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The Diffusion of Computers and the Distribution of Wages

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ABSTRACT

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When workers adopt technology at the point where the costs equal the increased productivity, output per worker increases immediately, while the productivity benefits increase only gradually if the costs continue to fall. As a result, workers in computer-adopting labor market groups experience an immediate fall in wages due to increased supply. On the other hand, adopting workers experience wage increases with some delay. This model explains why increased computer use does not immediately lead to higher wage inequality. More specifically, the results of the model are shown to be consistent with the question why within-group wage inequality among skilled workers as a result of computer technology adoption in the United States increased in the 1970s, while between-group wage inequality and within-group wage inequality among the unskilled did not start to increase until the 1980s. The model also suggests that the slow diffusion of computer technology in Germany along with the absence of major changes in the wage structure in the 1980s is consistent with the more compressed German wage structure. Finally, the theoretical predictions seem to be of the right magnitude to explain the empirical quantities observed in the data.

JEL Classification: J31, O15, O33

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1 Introduction

It has been well documented that wage inequality between college graduates and high school graduates in the United States has accelerated upon the emergence and diffusion of computer technology, and related information and communication technologies, in the labor market.[1] Many have suggested that the increase in wage inequality since the early 1980s has been caused by the complementarity between computer technology and skilled labor.[2] Indeed, the use of computer technology at work is more concentrated among skilled workers and associated with higher earnings: in 1984 (1993) 42.1 (70.2) percent of the college graduates used computer technology at work compared to 19.2 (34.6) percent of the high school graduates (Autor, Katz and Krueger, 1998, p. 1188), and Krueger (1993) estimated wage differentials between computer users and non users between 14 and 22 percent[3] explaining half of the widening of the educational wage gap in the period 1984-1989.

Linking increased wage inequality to the adoption and diffusion of computer technology leads to a number of questions, however. First, the use and impact of computer technology on the organization of work and the demand for labor dates back to at least the 1950s,[4] mainframe computers started to be extensively used in the early 1960s,[5] and already in the early 1970s a non-negligible part of the workforce had access to computer technology,[6]

[1] Greenwood and Yorukoglu (1997) argue that the mid-1970s are the watershed in the acceleration of wage inequality because the price of computer equipment fell faster after 1974 than before, which fostered adoption. Katz (2000) argues that relative wages began to rise in the early 1980s, just after the invention of microcomputers. See also Katz and Murphy (1992), Bound and Johnson (1992), Juhn, Murphy and Pierce (1993), Autor, Katz and Krueger (1998), Murphy, Riddell and Romer (1998), and Krusell, Ohanian, Ríos-Rull and Violante (2000) for analyzes of the U.S. wage structure over the past decades. Johnson (1997), Katz and Autor (1999), Acemoglu (2002), Aghion (2002), and Card and DiNardo (2002) provide overviews and criticism.

[2] Levy and Murnane (1996) and Autor, Levy and Murnane (2002) argue that the introduction of computers in a large U.S. bank has induced substitution of unskilled for skilled workers. Fernandez (2001) finds skill upgrading after a retooling of a large chocolate factory. Berman, Bound and Griliches (1994), Doms, Dunne and Troske (1997), Autor, Katz and Krueger (1998), Allen (2001), and Bresnahan, Brynjolfsson and Hitt (2002) observe that higher levels of computerization and investments in computer equipment are associated with higher levels of skill and education in the workforce. Chun (2003) finds that the use of computer technology is complementary with educated workers, and that educated workers have a comparative advantage in the adoption of computer technology. Finally, Autor, Levy and Murnane (2003) and Spitz (2003) find that computer technology generally substitutes for routine tasks and complements the performance of non-routine cognitive tasks.

[3] Whether this wage differential is causal and represents a measure of returns to (computer) skills or is to be explained by other factors is subject to debate (see e.g., Bell (1996), DiNardo and Pischke (1997) and Borghans and Ter Weel (2001)).

[4] See e.g., Shultz and Whisler (1960) for a bundling of papers describing the problems managers in five large firms faced when adopting computers. They describe how computers were applied for mathematical methods, statistical calculations, and mass integrated data processing and required large numbers of programmers and maintenance personnel.

[5] See e.g., Leavitt en Whisler (1958), Simon en Newell (1960), and Klahr and Leavitt (1967) for early descriptions and prospects of computer technology applications. They argue that mainframe computers changed the organization of work in services by offering new opportunities for the documentation of files and for calculating.

[6] See e.g., Bresnahan (1999) and Card and DiNardo (2002). Bresnahan notes that computer technologies were particularly applied in financial services since the 1960s. Card and DiNardo (2002) posit that computer investment was already high in the 1970s.

which did not lead to a rise in relative wages at that time. Only the introduction of the Apple II in 1977 and the PC in 1981 can be connected to the rise in between-group wage inequality since the early 1980s. So, why did wage inequality between skilled and unskilled workers resulting from the adoption of computer technology not already rise in the 1960s and 1970s and is computerization viewed as a factor contributing to acceleration in skill demand during the 1970s and 1980s only? Secondly, the behavior of within-group wage inequality reveals a steady increase in the 90th−10th percentile for college graduates in the period 1963-2000 and a rather constant pattern until 1980 and an increase afterwards for high school graduates (e.g., Juhn, Murphy and Pierce, 1993). Why is this?[7] Thirdly, wage inequality has increased strongly in the United States (and Great Britain) in the 1980s and 1990s but not in continental European countries such as Germany and France. Of course, institutional factors are likely to have a stronger impact on European wage structures (e.g., Katz, Loveman and Blanchflower, 1995, and Blau and Kahn, 1996), but is it really the case that the same technology did not have similar labor market effects in Europe too?

In this paper we propose a model to understand the impact of computerization on the pattern and timing of wage inequality. We do so by explicitly taking into account the diffusion process of computer technology, starting from the observation that computerization increases individual productivity but also the supply of efficiency units of labor. Hence, computer use by one worker negatively affects workers who are substitutes. The key innovation of the paper is to conceptualize the computer adoption problem from the perspective of the worker whether or not to adopt computer technology. The model contains three main features. First, we explicitly model the assignment of computer technology to workers. Secondly, the decision to adopt a computer is based on individual cost-benefit considerations weighing productivity benefits against costs, which induces adoption among high-wage workers first. Thirdly, we distinguish skilled and unskilled workers and allow for productivity differences between workers. As a result of these differences, not all workers adopt at the same time and limited substitution between the two types of workers leads to different effects on the wage structure.[8]

[7] Indeed, Autor, Katz and Krueger (1998, footnote 4) state that their empirical analysis suffers from criticism with regard to the fact that although relative wages and within-group wage inequality seem to move similarly in the 1980s, they appear to have evolved differently in the 1960s and 1970s.

[8] We assume that − in the end − there are computer applications for all workers and therefore treat computer technology as a general purpose technology based on its pervasiveness, technological dynamism, and innovational complementarities (Bresnahan and Trajtenberg, 1995) and its exogenous arrival and generic functions in the sector producing final goods

The main results from this model are the following. The timing and pattern of wage inequality is different for between-group and within-group wage inequality. Between-group wage inequality is falling when the first skilled workers adopt computers because the supply of additional efficiency units of labor outweighs productivity gains. When more skilled workers adopt computer technology, and when the first unskilled workers start to use computers, between-group wage inequality increases strongly because the productivity gains skilled workers experience outweigh the additional supply of skilled labor in efficiency units and the supply of additional units of unskilled labor increases relative wages. Eventually, when all workers have adopted computer technology, wage inequality falls to a level depending on differences in productivity gains: If skilled (unskilled) workers experience higher productivity gains, between-group wage inequality will be permanently higher (lower).[9] The short run effects of between-group wage inequality are much more pronounced than the long run effects. We also show that the maximum level of between-group wage inequality is higher the higher the initial relative wages and the (average) productivity differentials.

Within-group wage inequality for skilled (unskilled) workers is increasing once the first skilled (unskilled) workers adopt computer technology. This rise is caused by the fact that all workers in a group suffer from the additional supply of efficiency units, whereas only the adopters benefit from productivity increases. If all workers within a group have adopted computer technology, within-group wage inequality falls to the level prior to computer adoption if the productivity gains for every worker within the same group are equal.

Empirically, we obtain that the model is consistent with the development of the wage structure in the United States over the past decades. The increase in within-group wage inequality measured over the period 1974-1997 is consistent with a 30 percent increase in productivity related to the computer technology use of both skilled and unskilled workers, which is consistent with the estimates of the productivity effects of computer technology adoption presented by Bresnahan, Brynjolfsson and Hitt (2002). The mechanism we explore in this paper is able to explain approximately one-third of the time trend in wage inequality between skilled and unskilled workers. We also investigate the German

(Helpman and Trajtenberg, 1998b). In Section 4.3 and 4.4 we relax this assumption by exploring what happens if the use of computer technology would be limited to some fraction of the workforce only.

