^i, \quad i = I, II, III$, which represents the production possibility set at the city level, as follows

$$\tilde{f}^i(r_t^K, r_t^{PC}, S_t, 1 - S_t) = \max_{K_t, PC_t} f^i(K_t, PC_t, S_t, 1 - S_t) - r_t^K K_t - r_t^{PC}$$

and let us denote by the function $\tilde{PC}^i(r_t^K, r_t^{PC}, S_t, 1 - S_t)$, the optimal choice of PC equipment per worker for a city with a fraction S_t of skilled workers and a fraction $1 - S_t$ of unskilled workers. In order to be consistent with the observations presented in Table 1.1-1.7, the functions $\tilde{f}^i(\cdot)$ and $\tilde{PC}^i(\cdot)$ need to satisfy at least three properties. First, $\tilde{PC}^i(\cdot)$ should be such that the number of PC-per-workers increase with the fraction of the work force that is skilled. This requirement is necessary in order to be consistent with with the observations of Table 1.1. The next two requirements are that, following a decrease in the rental price of PCs (r^{PC}), the change in the wage of skilled workers should be greatest in cities where the ratio of $\frac{S}{U}$ is high, and the change in the wage of less skilled workers should be negatively related to the skill ratio. These conditions guarantee consistency with the results of Table 1.7 and therefore consistency with Tables 1.3 and 1.5. These two last conditions can be seen as restrictions on the cross-derivative of the functions $\tilde{f}^i(\cdot)$. In particular, to satisfy these conditions it is necessary that (1) the second derivative of wage of skilled workers (where the wage of skilled workers can be denoted $\tilde{f}_3^i()$) with respect to the rental cost of computers and to quantity of skill workers be negative, and (2) the second derivative of wage of unskilled workers (where the wage of unskilled workers can be denoted $\tilde{f}_4^i()$) with respect to the rental cost of computers and to quantity of skill workers be positive. These two conditions as expressed below.

$$\frac{\partial^2 \tilde{f}_3^i(r_t^K, r_t^{PC}, S_t, 1 - S_t)}{\partial r^{PC} \partial S} < 0$$

$$\frac{\partial^2 \tilde{f}_4^i(r_t^K, r_t^{PC}, S_t, 1-S_t)}{\partial r^{PC} \partial S} > 0$$

For all three of these parameterizations, the function $\tilde{PC}^i(r_t^K, r_t^{PC}, S_t, 1-S_t)$ can exhibit the property that the number of PCs per worker is an increasing in the fraction of skilled workers. Hence, the results of Table 1.1 could be generated by either of these models in addition to our choice of technique model. However, it can be verified that none of these parameterizations can simultaneous satisfy all three conditions. For case I, it is easy to see the reason by recognizing that the accumulation of PC capital has a similar effect of both the wages of skilled and unskilled workers. In case II, when PC capital increases with the ratio of skilled to unskilled ratio, then the condition $\frac{\partial^2 \tilde{f}_4^i(r_t^K, r_t^{PC}, S_t, U_t)}{\partial r^{PC} \partial S} > 0$ will not be satisfied due to the fact that increases in PC capital leads to an increase in the wage of less skilled workers. In case III, the change in relative wages due to a change in the cost of PC is independent of of local factor supplies (as in case I), and accordingly can't satisfy the conditions. Hence, these standard parameterization of the aggregate production function are not sufficiently flexible to offer an explanation to the set of observations that are easily explained with an endogenous technology model.