[9] Consistent with Galor and Moav (2000) the new level of relative wages – after complete diffusion of computer technology – may reflect in the long run either a skill-biased or skill-saving technological change. However, in the transition state towards full adoption of computer technology relative wages within and between groups of workers are mostly in accordance with a skill-biased technological change explanation.

wage structure in the 1980s and 1990s and find that the diffusion of computer technology is consistent with the properties of the German wage distribution. Because of a more compressed wage structure, computer technology has initially been adopted at a slower pace compared to the United States. For that reason no large effects on the wage structure were to be expected in the 1980s. However, this compressed wage structure has resulted in a strong increase in computer use in the 1990s. Current computer technology use in Germany is now as high as in the United States and we find figures suggesting that wage inequality has a tendency to rise. In addition, the pattern of wage inequality is consistent with the adoption of computer technology among different groups in the labor market.

This paper is related to the older literature on the diffusion of technology, including the work of Griliches (1957; 1958), Mansfield (1961; 1965), David (1969), Stoneman (1976), and Davies (1979), who argue that the costs of technology are important determinants of adoption and diffusion. In this paper, (endogenous) wages and productivity gains determine whether computer adoption is beneficial, whereas previous models treat the determinants of the diffusion process mostly exogenously. Our paper is also related to and extends the recent models of Acemoglu (1998) and Galor and Moav (2000) by explaining both the timing and the pattern of between-group and within-group wage inequality. Acemoglu (1998) uses the argument that, once invented, technologies are nonrival goods and can be used at low marginal cost. He then shows that the direction of technological change is directed towards the production of skill-complementary technologies because the market size for these technologies has become larger since the 1970s (see also Kiley, 1999). To explain between-group wage inequality, the upward pressure on relative wages from directed technological change has to dominate the downward pressure resulting from substitution. To explain within-group wage inequality he applies the assumption that not all skilled workers have the same ability.[10] Increased supply of skilled labor initially depresses the skill premium, but endogenous technological change immediately benefits the more able workers in both the skilled and unskilled groups. We argue that within-group wage inequality for unskilled workers did not increase until the early 1980s, we do not need an ability bias or adaptability assumptions to explain adoption patterns, and we argue that the costs of computer adoption and its use are non-negligible relative to wages.

[10] See also Galor and Tsiddon (1997) who argue that ability is more valuable in periods of rapid technological change, and Betts (1994) and Caselli (1999) who suggest that high-ability workers benefit from (skill-biased) technological change thereby explaining wage inequality.

Galor and Moav (2000) assume that the level of human capital of skilled and unskilled workers is determined by their ability as well as the technological environment because human capital is assumed to be technology specific. In this way, technological change reduces the adaptability of existing human capital for the new technological environment but increases the productivity of workers operating with the new technology.[11] Finally, an increase in the rate of technological change raises the returns to skilled labor, which induces more agents to become skilled. We improve upon their analysis by arguing that eventually there are applications for every worker, the increase in skilled labor supply happened before computer technology was widely applied which seems inconsistent with their story of increasingly more people becoming skilled when the returns go up, and we do not need to assume that adaptability to computer technology plays a major role in its adoption to explain the developments of the U.S. and German wage structures.

The plan of the paper is as follows. Section 2 presents the patterns of wage inequality in the United States and provides a comparison with the German wage structure. Section 3 presents the basic model. Section 4 shows the pattern and timing of wage inequality. Section 5 presents estimates for the United States and Germany consistent with the model and provides a benchmark for assessing whether the theoretical predictions are of the right magnitude to explain the empirical quantities observed. Section 6 concludes.

2 Changes in the Wage Structure

Computer technology is likely to have influenced the wage structure and labor demand in several ways. Assuming that the adoption of computer technology increases productivity, two factors influencing the wage structure have to be distinguished. First, there will be an individual productivity increase for workers adopting computers, which increases their wages. Secondly, increased productivity also increases the number of efficiency units of labor, influencing all workers' wages, depending on how substitutable they are. Hence, besides an individual effect, related to productivity, changes in the wage structure depend on the composition of distinctive groups of workers in the labor market. We define wage differences between workers with different productivity levels belonging to the same labor

[11] See also Chari and Hopenhayen (1991), Heckman, Lochner and Taber (1998), Gould, Moav and Weinberg (2001), Weinberg (2001), Aghion, Howitt and Violante (2002) and Violante (2002) for similar assumptions about obsolescence and transferability problems of (parts) of the human capital stock when a new technology arrives.

market group as *within-group wage inequality* and differences between workers in different groups as *between-group wage inequality*. We assume that all workers within a group are perfect substitutes and that substitutability between both groups is limited. We define skilled workers as those with at least a college degree, and unskilled workers as the ones with a level of education below a college degree.[12]

Figure 1 shows three pictures of relative annual wages in the United States in the period 1963-2000 and three pictures for Germany in the period 1984-2001. The picture presented in the first panel of Figure 1 contains the difference between log wages of the 90th percentile of the skilled workers and the 10th percentile of the unskilled workers, which we apply as a measure of between-group wage inequality. The picture for the United States − using the March CPS files[13] − reveals that until 1980 this wage differential remains fairly constant, but afterwards it rises substantially (almost 20 percent).[14] The second and third panel of Figure 1 show the 90th−10th wage differential within the groups of skilled and unskilled workers, which we apply as measures of within-group wage inequality. For the United States, the patterns that become apparent in these pictures look somewhat distinct. Within-group wage inequality among skilled workers steadily increases since the mid-1960s, and within-group wage inequality among unskilled workers seems to be fairly constant until 1980 and rising ever since.

Autor, Katz and Krueger (1998, Table 1) report that the employment shares of higher educated workers have been increasing in the period 1960-1996. The share of college graduates increased from 10.6 percent in 1960 to 28.3 percent in 1996, where the largest increase took place in the period 1960-1980 (from 10.6 to 20.4 percent). In the same period the number of high school graduates increased modestly from 27.7 to 33.4 percent, but the share of high school dropouts has fallen from 49.5 to 9.4 percent. This increase in the relative supply of skilled labor has been documented too by Acemoglu (2002, Figure 1) who shows that there has been no tendency for the returns to college education to fall

[12] An analysis of the entire labor market distinguishes our study of the impact of computer technology on wages from the one by Autor, Katz and Krueger (1998). They analyze the impact of computer adoption on the employment and wages of constructed series of college graduates and high school graduates. Since for our argument the distribution of productivity differentials plays a crucial role, an analysis of the entire wage distribution is more appropriate for the purpose of this paper.

[13] Recently, DiNardo, Fortin and Lemieux (1996) and Lemieux (2003) have argued that it would be better to use the MAY/ORG CPS files instead of the March files. In Appendix C we provide arguments why for the purpose of the present paper it is better to use the March series. The samples are constructed as described in Appendix A.

[14] These numbers are consistent with the ones presented by Katz and Autor (1999, Figure 3) and Juhn, Murphy and Pierce (1993, Figure 4) using weekly wages by percentile. Katz and Autor split the sample between male and female workers, but the overall picture looks similar. It is also consistent with their figures on overall wage inequality for the period 1963-1995 (Katz and Autor, 1999, Figure 4).

after this remarkable increase in supply. Only in the 1970s the returns to college education fell, but then rose sharply during the 1980s and early 1990s. The increase in relative wages since 1980 seems to be too high to be accounted for by the slowdown in the growth of the supply of higher educated since the 1980s only (e.g., Katz and Murphy, 1992, Murphy, Riddell and Romer, 1998, and Card and Lemieux, 2001).[15] More importantly, the timing of the increase in between-group wage inequality around 1980 and the increase in within-group wage inequality among unskilled workers (Figure 1, Panel C) is unexplained. In addition, within-group wage inequality among skilled workers seems to have increased independently of the fall in returns to schooling in the 1970s and the sharp rise in the 1980s and early 1990s.

For Germany three similar pictures are reported in Figure 1. We use the German Socio-Economic Panel (GSOEP) to construct the series. Between-group wage inequality in Germany seems to be falling until the mid-1990s and rising somewhat afterwards. Within-group wage inequality among skilled workers is fluctuating but reveals no trends. The level of within-group wage inequality among unskilled workers has narrowed until about 1994 and remains constant afterwards. The overall pattern of wage inequality in Germany stands in sharp contrast to the trends in wage inequality in the United States.[16] In the United States a change in the trends of between-group and within-group wage inequality among the unskilled can be observed around 1980, while in Germany no major changes are observed in the 1980s. However, the changes since the mid-1990s in Germany are similar, although less pronounced, to the U.S. trends in the 1980s.

Insert Figure 1 over here

Differences in the wages of skilled and unskilled workers will be affected by both differences in the timing of individual computer adoption and aggregate effects related to the supply of skilled and unskilled labor. Assuming that workers with the same wage have

[15] Competing explanations are the role of globalization pressures in reducing the relative demand for less educated workers, the decline in unionization and the value of the minimum wage. See Katz and Autor (1999) for an overview of the limited impact of these explanations to explain the developments in the United States since the 1960s.

[16] See e.g., Abraham and Houseman (1995) for an analysis concerning the differences in wage inequality in Germany and the United States. They find that wage setting institutions are one explanation for the different trends in both countries. In addition, the German supply of skilled workers accelerated relative to the United States in the 1980s, which may help explain the divergent trends in wage inequality in Germany and the United States (given demand). Finally, the distinction between skilled and unskilled labor is likely to be less clear in Germany because the German educational system does a better job of supplying workers with skills. This is likely to compress the wage structure relative to the United States, where there is a more clear distinction between college graduates and other workers.

the same probability to adopt a computer, it is possible to isolate the aggregate supply effects from the individual effects by comparing workers from both groups earning the same wages at some point in time. We have taken the annual wages of the skilled U.S. workers at the 40th and 50th percentile and looked for the unskilled workers earning the same annual wages in 1963. It turns out that these are the wages of the unskilled workers at the 75.7th and 83.9th percentile of the unskilled wage distribution.[17] Figure 2 shows the wage differentials between both groups keeping the relative position within each group constant at these percentiles. The picture reveals that wage differentials rise somewhat and are positive until the early 1970s. From then on until the mid-1980s the wages for unskilled workers are higher. Around 1980 there is a turning point in the wage differential in favor of skilled workers.[18] Figure 2 reveals that workers with the same productivity in 1963, but who differ with respect to the group they belong to, have experienced a different pattern of wages over time.[19]

Insert Figure 2 over here

3 Model

Analyzing these simple pictures suggests that wages are both determined by individual productivity levels within each group and by differences between the two groups of workers. These two effects have a different impact on the wage structure over time and need to be analyzed separately. To do so, consider a competitive economy producing a homogeneous good Y. The good is produced by a labor input consisting of skilled and unskilled workers. Because of productivity differences among skilled and unskilled workers, we define the supply in terms of efficiency units as S and U.

[17] These percentiles of the wage distribution of both groups are taken because at these percentiles there exists a great deal of overlap between the wages of both groups of workers. The percentiles do not exactly match because not all possible values of wages are present in the sample. Actually the 75.7th and 83.9th percentile of the unskilled wage distribution are somewhat above the 40th and 50th percentile of the skilled wage distribution.

[18] This pattern of between-group wage inequality is consistent with the figures presented by Katz and Murphy (1992) using similar data for the period 1963-1987, and the analysis of Krusell, Ohanian, Ríos-Rull and Violante (2000) for the period 1963-1992.

[19] Some have argued that the composition of the groups of workers is likely have changed over time, influencing the "quality" of the groups workers belong to. Acemoglu (2002, Appendix) shows that composition effects are unlikely to have influenced wages over time. His exercise shows that changes in the structure of wages over the past four decades cannot be explained by composition effects, and reflect mainly changes in the returns to skills.

Production

Production occurs according to a CES production function and equals

$$Y = ((\chi S)^{\rho} + (\psi U)^{\rho})^{\frac{1}{\rho}}, \tag{1}$$

where $\rho \leq 1$, and the elasticity of substitution between S and U equals $\sigma = \frac{1}{1-\rho}$. The corresponding wages in efficiency units are w_s^{eu} and w_u^{eu} for S and U, and competitive wages give a standard relative demand equation:

$$w^{eu} \equiv \frac{w_s^{eu}}{w_u^{eu}} = \left(\frac{\psi U}{\chi S}\right)^{\frac{1}{\sigma}}. \tag{2}$$

For convenience, w_u^{eu} is normalized to 1, so $w_s^{eu} = \left(\frac{\chi S}{\psi U}\right)^{1-\rho}$.

Worker Heterogeneity

Productivity levels not only differ between groups, but also within groups. This might be due to unobserved heterogeneity, but individual productivity levels might also differ from year to year due to on-the-job learning, aging, sector shifts and other influences, which need not be specified further.[20] We assume that workers are perfectly substitutable within groups, so any productivity difference is reflected in wages.

Productivity depends on the parameters $a_i \sim [\underline{\alpha}, \overline{\alpha}]$, with $\underline{\alpha} > \overline{\alpha}$ for skilled worker i and $b_j \sim [\underline{\beta}, \overline{\beta}]$, with $\underline{\beta} > \overline{\beta}$ for unskilled worker j. Productivity parameters of skilled and unskilled workers can only be compared when wages in efficiency units are taken into account. We allow the wage intervals of both groups to overlap. This is consistent with the empirical observation that the wages of the most productive unskilled worker are higher than the wages of the least productive unskilled worker, i.e. $\overline{\beta} w_u^{eu} > \underline{\alpha} w_s^{eu}$.[21]

To enable an analytical solution of the model, the distribution of the productivity parameters for skilled and unskilled workers is assumed to take the following form: $P^s(a) = \frac{1}{1-\rho} a^{\frac{2\rho-1}{1-\rho}} p^s$ and $P^u(b) = \frac{1}{1-\rho} b^{\frac{2\rho-1}{1-\rho}} p^u$, where $p^s = \frac{\sigma-1}{\sigma} \frac{1}{\overline{\alpha}^{\sigma-1} - \underline{\alpha}^{\sigma-1}}$ and $p^u = \frac{\sigma-1}{\sigma} \frac{1}{\overline{\beta}^{\sigma-1} - \underline{\beta}^{\sigma-1}}$

[20] Gould, Moav and Weinberg (2001), Aghion, Howitt and Violante (2002), and Violante (2002) also explain differences in the development of within-group and between-group wage inequality. They assume workers to differ in their adaptability to new technologies as a result of random shocks or assignment, and Violante (2002) also assumes that technologies differ in their productivity or quality to generate temporary within-group wage inequality. Aghion, Howitt and Violante (2002) use an overlapping generations model to get similar effects of technology adoption on wages. Caroli and García-Peñalosa (2002) build a model in which they use different attitudes towards risk to generate heterogeneity between workers.

[21] To make this overlap of productivity levels consistent with rational individual schooling decisions, we assume that productivity does not only depend on years of schooling. Differences in innate ability, talent to perform certain tasks, or age and experience all provide plausible arguments for this assumption.

are obtained from solving the integral for the distributions of productivity parameters of both types of workers. If $\sigma = 2$ the assumed distribution is such that the wage bill is uniformly distributed over the productivity parameters a and b. This assumption about the uniform distribution of productivity parameters is equivalent to the assumption made by Galor and Moav (2000, p. 477) about the uniformly distributed ability parameters in their model.

Productivity

Each worker's productivity depends on his productivity parameter and whether or not he uses computer technology. Productivity equals $q_i^s = a_i$ and $q_j^u = b_j$ without using computer technology and $q_i^s = a_i\theta^s$ and $q_j^u = b_j\theta^u$ when using the technology, where $\theta^s, \theta^u > 1$ are the proportional productivity gains from working with computer technology. We assume that within groups the productivity gain from using computer technology is the same, while between groups it is allowed to differ, and that for all workers there exists some computer application, which makes production more efficient.[22] Since within groups workers are producing the same product, these assumptions are justified.

Wages

In a competitive labor market, each efficiency unit of labor receives the same return and the individual wage equals the productivity parameter multiplied by the return to an efficiency unit of labor. In such a setting, employers are indifferent between employing a worker who uses computer technology and one who does not because they pay the same wage for each efficiency unit of labor. This means that both the productivity gain and the costs of using computer technology are passed on to the worker. Hence, wages equal $w_i^s = a_i w_s^{eu}$ and $w_j^u = b_j$ for workers who do not use computer technology and $w_i^s = a_i w_s^{eu}\theta^s - V$ and $w_j^u = b_j\theta^u - V$ for those who do, where V represents the cost of computer technology. Note that V is (implicitly) expressed in terms of w_u^{eu} and could be viewed as the annual rental price of computer technology.[23]

[22] The alternative assumption would be to model a complementary relationship between the productivity parameters a and b and θ. Assuming such a relationship leads to earlier adoption of computer technology (given the costs of adoption) by workers with a proportional productivity gain $\theta^i > \theta^s$ and $\theta^j > \theta^u$ and to later adoption by workers experiencing proportional productivity gains smaller than θ^s and θ^u. As will be shown below, such an assumption would lead to a similar pattern of diffusion but to a permanently higher level of within-group wage inequality. In addition, the pattern and timing of between-group wage inequality depends on whether $\theta^s > \theta^u$ or not.