5.1 Labor Mobility and Trade

We now briefly examine the possibility that our cross-cities observations could be primarily driven by some non-technological forces as opposed to the technological forces emphasized by the model. In particular, we want to ask whether the observed patterns could be easily explained by either increased labor mobility across cities, or by increased goods market integration (free trade). Let us start with labor mobility. Since in year 2000, we are finding that there is less systematic differences in returns to skill across cities than in 1980, this could reflect an increase in labor mobility across cities with highly skilled individuals having left cities where skill is abundant to move to where it is scare . There are two problems associated with this conjecture as an explanation to the observed patterns. First, it is not clear that labor flows where in a direction that would favor convergence.[22] For example, the correlation between the change in college equivalent share by city over the period 1980-2000 with the level of the college equivalent share in 1980 (or the return to skill in 1980) is very close to zero; indicating that labor mobility likely played little role in favoring a convergence

[22]Barry & Glaeser (2005) actually suggest that flows favored divergence

in returns to skill across cities.[23] Furthermore, if labor mobility were the dominant force favoring a convergence in returns to skill across cities over this period – as opposed to resulting from different speed of technological adoption– we would not expect to observe the pattern presented in Table 1.5. Recall that in Table 1.5, we observed that changes in the college-high school wage differential over 1980-2000 were positively and significantly related to the fraction of college workers in 1980, and only weakly related to the change in the education composition of the city . If labor mobility was paying the dominant role, there is no reason to expect a positive association between the change in return and the initial skill mix once we control for the change in the city level skill mix. Another way to see this is by comparing figures 6, 7 and 8. If increased mobility was the dominant force, we should see the dispersion of skill mix reduce significantly but no change in the slope relating returns to skill and skill mix. However, the data indicates the opposite. The dispersion in skill mix across cities has not changed much, instead it is the slope of the relationship between returns to skill and skill mix that appears to have flattened.

A different mechanism that could remove systematic differences in returns to skill across cities is increase goods market (trade) integration. If the cost of trading between cities diminished significantly over the period, this should favor a reallocation of industries to take advantage of differences in skill supply across cities, thereby leading to factor price equalization. However, the difficulty with this explanation is that, controlling for industry structure, there should be no systematic differences in pc-use across cities: cities with more educated workers should have more skill and pc intensive industries but should not use pcs more intensively within an industry. However, as documented in Table 1.1 and illustrated in Figure 4, there is a strong positive link between pc-use with industries and the local supply of skill.

6 Conclusion

In this paper we set out a relatively concise neoclassical model of endogenous technology adoption. Such a model generates a number of predictions that we were able to test using a data set on technology, skills, and wages for a set of cities during the IT revolution. The predictions of the model were nearly universally accepted by the data.

[23]Barry & Glaeser (2005) actually suggest that flows favored divergence. The difference with the result reported here is they did not include any of the workers with post-secondary degrees in their measure of skilled workers, while our college equivalent share measure includes a fraction of post-secondary workers.

One important aspect of the model and the empirical results is that it ties together two rather disparate strands of the literature. One strand has focused on how technological change affects the demand for skilled labor while the other has examined how the supply of skilled labor affects technological adoption. Our model and estimation ties these two strands together, demonstrating how relative wages and changes in relative wages are related to technological change in a cohesive manner.

At the heart of the model is a choice facing firms on which production technique to employ. In our model, we choose a parsimonious approach and focus on just two choices. However, having these two choices produces a rich set of implications (richer than can be generated from more standard nested CES specifications). Our results are in many ways similar to those in the economic history literature, notably Goldin and Sokoloff (1984). We find that cities that enjoyed relative abundance of skilled labor in 1980 were those cities that adopted PCs (a skill-biased technology) most aggressively. Further, cities that adopted PCs the most aggressively were also cities that witnessed the largest increase in relative wages. In fact, the downward sloping relationship between relative wages and the supply of skilled labor that existed in 1970, 1980, and 1990 had lessened considerably by 2000. The increase in relative wages in response to PC adoption appears to be driven by gains in wages of high-skilled workers and relative declines of wages of low-skilled workers.

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Table 1.1: PC Adoption and Education

	OLS	OLS	OLS	IV	IV	IV
	1	2	3	4	5	6
$\left(\frac{C}{H}\right)_{2000}$	0.166	-	-	0.174	-	-
	(0.011)			(0.019)		
$\left(\frac{C}{H}\right)_{80}$	-	0.167	0.152	-	0.171	0.211
		(0.011)	(0.014)		(0.020)	(0.104)
$\Delta\left(\frac{C}{H}\right)$	-	0.145	0.130	-	0.228	0.169
		(0.026)	(0.034)		(0.059)	(0.025)
City Controls	-	-	yes	-	-	yes
R^2	0.50	0.50	0.58			
p-value	-	0.39	0.44	-	0.33	0.62

The dependant variable is the number of PCs per worker at the city level corrected for industry composition and there are 230 observations. The variable $\frac{C}{H}$ corresponds to the log of the ratio of college equivalent workers to high school equivalent workers. The instruments used are measures of local college availability and attendance patterns as of 1971. The reported p-value is associated to the test of equality of coefficients on $\left(\frac{C}{H}\right)_{80}$ and $\Delta\left(\frac{C}{H}\right)$, where the latter is the change over the period 1980-2000. The city level controls correspond the the log of the labor force, the unemployment rate, the fraction of city population which is female, African-American, and U.S. citizens.

Table 1.2: PC Adoption and Initial Returns to Skill

	OLS	OLS	OLS	IV
	1	2	3	4
$\left(\frac{w^C}{w^H}\right)_{80}$	-0.353	-0.357	-0.243	-0.257
	(0.070)	(0.074)	(0.071)	(0.111)
$\Delta\left(\frac{C}{H}\right)$	-	0.006	0.087	0.114
		(0.036)	(0.038)	(0.167)
City Controls	yes	yes	yes	yes
Ind. Shares	-	-	yes	yes
R^2	0.43	0.43	0.56	

The dependant variable is the number of PCs per worker at the city level corrected for industry composition and there are 230 observations. The variable $\left(\frac{w^C}{w^H}\right)_{80}$ corresponds to the relative wage of college to high-school workers. The instruments used are measures of local college availability and attendance patterns as of 1971. The variable $\Delta\left(\frac{C}{H}\right)$ corresponds to the 1980-2000 change in the skill level of the city's workforce. The city level controls correspond the the log of the labor force, the unemployment rate, the fraction of city population which is female, African-American, and U.S. citizens.

Table 1.3: Changes in Returns and PC Adoption

	OLS	OLS	OLS	IV	IV	IV
	1	2	3	4	5	6
$\left(\frac{P}{L}\right)_{2000}$	0.148	0.074	0.085	0.566	0.782	0.589
	(0.056)	(0.063)	(0.063)	(0.113)	(0.234)	(0.174)
$\Delta\left(\frac{C}{H}\right)$	-	-	-0.064	-	-	-0.088
			(0.035)			(0.041)
City Controls	yes	yes	yes	yes	yes	yes
Ind. Shares	-	yes	yes	-	yes	yes
R^2	0.27	0.35	0.36	-	-	-

The dependent variable is the change in the log ratio of college to high school wages, where wages are adjusted for experience and gender. The instrument used for PCs is the ratio of college to high school equivalent workers in 1980. The city level controls correspond the the log of the labor force, the unemployment rate, the fraction of city population which is female, percent African-American, percent us citizens. The industry shares correspond the the fractions of the work force in by major industry in 1980.

Table 1.4: Returns to Education and PCs in 2000

	OLS	OLS	OLS	IV	IV	IV
	1	2	3	4	5	6
$\left(\frac{PC}{L}\right)_{2000}$	-0.097	-0.172	-0.039	-0.280	-1.083	-2.483
	(0.060)	(0.066)	(0.068)	(0.114)	(0.247)	(2.213)
$\left(\frac{C}{H}\right)_{2000}$	-	-	-0.123	-	-	0.225
			(0.024)	-		(0.321)
City Controls	yes	yes	yes	yes	yes	yes
Ind. Shares	-	yes	yes	-	yes	yes
R^2	0.38	0.38	0.51	-	-	-

The dependant variable is the log ratio of college to high-school wages, where the wages are adjusted to control for education and sex. The PC-measure controls for industry composition.The city level controls correspond the the log of the labor force, the unemployment rate, the fraction of city population which is female, percent African-American, percent us citizens. The industry shares correspond the the fractions of the work force in by major industry in 1980.