[23] We do not specify the production of computer technology further in this paper and assume that the costs of using computer technology are falling exogenously over time. This is consistent with the modelling of the exogenous arrival

Wages and Computer Technology Adoption

The individual decision to adopt computer technology can be written as a trade-off between the increased productivity θ and the costs of the computer V, given the worker's productivity.[24] The break-even productivity for computer adoption for both types of workers then equals

$$a_i^{be} = \frac{V}{(\theta^s - 1)w_s^{eu}} \tag{3}$$

and

$$b_j^{be} = \frac{V}{(\theta^u - 1)}. \tag{4}$$

Equations (3) and (4) show that the break-even productivity at which it becomes beneficial to adopt computer technology falls when (i) the costs of computer use (V) fall,[25] (ii) the proportional productivity gain (θ^s, θ^u) becomes larger, and (iii) the wage per efficiency unit of labor (w_s^{eu}, w_u^{eu}) is higher. Assuming that the costs of the computer are the same for each worker and fall exogenously and continuously over time, the productivity gain and the wage in terms of efficiency units determine the adoption of computer technology for the individual worker.[26] Hence, computer costs relative to wages determine whether or not it is beneficial for a worker to adopt computer technology. In addition, differences in computer use between skilled and unskilled workers also depend on differences in the proportional productivity gains from using a computer.[27] Finally, these equations reveal that the wages of workers adopting computer technology are not rising immediately by

of general purpose technologies by Helpman and Trajtenberg (1998a), except that they include a R&D sector in which resources diverted from final production are used to develop the new supporting components for different applications.

[24]Note that the adoption decision may be different for each individual worker within a firm. This is consistent with the literature investigating inter- and intra-firm technology diffusion showing that the diffusion of new technology within firms is similar to the diffusion between firms (e.g., Karshenas and Stoneman, 1993 and Stoneman and Kwon, 1996). Hence, it is unlikely that firms adopt computers for all workers at once. We do not take into account different vintages of workers. Card and Lemieux (2001) find some vintage effects in the returns to education in recent cohorts of college graduates, which might be due to easier adaptability among younger workers. However, Friedberg (2003) finds that computer technology use is surprisingly flat over the life cycle, and if there are differences they are likely to be reflecting a lower rate of computer use among young workers.

[25]Autor, Levy and Murnane (2003) develop a related model using the costs of computer adoption as the driving force behind adoption. However, they focus on the allocation of human labor input across different tasks and not on the pattern and timing of wage inequality resulting from computer technology adoption. Borghans and Ter Weel (2004) demonstrate how computer technology alters the division of time between different tasks. They derive that the allocation of time shifts from routine towards non-routine tasks.

[26]The development of computers might also be endogenized by directing a certain fraction of production towards the development of computers. The allocation of labor to R&D then leads to falling costs and higher quality. However, endogenizing the development of computers does not yield additional insight in explaining wage inequality. David and Olsen (1986) and Helpman and Trajtenberg (1998b) develop such diffusion models in which the (further) development of new technology is endogenized after its arrival.

[27]If, all things being equal, $(\theta^s - 1) > (\theta^u - 1)$, skilled workers gain more in terms of productivity from using a computer, which is equivalent to arguing that they are more efficient in using the computer. Chennells and Van Reenen (1997), Entorf and Kramarz (1997), and Entorf, Gollac and Kramarz (1999) interpret their findings for the United Kingdom and France of high-wage workers using computers in favor of such an explanation.

the size of the proportional productivity gain because the costs of the computer have to be taken into account. This way of modelling is consistent with the findings of Entorf and Kramarz (1997) − using longitudinal data for France − who show that the wages of computer adopters relative to similar workers not adopting have been rising by some 1-2 percent a year after adoption.[28]

Supply of Efficiency Units

The supply of efficiency units of labor consists of two components: (i) the sum of all productivity parameters representing total productivity before computerization, and (ii) the productivity gains workers experience from using a computer, which equal $S = S^e \int_{\underline{\alpha}}^{\overline{\alpha}} a_i P^s da_i + S^e \int_{\underline{\alpha}}^{\overline{\alpha}} (\theta^s - 1) a_i P^s da_i$ and $U = U^e \int_{\underline{\beta}}^{\overline{\beta}} b_j P^u db_j + U^e \int_{\underline{\beta}}^{\overline{\beta}} (\theta^u - 1) b_j P^u db_j$, where S^e and U^e are defined as the supply of skilled and unskilled workers in persons. This results in the following expressions for the supply of efficiency units of labor:

$$S = S^e p^s \left((\overline{\alpha}^\sigma - \underline{\alpha}^\sigma) + (\theta^s - 1) \left(\overline{\alpha}^\sigma - \left(\frac{V}{(\theta^s - 1) w_s^{eu}} \right)^\sigma \right) \right) \tag{5}$$

and

$$U = U^e p^u \left((\overline{\beta}^\sigma - \underline{\beta}^\sigma) + (\theta^u - 1) \left(\overline{\beta}^\sigma - \left(\frac{V}{(\theta^u - 1)} \right)^\sigma \right) \right). \tag{6}$$

Equations (5) and (6) show that the supply of labor depends positively on the size of the distribution of the productivity parameters a and b, the productivity gain from using computer technology θ, and the elasticity of substitution between skilled and unskilled workers σ; it depends negatively on the costs of computer technology V.

Relative Wages after Complete Diffusion with No Computer Costs

To solve the equilibrium relative wages in efficiency units, equations (5) and (6) are substituted into the relative demand equation (2). Before turning to the equilibrium wages, consider relative wages after the complete diffusion of computers and $V = 0$:

$$\frac{\overline{w}_s}{\overline{w}_u} = \left(\frac{\theta^s}{\theta^u} \right)^\rho \frac{\overline{w}_s^0}{\overline{w}_u^0}. \tag{7}$$

[28] It reverses the causality of Krueger's controversial paper (Krueger, 1993), claiming that computer technology use induces higher wages, because we argue that the higher wages of adopters are a reflection of the lower costs they face in adopting computer technology.

Equation (7) shows that relative wages after diffusion have changed with a factor $(\frac{\theta^s}{\theta^u})^\rho$. Wage inequality will be higher if $\theta^s < \theta^u$ and skilled and unskilled workers are complements ($\rho < 0$), and if $\theta^s > \theta^u$ and skilled and unskilled workers are substitutes ($\rho > 0$). The empirical literature seems to point at $\rho > 0$, but the model leaves open both alternatives.[29]

Computer Costs

However, $V > 0$. We estimate the annual costs of using a computer to be \$6,567 in 1997, which accounts for about 21 percent of the average worker's real annual wage in the United States. This figure is computed as follows.

First, using the "investment in information processing equipment and software" data collected by NIPA and dividing this number by the computer using workforce in full-time equivalents[30] yields computer costs of \$4,530.[31] Secondly, regressing the relative number of workers in computer related jobs (cw)[32] on computer users (c) by sector and weighing by industry size, yields (standard errors in brackets) $cw = 1.38(.003) + .063(.005)c$. To obtain a conservative estimate for the cost of technical assistance, we left out the sectors of industry with relatively high fractions of computer related job.[33] Since the average monthly wages of workers in computer related jobs equal \$2,692, we estimate the costs of assistance for each individual worker to be equal to \$2,037.

It has been well documented that the price of computer equipment has been falling ex-

[29] A case in which $\rho < 0$, often pointed at, is the complementarity between the manager and the secretary. If $\theta^s < \theta^u$ the secretary benefits more from computer use than the manager. This means that, given the amount of work, the demand for secretaries will fall.

[30] Full-time equivalent employees equal the number of employees on full-time schedules plus the number of employees on part-time schedules converted to a full-time basis. The number of full-time equivalent employees in each industry is the product of the total number of employees and the ratio of average weekly hours per employee for all employees to the average weekly hours per employee on full-time schedules.

[31] Autor, Katz and Krueger (1998) report computer investments per full time equivalent worker to be \$2,545 in 1990, which is equivalent to about \$5,000 per full time equivalent computer user. Figures for 1960, 1970 and 1980 yield comparable investments per full-time equivalent computer user. Computer use is taken from the October 1997 School Enrollment Supplements to the CPS. There is likely to be measurement error in the NIPA data because the Bureau of Economic Analysis does often not directly measure information processing equipment and software at high frequency, but imputes these data. See Berndt and Morrison (1995), and Autor, Katz and Krueger (1998) for a discussion. See also Allen (2001) for a more detailed treatment of computer investments and investments in science and technology related to the wage structure in the United States.

[32] These occupations are "Computer systems analysts and scientists" (CPS Occupational Classification Code for Detailed Occupational Categories 064), "Operations and systems researchers and analysts" (065), "Computer science teachers" (129), "Computer programmers" (229), "Tool programmers, numerical control" (233), "Computer operators" (308), "Peripheral equipment operators" (309), "Data-entry keyers" (385), "Data processing equipment repairers" (525), and "Office machine repairers" (538).