Table 1.5: Changes in Relative Wages and Skill: Reduced Form Relationships

	1	2	3	4	5	6
$\left(\frac{C}{H}\right)_{1980}$	0.054	0.063	0.086	-	-	-
	(0.011)	(0.014)	(0.022)			
$\Delta\left(\frac{C}{H}\right)$	-0.083	-0.040	0.001	-0.079	-0.047	0.013
	(0.027)	(0.034)	(0.037)	(0.027)	(0.029)	(0.032)
$\left(\frac{w^C}{w^H}\right)_{1980}$	-	-	-	-0.320	-0.442	-0.474
				(0.062)	(0.057)	(0.059)
City Controls	-	yes	yes	-	yes	yes
Ind. Shares	-	-	yes	-	-	yes
R^2	0.16	0.35	0.41	0.17	0.44	0.51

Dependent variable is the change in log ratio of college to high school wages, where wages are adjusted for experience and gender. The city level controls correspond the the log of the labor force, the unemployment rate, the fraction of city population which is female, percent African-American, percent us citizens. The industry shares correspond the the fractions of the work force in by major industry in 1980.

Table 1.6: Relative Wages and Supply of Skills (all OLS)

	1(2000)	2(1990)	3(1980)	4(2000)	5(1990)	6(1980)
$\left(\frac{C}{H}\right)_{2000}$	-0.001	-	-	-0.028	-	-
	(0.014)			(0.015)		
$\left(\frac{C}{H}\right)_{1990}$	-	-0.055	-	-	-0.055	-
		(0.012)			(0.014)	
$\left(\frac{C}{H}\right)_{1980}$	-	-	-0.066	-	-	-0.106
			(0.011)			(0.012)
C. Cont.	-	-	-	yes	yes	yes
R^2	0.00	0.08	0.13	0.38	0.31	0.38

Dependent variable is log ratio of college to high school wages, where wages are adjusted for experience and gender. The variable $\frac{C}{H}$ corresponds to the log of the ratio of college equivalent workers to high school equivalent workers. The city level controls correspond the the log of the labor force, the unemployment rate, the fraction of city population which is female, percent African-American, percent us citizens. The industry shares correspond the the fractions of the work force in by major industry in 1980.

Table 1.7: Changes in Wages and PCs: College and High School Educated Workers

	1	2	3	4	5	6
	HS	Coll	HS	Coll	HS	Coll
	OLS	OLS	IV	IV	IV	IV
$\left(\frac{PC}{L}\right)_{2000}$	-0.145	0.002	-0.316	0.290	-0.257	.210
	(0.061)	(0.072)	(0.112)	(0.135)	(0.105)	(0.125)
$\Delta\left(\frac{C}{H}\right)$	-	-	-	-	0.036	-0.050
					(0.033)	(0.039)
City Controls	yes	yes	yes	yes	yes	yes
R^2	0.48	0.48	-	-	-	-

The dependant variable is either the percentage increase in the wage of high school educated workers or the percentage increase in the wage of college educated workers. For the columns indicated by IV, the variable $\frac{PC}{L}$ is instrumented by the ratio of college to high school educated workers in 1980 and the return to college in 1980.

Figure 5: PCs per 100 Employees by City: Difference from the San Francisco Bay Area

(after controlling for industry and establishment size)