[33] Sectors of industry with more than 10 percent computer related employment are "Computer and data processing services" (CPS Industry Classification Code for Detailed Industry 732), "Telegraph and miscellaneous communications services" (442), "Not specified utilities" (472), "Computers and related equipment" (322), "Electrical repair shops" (752), "Professional and commercial equipment and supplies" (510), and "Radio, TV, and computer stores" (633).

tremely rapidly over time (e.g., Jorgenson and Stiroh, 1999 and Jorgenson, 2001). Figures collected by NIPA suggest that investments in computer equipment are only some 20-25 percent of total investments in information processing equipment and software over the 1990s. Investments in software account for some 30-40 percent, while other investments make up some 35-50 percent of total investments. The quality-adjusted prices of software (e.g., Jorgenson, 2001, Figure 2), and other computer related investments have hardly been falling over time. The overall annual decline in the costs of information processing equipment and software has been 2.1 percent over the period 1959-2001.[34] This suggests that the adoption rate of computers at work is likely to be slower than the rate of fall in the price of computer equipment, and that the costs of using computer technology are non-negligible relative to the workers' wages.

Differences in the quality of computer technology used by different workers are not explicitly considered in the model. When considering different vintages of computers in a perfectly competitive market, the most productive workers would be assigned to the most recent vintage. In addition, the costs of computer technology might also be different for different workers. For example, large firms might have an advantage in maintenance and technical assistance, which leads to lower computer costs per worker. Next to that, some workers need less expensive computer technology than others, which induces earlier adoption, all other things equal. Finally, some workers perform tasks on the basis of ready-made applications, whereas for others with higher wages and higher productivity gains no application is available yet. However, for simplicity we make the assumption that the costs of the computer technology are given to the worker and are equal for all workers.

Equilibrium Relative Wages in Efficiency Units

With an exogenously falling price of computer technology, the benefits of adopting are changing over time for all workers. Since the productivity levels of both skilled and unskilled workers are concentrated on the intervals $[\underline{\alpha}, \overline{\alpha}]$ and $[\underline{\beta}, \overline{\beta}]$, different stages in the computer technology adoption process will occur. The order of these stages depends both on the level of wages and break-even wages of skilled and unskilled workers. Since a diffusion pattern in which the most productive skilled workers are the first to adopt −

[34] These numbers and calculations are based on NIPA figures and consistent with the number and calculations presented by Jorgenson (2001).

followed by the most productive unskilled workers, the least productive skilled workers, and finally the least productive unskilled workers − seems to be consistent with the actual patterns of adoption, our analysis focuses on this sequence of adoption.[35]

Equilibrium wages in efficiency units are computed in each of the five stages of the diffusion process: (i) no computer use, (ii) the high-wage skilled workers adopt, (iii) both types of workers adopt, (iv) all skilled and a fraction of the unskilled workers adopt, and (v) all workers use computers technology at work.[36] Table 1 shows the relative wages in efficiency units in each of the five stages. When there is no computer use, relative wages depend on the supply of efficiency units, the distribution of productivity parameters and the elasticity of substitution between skilled and unskilled labor. In the other four stages, relative wages in efficiency units also depend on θ, V, and the additional units supplied. Note that relative wages in *efficiency units* do not change anymore once every worker has adopted a computer, even when $V > 0$. This is because the supply of the number of efficiency units of labor, once all workers have adopted a computer, remains constant and is independent of V.

Insert Table 1 over here

Table 2 shows individual wages for two workers with productivity parameters a_1 and a_2 relative to worker j with productivity $\underline{\beta}$. The level of the wages in efficiency units and the size of the proportional productivity gain are assumed in such a way that the adoption of computer technology takes place in the following order: $\overline{\alpha}$, a_1, $\overline{\beta}$, $\underline{\alpha}$, $\underline{\beta}$ and $\overline{\alpha}$, $\overline{\beta}$, a_2, $\underline{\alpha}$, $\underline{\beta}$. From the equations in Table 2 it becomes clear that the wages of all workers are influenced once the first worker adopts computer technology. In addition, once every workers has adopted computer technology, it is not until $V = 0$ that wages do not change any more (stage 6).[37] To see this, we can compare the relative wages in

[35]This assumption is consistent with the figures on computer use for 1984, 1989, and 1993 presented by Autor, Katz and Krueger (1998). They show that computer technology use is higher for more educated workers but it is rising among all different educational groups. It is also consistent with the characterization of the order of adoption modelled by Helpman and Trajtenberg (1998b), except that we do not model explicitly the R&D process underlying the development of computer technology, but merely focus on adoption.

[36]Note that it is possible that certain stages of diffusion will never become effective because of the overlapping productivity parameters between skilled and unskilled workers. For example, given wages, proportional productivity gains and the distribution of productivity parameters, an unskilled worker with productivity $\overline{\beta}$ could reach the break-even point for computer use later than a skilled worker with productivity $\underline{\alpha}$, which would induce computer use among unskilled workers when all skilled workers already have one.

[37]The equilibrium wages for other skilled workers with different productivity parameters follow straightforwardly from the results presented in Table 2. In addition, the derivation of the wages for unskilled workers is similar to the derivation

each of the 6 stages. In Stage 1 and Stage 2a the wage ratio of Worker 1 and Worker 2 equals $\frac{a_1}{a_2}$. In Stage 2b Worker 1 adopts computer technology which raises the wage ratio to $\frac{a_1\theta^s-V}{a_2}$ This ratio is equal to $\frac{a_1}{a_2}$ at the break-even point but larger afterwards, leading to an increase in within-group wage inequality. In Stage 3b, Worker 2 adopts computer technology and inequality between the two workers becomes $\frac{a_1\theta^s-V}{a_2\theta^s-V}$. At the break-even point at which Worker 2 adopts, the level of inequality between the two workers is at its maximum level. Thereafter, it is falling depending on the pace at which the costs of computer use fall. Because V is the same for both workers, Worker 1 suffers less from paying the annual rent to use the computer technology. Hence, it is not until $V = 0$ that the ratio of wages for these two workers is at its level prior to computerization.

Insert Table 2 over here

4 Pattern and Timing of Wage Inequality

4.1 Within-Group Wage Inequality

The individual wages in Table 2 are now used to more carefully analyze the pattern of within-group wage inequality over time. Figure 3 provides the wage pattern that results from the model for skilled (Panel A) and unskilled (Panel B) workers. Since no worker has yet adopted computer technology, in the first stage all wage differentials remain the same. The wage structure starts to change when V is sufficiently low for the most productive skilled workers to adopt computer technology. In this second stage (which lasts until the most productive unskilled worker adopts computer technology), skilled worker l adopts a computer at $a_l(\theta^s - 1)w_s^{eu} = V$ and the wages of skilled workers change according to

$$\frac{\partial w_k/\partial{-V}}{a_k} = \frac{1}{a_k} - \frac{a_l^{\sigma-1}\theta^s}{\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma} \tag{8}$$

for skilled workers k who already adopted computer technology ($a_k \geq a_l$), and according to

$$\frac{\partial w_m/\partial{-V}}{a_m} = -\frac{a_l^{\sigma-1}}{\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma} \tag{9}$$

for skilled workers m who did not yet adopt ($a_m < a_l$).

of the equilibrium wages shown here.

From equations (8) and (9) a number of model features become apparent. First, once it becomes beneficial for worker l to adopt computer technology his wage increases relative to the wage of worker m leading to wage inequality within the group of skilled workers because $\frac{\partial w_l/\partial{-V}}{a_l} > \frac{\partial w_m/\partial{-V}}{a_m}$.[38] The wages for the non-adopters change, but only proportionally, and there is no increase in wage inequality among non-adopters in the group of skilled workers. Since $\frac{1}{a_k} < \frac{1}{a_l}$, there is wage convergence within the group of computer users, leading to less wage inequality among computer users in the same group.

Secondly, it is not necessarily the case that the wages of computer adopters rise immediately after adoption. Wages fall, relative to worker j with productivity $\underline{\beta}$, for the first adopter $\overline{\alpha}$ because $\frac{\partial w_{\overline{\alpha}}}{\partial{-V}} = 1 - \frac{\overline{\alpha}^\sigma \theta^s}{\theta^s \overline{\alpha}^\sigma - \underline{\alpha}^\sigma} < 0$. However, the wages for the workers not adopting a computer fall by more because $a_k^\sigma \theta^s - (\theta^s \overline{\alpha}^\sigma - \underline{\alpha}^\sigma) < a_k^{\sigma-1} a_l$, so it is rational to adopt computer technology at the break-even point. In this stage of the diffusion process, wages relative to worker j with productivity $\underline{\beta}$ rise immediately after adoption only if equation (8) is positive. This situation might never occur in this stage but is more likely to occur if $\overline{\alpha} - \underline{\alpha}$ is relatively large.[39]

If $\frac{\partial w_{a_l}}{\partial{-V}} = 1 - \frac{{a_l}^\sigma \theta^s}{\theta^s \overline{\alpha}^\sigma - \underline{\alpha}^\sigma} = 0$, wages for worker l rise immediately after adoption. Note that, because $\frac{1}{a_k} < \frac{1}{a_l}$, the wages for worker k are still falling, relative to $\underline{\beta}$, at this point in time. Wages of computer users and non-users are still diverging, but at a lower pace, because when skilled and unskilled workers are substitutes ($\sigma \geq 1$), the effect of less productive skilled workers adopting, ${a_l}^{\sigma-1}$, decreases for $a_l < a_k$.

In the third stage, when unskilled workers start to adopt computers ($\overline{b}(\theta^u - 1)w_u^{eu} = V$), the wage development of skilled workers, if worker l adopts computer technology ($a_l(\theta^s - 1)w_s^{eu} = V$) can be described by

$$\frac{\partial w_k/\partial{-V}}{a_k} = \frac{1}{a_k} - \frac{a_l^{\sigma-1}\theta^s}{\theta^s \overline{\alpha}^\sigma - \underline{\alpha}^\sigma} + \left(\frac{\psi U^e p^u}{\chi S^e p^s}\right)\left(\frac{\theta^s - 1}{\theta^u - 1}\right)^{\sigma-1} \frac{a_l^{\sigma-1}\theta^s}{\theta^s \overline{\alpha}^\sigma - \underline{\alpha}^\sigma} \tag{10}$$

[38] If θ is high relative to V, adoption of the whole group will occur at earlier stages. The maximum level of wage inequality will be experienced earlier because the least productive worker will reach the break-even point of adoption earlier on. On the other hand, V becomes negligible relative to the wage costs earlier on, which leads to a faster drop in within-group wage inequality. If V falls faster over time, the adoption of computers and the effects on the wage structure will occur faster and earlier on. The maximum level of within-group wage inequality will remain the same because this only depends on $\overline{\alpha} - \underline{\alpha}$ and θ^s.

[39] The pattern and length of time of within-group wage inequality also depend on the productivity differential $\overline{\alpha} - \underline{\alpha}$, the costs of the computer relative to the productivity gain, and the speed at which V is falling over time. The maximum level of within-group wage inequality only depends on $\overline{\alpha} - \underline{\alpha}$ and θ^s. When the initial productivity differential is smaller, or the productivity gain relative to the computer cost is higher, or V is falling more rapidly over time, the length of time of increasing and overall within-group wage inequality is shorter. A higher productivity differential and a higher proportional productivity gain will induce a higher maximum level of within-group wage inequality.

for skilled workers k who already adopted computer technology ($a_k \geq a_l$), and by

$$\frac{\partial w_m/\partial{-V}}{a_m} = -\frac{a_l^{\sigma-1}\theta^s}{\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma} + \left(\frac{\psi U^e p^u}{\chi S^e p^s}\right)\left(\frac{\theta^s - 1}{\theta^u - 1}\right)^{\sigma-1}\frac{a_l^{\sigma-1}}{\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma} \tag{11}$$

for skilled workers m who did not yet adopt ($a_m < a_l$). If skilled and unskilled labor are substitutes, both the skilled computer users and the skilled non-users benefit from the increased productivity among unskilled workers, reflected in additional term in equations (10) and (11) compared to equations (8) and (9). Due to the increased productivity of skilled computer users, these workers gain more in relative terms than the skilled non-users. Computer use among unskilled workers therefore stimulates the increasing within-group wage inequality among skilled workers. Note that the development of relative wages of two computer users or two non-users are not affected by computer adoption among unskilled workers.

In the fourth stage, all skilled workers have adopted computer technology. Until adoption is complete among unskilled workers (stage 5), the wage developments for skilled workers are described by

$$\frac{\partial w_k/\partial{-V}}{a_k} = \frac{1}{a_k} + \left(\frac{(\theta^u - 1)}{(\theta^s - 1)}\right)^{1-\sigma}\frac{\psi U^e p^u \theta^s a^{be(\sigma-1)}}{\chi S^e p^s \theta^s(\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}. \tag{12}$$

From equation (12) it follows that if all skilled workers have adopted computer technology, but not all unskilled workers have adopted yet, there will be wage convergence within the group of skilled workers because $\frac{1}{\overline{\alpha}} < \frac{1}{\underline{\alpha}}$.

If all workers have adopted computers, $\frac{\partial w_k/\partial{-V}}{a_k} = \frac{1}{a_k}$, wage inequality within the group of skilled workers behaves similarly to the previous situation. Finally, if $V = 0$, relative within-group wage inequality is back at its level prior to computerization.[40]

A similar pattern of wage inequality within the group of unskilled workers can be obtained. The only difference is that the timing of the different stages of adoption is different. Essentially, the wage structure within both groups is characterized by only three phases: (i) no computer use, (ii) some computer use, and (iii) every worker uses computer technology. It is not until unskilled workers start to adopt computers that the adoption process of skilled workers and within-group wage inequality accelerates because of the increase in skilled workers' wages. Such increasing wages are equivalent to faster

[40] Some have argued that within-group wage inequality has risen after complete diffusion of computer technology because when all workers gain a proportional term θ the workers with the highest initial productivity have gained most. However, in relative terms within-group wage inequality is back at its level prior to computerization if one assumes a similar proportional productivity gain for all workers.

decreasing computer technology prices, since the wage/computer technology price ratio drives the adoption process.

Insert Figure 3 over here

4.2 Between-Group Wage Inequality

Defining the wage ratio of the workers with productivity $\overline{\alpha}$ and $\underline{\beta}$ as between-group wage inequality, it follows from equations (8) and (9) that this ratio is falling when the first skilled worker adopts computer technology, leading to a lower level of between-group wage inequality. Between-group wage inequality continues to fall until $\frac{\partial w_{a_i}}{\partial -V} = 0$, where $\overline{\alpha} > a_i$, or until the first unskilled worker adopts computer technology. Between-group wage inequality then increases because of two effects. The first effect results from benefits of the falling costs of computer use for skilled workers, and the second effect results from the increasing supply of efficiency units of unskilled labor after computer technology adoption, which depresses the unskilled wages in terms of efficiency units. Note that these effects do not depend on differences between θ^s and θ^u.

The development of between-group wage inequality in each stage of computer adoption is displayed in Figure 4. It reveals that between-group wage inequality is not likely to increase after the first workers have adopted computer technology. It is not until a non-negligible group of skilled workers or the first unskilled workers adopt computers that between-group wage inequality starts to rise. The figure also shows that the pattern of between-group wage inequality is levelling off at the end of stage 3 and again at the end of stage 4. At the end of stage 3 almost all skilled workers have adopted computers, and at the end of stage 4 all workers have adopted computers. Eventual between-group wage inequality (when $V = 0$) is described by equation (7).

Between-group wage inequality reaches its maximum level at the point where the least productive unskilled worker is just about to adopt a computer. At that point, the wage of the worker with productivity $\overline{\alpha}$ equals

$$w^c_{\overline{\alpha}} = \frac{1}{\underline{\beta}} \left(\left(\frac{\psi U^e p^u \theta^u (\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s \theta^s (\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)} \right)^{\frac{1}{\sigma}} \overline{\alpha}\theta^s - \underline{\beta}(\theta^u - 1) \right) \tag{13}$$

compared to

$$w^{nc}_{\overline{\alpha}} = \frac{\overline{\alpha}}{\underline{\beta}} \left(\frac{\psi U^e p^u (\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s (\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)} \right)^{\frac{1}{\sigma}} \tag{14}$$

before computerization. The ratio of these two wages equals

$$\frac{w^c_{\overline{\alpha}}}{w^{nc}_{\overline{\alpha}}} = \left(\frac{\theta^u}{\theta^s} \right)^{\frac{1}{\sigma}} \theta^s - \frac{\underline{\beta}(\theta^u - 1)}{w^{nc}_{\overline{\alpha}}}. \tag{15}$$

Equation (15) has two interesting properties. First, the ratio of wages is increasing in $w^{nc}_{\overline{\alpha}}$ meaning that a higher level of initial wage inequality between the most and least productive worker leads to a higher peak in between-group wage inequality. Secondly, it is also increasing in θ^s for $\rho > 0$, which means that a higher productivity gain for skilled workers leads to a higher maximum level of between-group wage inequality.

Immediately after the least productive worker has adopted a computer, $\frac{\partial w_{\overline{\alpha}}/\partial - V}{\overline{\alpha}} < \frac{\partial w_{\underline{\beta}}/\partial - V}{\underline{\beta}}$ so between-group wage inequality falls. Finally, if $V = 0$, between-group wage inequality is described by equation (7), which shows that the level of between-group wage inequality after complete diffusion depends on differences in the proportional productivity $\frac{\theta^s}{\theta^u}$ gains and the elasticity of substitution σ between both types of workers.