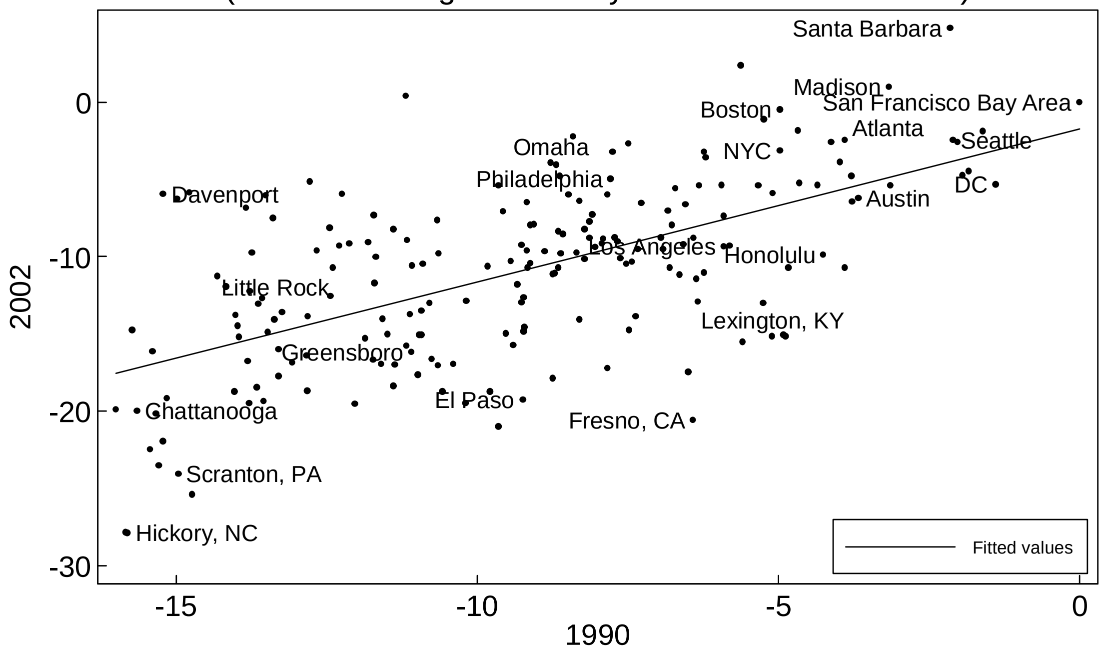

Figure 6: PC Intensity and Skills in 2000

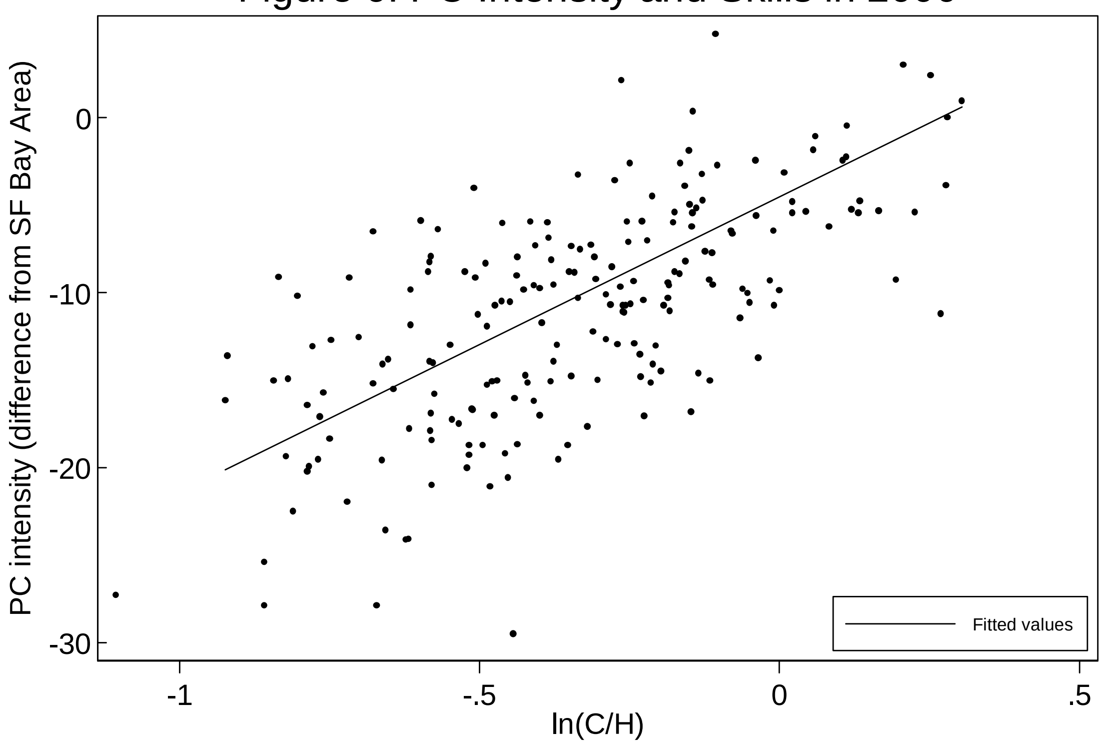

Figure 7: Initial Skill and Changes in the Return to Skill

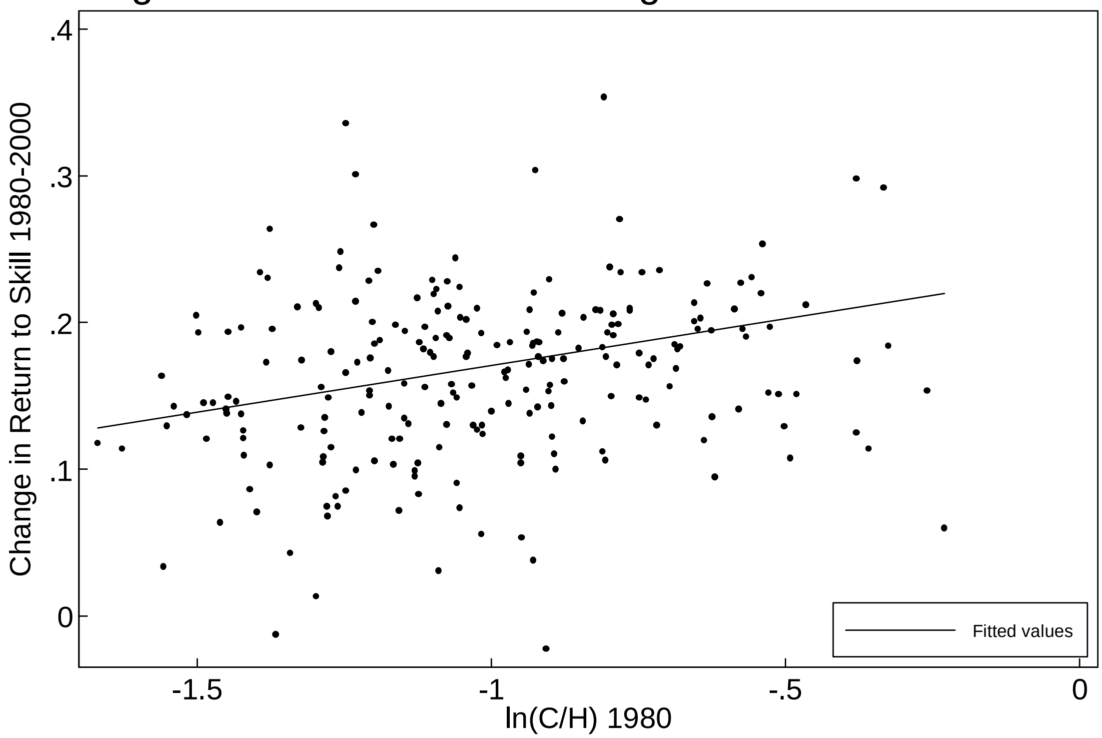

Figure 8: Relative Wages and Supply of Skilled Labor