Insert Figure 4 over here

4.3 Eventually, Not All Workers Adopt

Despite the general purpose character of computer technology, the assumption that in the end the costs of annually renting computer technology are at a level so that every single worker is able to use computer technology at work might be too strict. In addition, it might be the case that when all possible (or cost efficient) inventions have been explored there are no feasible applications for some workers' jobs. Since the top earners among both skilled and unskilled workers have adopted computer technology, it is likely that problems of costs relative to wages and the unavailability of feasible applications will be occurring at the bottom end of the wage distribution. Two cases will be explored. In the first the least productive workers in both groups do not adopt; in the second the bottom earners among the unskilled do not adopt. Both cases are modelled in a way that $\underline{\alpha}_i = \frac{V}{(\theta^s - 1) w^{eu}_s}$ and/or $\underline{\beta}_j = \frac{V}{(\theta^u - 1)}$ will never be satisfied; e.g., equations (3) and (4). We do so by assuming that V never reaches the point $v = \underline{\alpha}_i(\theta^s - 1)w_s^{eu}$ and/or $v = \underline{\beta}_i(\theta^u - 1)$.[41]

Within-group wage inequality for skilled workers will then be permanently higher, if $v > 0$ and/or $\theta^s > 1$, and converge to $\frac{\overline{\alpha}\theta^s - v}{\underline{\alpha}} > \frac{\overline{\alpha}}{\underline{\alpha}}$ when every worker whose break-even condition is met has adopted computer technology. The size of within-group wage inequality when all but one worker adopt computer technology depends positively on the difference in productivity between the most and least productive worker in the group of skilled workers and on the the size of the proportional productivity gain, and negatively on the eventual cost of using computer technology at work. A similar condition holds for long run within-group wage inequality among unskilled workers: $\frac{\overline{\beta}\theta^u - v}{\underline{\beta}} > \frac{\overline{\beta}}{\underline{\beta}}$.

For our measure of between-group wage inequality $(\overline{\alpha} - \underline{\beta})$ the following happens. When the least productive worker does not adopt, and V converges to a level v, between-group wage inequality equals $\frac{\overline{\alpha}\theta^s - v}{\underline{\beta}} > \frac{\overline{\alpha}\theta^s - v}{\underline{\beta}\theta^u - v}$. Long-run between-group wage inequality depends positively on the distance $\overline{\alpha} - \underline{\beta}$ and the size of the proportional productivity gain, and negatively on v.

4.4 Eventually, $V > 0$

Another possibility would be that although all workers adopt, the annual computer costs do not become negligible relative to wages. This can be modelled as $V > 0$ in the long run, after the complete diffusion of computer technology. Long-run within-group wage inequality will be higher after computerization, since $\frac{\overline{\alpha}\theta^s - V}{\underline{\alpha}\theta^s - V} > \frac{\overline{\alpha}\theta^s}{\underline{\alpha}\theta^s}$ and $\frac{\overline{\beta}\theta^u - V}{\underline{\beta}\theta^u - V} > \frac{\overline{\beta}\theta^u}{\underline{\beta}\theta^u}$, i.e. the annual costs of renting computer technology are a heavier burden on workers with lower levels of productivity and wages. The same argument holds for long run between-group wage inequality: $\frac{\overline{\alpha}\theta^s - V}{\underline{\beta}\theta^u - V} > \frac{\overline{\alpha}\theta^s}{\underline{\beta}\theta^u}$. Note that if in the long run $V > 0$, this has less impact on wage inequality than if in the long run not all workers have adopted computer technology. To see this, within-group wage inequality for skilled when not all skilled workers have adopted computer technology equals $\frac{\overline{\alpha}\theta^s - V}{\underline{\alpha}} > \frac{\overline{\alpha}\theta^s - V}{\underline{\alpha}\theta^s - V} > \frac{\overline{\alpha}\theta^s}{\underline{\alpha}\theta^s}$. The same argument holds for within-group wage inequality among unskilled workers. Between-group wage inequality will also be higher if not all workers have adopted computer technology than if in the long run $V > 0$: $\frac{\overline{\alpha}\theta^s - v}{\underline{\beta}} > \frac{\overline{\alpha}\theta^s - V}{\underline{\beta}\theta^u - V} > \frac{\overline{\alpha}\theta^s}{\underline{\beta}\theta^u}$.

[41] The way of modelling the diffusion of computer technology up to a certain level of usage is consistent with the model on the diffusion of general purpose technologies by Bresnahan and Trajtenberg (1995). They model an instance in which the coordination between the developers of computer technology and the application sectors is characterized by coordination and information problems and uncertainty. This leads to a too low level of development of new applications in equilibrium; in terms of our model a too high V relative to wages, given θ^s and θ^u.

5 Empirical Analysis

The model offers an explanation how recent increases in wage inequality can be connected to the adoption and diffusion of computer technology at work. Here we will document new empirical findings for the United States and Germany that are consistent with the the main message of the model.[42]

5.1 Use of Computer Technology

Table 3 reports the percentage computer technology use for skilled and unskilled workers in the United States and Germany. The U.S. data are taken from the October supplements to the CPS in 1984, 1989, 1993 and 1997 and the German data are taken from the Qualification and Career Survey of the German Federal Institute for Vocational Training (BIBB) and the Federal Employment Service (IAB) in three years close to the points of measurement in the CPS (1985, 1992, and 1998). The U.S. figures show that for both groups of workers the largest increase in computer technology use at work has taken place between 1984 and 1989. In Germany the process of computer adoption has evolved more gradually. In absolute terms the rise in computer technology use is more or less similar when comparing the increases in computer technology use over the periods 1985-1992 and 1992-1998. The bottom part of the table reports the differences in computer use between U.S. and German workers in 1984, 1993 and 1997. It is interesting to observe that computer technology use is higher among both groups in the United States in the early 1980s and 1990s and that computer technology use in Germany is higher in the late 1990s. Overall, in 1997/8 computer use per worker is almost equal in the USA and Germany.

Insert Table 3 over here

5.2 Wage Distributions and Technology Diffusion

An important implication of the diffusion model is that wages are a major determinant of computer use. Many authors since Krueger (1993) have reported a high correlation between computer use and wages by estimating a wage equation including a dummy for

[42]See the Appendix for more details concerning the data used in this section of the paper.

computer use. Frequently this relationship has been interpreted as an effect of computer use on wages. By using panel data, Entorf and Kramaz (1997) and Entorf, Gollac and Kramarz (1999) have shown that this interpretation is based on a spurious correlation. The best way to show that wages determine to a large extent computer adoption is to estimate the relationship between computer use and wages, without any other control variable to predict differences in computer use between groups for which there exist well documented wage differentials. The best example is to investigate the relationship between computer use (cu) and age. To do so, we ran the OLS regression $cu = c + \alpha ln(w) + \epsilon$ for both countries (using the 1997/8 data) and plot the actual computer use and the predicted computer use per age group. Figure 5 presents the results. Both panels show that by only using wages we are able to replicate the age pattern of computer use in a precise manner. There is some tendency for lower computer use among the oldest workers, but the pattern predicted by the wage captures the main pattern.[43]

Insert Figure 5 over here

An interesting implication of this relationship between wages and computer use is that differences between the United States and Germany should be related to differences in the wage structure in these countries. To test whether differences in the wage distributions between both countries are determining the different adoption patterns, we performed a shift-share analysis of the diffusion of computer technology use in the United Stated and Germany, disentangling increased computer use conditional on wages and the effect of changes in the wage structure on the adoption of computer technology. Monthly wages in each year have been divided into 300 U.S. Dollar intervals. For each interval the fraction of computer users in the workforce in a certain year has been calculated, which suggests a strong positive relationship between computer use and wages. Based on this information for the periods 1984/85 - 1992/93 and 1992/93 - 1997/98, we calculated the increase in computer use keeping the wage structure constant. In Table 4 it is shown that although the increase in computer use in the United States has been larger between 1984

[43]Comparable pictures are obtained when using only a dummy for workers earning more than the 46th percentile in the wage distribution (46 percent of the workers in both the United States and Germany do not use computer technology at work in 1997/8), using a set of dummies for several wage brackets, including a gender dummy, etc. Similar exercises for earlier years provide similar patterns with the negative effect of age on computer use rising when we go back further in time.

and 1993 than in Germany over the period 1985-1992 (20.2 relative to 17.2 percentage points), the absolute increase conditional on the 1984 wage distribution has been almost equal to the changes in Germany (4.8 versus 3.9 percentage points). Hence, it is likely that the faster increase in computer technology adoption over this period is to a large extent due to changes in the wage structure in the United States. In the second period, the increase in computer adoption in Germany is higher than in the United States (17.8 versus 7.7 percentage points), but again this seems to result from the specific shape of the wage structure rather than from increased adoption as such (4.5 versus 2.9 percentage points). The changes in the wage structure might of course be endogenous and result from computer adoption, but the analyses show that the pattern of diffusion is consistently explained by the wage structure at a given point in time.