Figure 8a: 1980

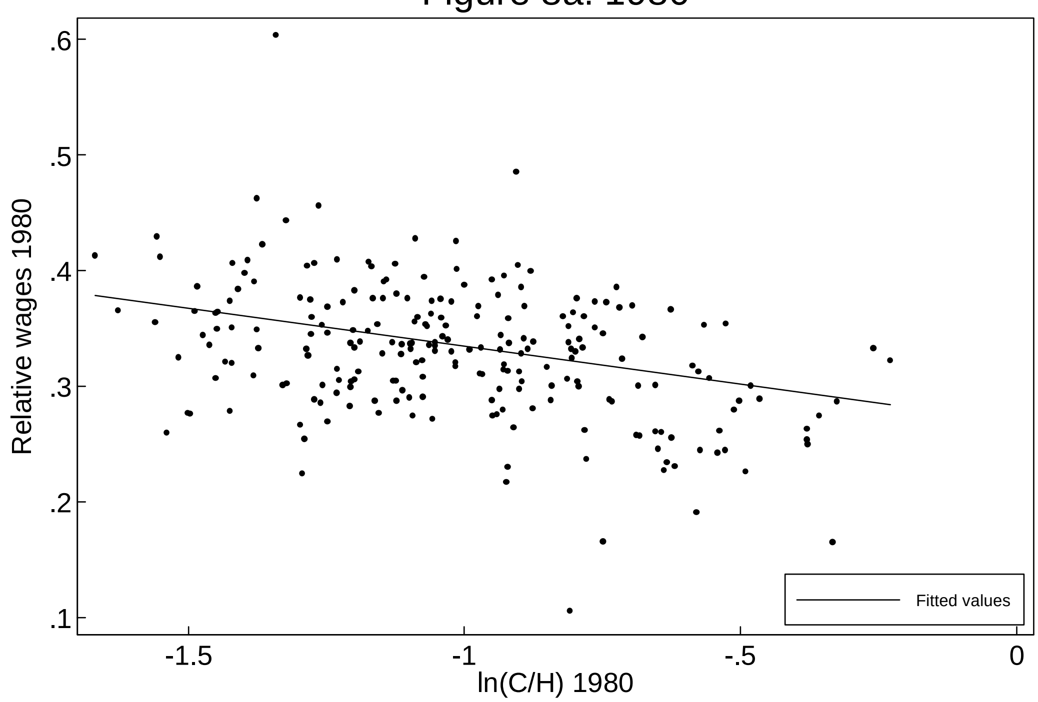

Figure 8b: 1990

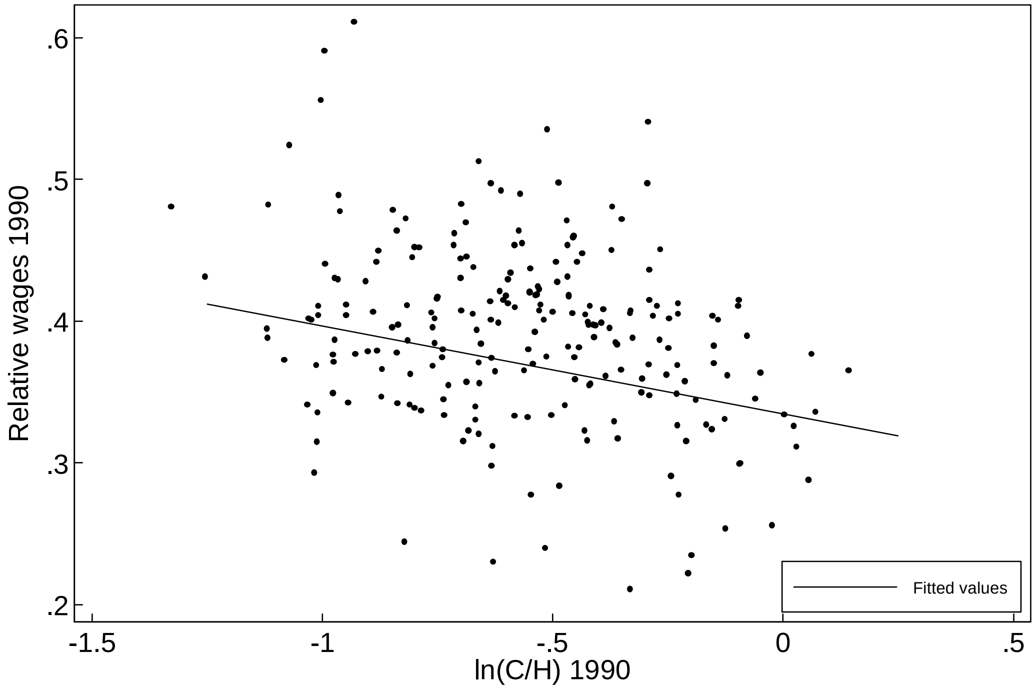

Figure 8c: 2000