Insert Table 4 over here

If wages determine computer use and the United States and Germany have access to the same technology at the same price, the adoption of computers should be the same in both countries when we condition on wages. We therefore transformed the wages of German working into dollar equivalents, using the appropriate exchange rate, and divided all workers in wage groups of .2 in terms of log wages. Figure 6 presents the average computer use for US and German workers for each wage group. The panels show that the adoption by wage group is remarkably similar in both countries. Especially in 1984/5 and 1997/8 both curves fit well, with only slightly higher computer use among high wage workers in Germany and slightly higher computer use in the middle income groups in the United States. In 1992/3 German computer adoption seems to be lagging behind somewhat. Of course there is a one year difference in the data between Germany and the United States in a period of rapid computer diffusion, but the fact that the exchange rate fell rapidly in the years prior to 1992/3, thereby increasing German wages in dollars, might explain why the adoption is lagging behind somewhat in this year. Overall, the pictures reveal that differences in the wage structure explain to a large extent differences in adoption rates between both countries.

Insert Figure 6 over here

5.3 Between-Group Wage Inequality

In addition to different wage distributions in the United States and Germany, the model predicts that the level and pattern of between-group wage inequality depends on differences in the relative rates of adoption over time. More precisely, if the rate of computer technology adoption among unskilled workers is higher than the rate of adoption among skilled workers, skilled workers benefit as a group thereby increasing between-group wage inequality.

Table 5 reports changes in the wage differentials between percentile groups of skilled and unskilled U.S. workers earning the same wages in 1963; i.e., the same workers as analyzed in Figure 2. The first column in the upper panel reports the 1984-1989, 1989-1993 and 1993-1997 changes in the log wage differential between a skilled worker at the 40th percentile of the skilled distribution and an unskilled worker at the 75.5th percentile of the unskilled wage distribution. Similar numbers are reported in the second column for the skilled and unskilled workers at the 50th and 83.9th percentile of their respective wage distributions. The third column reports the change in the fraction of computer technology use among unskilled workers minus the change in the fraction computer use among the skilled workers: $CU^t_{skilled} - CU^t_{unskilled} - (CU^{t-d}_{skilled} - CU^{t-d}_{unskilled})$. A similar analysis is performed for Germany and shown in the lower panel of Table 5.

Between-group wage inequality should rise (fall) if the rate of adoption of computer technology is higher among unskilled (skilled) workers because the rise in the number of efficiency units of unskilled (skilled) workers depresses the wages of the group. This means that there should exist a positive relationship between the numbers in the first two columns and the third column in Table 5. For the United States this positive correlation is present because a relatively higher rate of relative computer technology adoption among unskilled workers seems to lead to a relatively larger change in the wage differential between skilled and unskilled workers, e.g., compare the wage changes in the first row of Table 5 (.045 and .076, respectively) in which the relative rate of computer adoption is high with the negative wage changes in the second row of Table 5 ($-.063$ and $-.061$, respectively) in which the relative rate of computer adoption is low. In the period 1993-1997 the pattern of adoption is reversed again, and likely to increase between-group wage inequality; although to a lesser extent. Comparing these calculations to the pattern of between-group wage inequality displayed in Figure 1 suggests a consistent pattern of increasing between-group wage inequality in the 1980s and a slowdown in the 1990s.

For Germany a similar, but less strong pattern is obtained. For the period 1992-1998, in which the relative rate of computer adoption among unskilled workers is high, we would expect the wage differential to rise. In comparison with the 1985-1992 period it does rise, but in absolute terms the pattern is not very strong. Investigating the pattern of between-group wage inequality in Germany over time in Figure 1 suggests that falling between-group wage inequality until the early 1990s and the tendency towards rising between-group wage inequality since the mid-1990s is consistent with the pattern of higher relative rates of computer technology adoption for skilled workers in the 1980s and higher relative rates of adoption for unskilled workers in the 1990s.

Changes in the relative wages are of course also affected by changes in supply of skilled and unskilled workers. The fourth column of Table 4 therefore reports the changes in the fractions of skilled workers in the periods concerned. In contrast with the change around 1980, the increase in the supply of skilled workers turns out to be relatively constant in the 1980s and 1990s. It is therefore unlikely that shifts in the supply of skilled workers can account for the dynamics in the wages as have been reported in this paper.

Insert Table 5 over here

Our overall reading of the comparative empirical analysis is that the figures suggest that the diffusion of computer technology and the distribution of wages is consistent with our theory of high-wage workers adopting computers first, that the rate of computer technology adoption is in accordance with the wage distributions in both countries, and that the relatively early effects of computer technology on between-group wage inequality in the United States are likely to be due to the early computer adoption of unskilled workers compared to Germany where these effects are likely to take place since the mid-1990s.

5.4 Exploring the Magnitude of the Model

A crucial question arising from these analyzes is whether the theoretical predictions made by our diffusion model are in a order of magnitude that corresponds to the empirical data on increased wage inequality in the United States.

To think about the magnitude of these effects, compare two skilled workers, one with a wage corresponding to the 90th percentile of the wage distribution and the other earning the 10th percentile wage. If we compare the position of these two workers between 1974 and 1997, it is reasonable to assume that none of these workers made use of computer technology in 1974, while according to the diffusion argument made in this paper one might expect only high-wage workers using computer technology in 1997. This means that in 1997 only the worker with a wage corresponding to the 90th percentile of the wage distribution is using computer technology at work. Hence, for this worker only the joint productivity of his labor and the computer he is using has to be taken into account in 1997.

We assume that inflation and exogenous productivity shocks affect all skilled workers to a similar extent. So, the productivity $p_n c$ of the 90th percentile workers – had they not adopted a computer – in 1997 can be predicted by:

$$p_{nc} = \frac{w_{97}^{10th}}{w_{74}^{10th}} w_{74}^{90th} \tag{16}$$

where w_{97}^{10th} equals the 1997 wage of the skilled worker at the 10th percentile of the wage distribution, and w_{74}^{10th} and w_{74}^{90th} are representing the wages of the skilled workers at the 10th and 90th percentile of the wage distribution in 1974. Actual productivity (p_c) of the workers at the 90th percentile of the wage distribution will be equal to wages plus the annual rental costs of computer technology in 1997 (V_{97}), i.e.

$$p_c = w_{97}^{90th} + V_{97} \tag{17}$$

A back of the envelop estimate of the productivity increase that can be attributed to computer technology adoption can be obtained by taking the ratio's of these two productivity measures:

$$1 + \theta = \frac{p_c^{90th}}{p_{nc}^{90th}} = \frac{w_{97}^{90th} + V_{97}}{\frac{w_{97}^{10th}}{w_{74}^{10th}} w_{74}^{90th}} \tag{18}$$

Using our estimate of the annual cost of computer technology use from Section 3 of \$ 6,567 in 1997, all components of this calculation are known. For skilled workers we find $\theta = .292$. Similar reasoning yields $\theta = .282$ for unskilled workers. Such productivity gains of about 30 percentage seem to be reasonable and are in line with the estimates presented by Bresnahan, Brynjolfsson and Hitt (2002, Table 8, p. 365). They argue that there are large adjustments costs to the successful use of computers, which are not only due to the installation of computers itself but also to the change in organization structure, technical assistance and other co-inventions going along with computerization.

Furthermore, combining the annual costs of computer use with this productivity increase provides us with break-even wages for computer adoption among both types of workers. For 1997 this break-even wage is equal to $ 21,890. This corresponds to the 17th percentile skilled worker, and the 50th percentile of unskilled worker. Predicted adoption of 83 percent among skilled workers and 50 percent among unskilled workers therefore fits relatively well to observed computer use in both groups in 1997 (Table 3: 76.6 and 42.8 percent, respectively).

Changes in between-group wage inequality are a result of both productivity changes due to computer technology use and changes in the price per efficiency unit of labor due to shifts in supply and demand. Comparison of the 90th percentile skilled worker to the 10th percentile unskilled workers – again assuming the first to use computer technology from 1984 onwards, while the latter has not yet adopted a computer in 1997 – allows us to calculate the wage in efficiency units of the skilled workers as

$$w_s^{eu} = \frac{w_s + V_t}{1 + \theta} \tag{19}$$

Multiplying the supply in terms of people by $1 + \theta$ times the fraction of the wage sum of computer users within the group of skilled and unskilled workers, yields estimates of the development of the supply in terms of efficiency units. Regressing the log wage ratio on the log supply ratio and a time trend for the four years for which computer technology use at work (1984, 1989, 1993, and 1997) is available reduces the time trend in the regression equation from .018 to .012. This estimate suggests that our diffusion argument explains approximately one-third of the increase in wage inequality between skilled and unskilled workers in the United States.

6 Concluding Remarks

When considering the allocation of computer technology within and between groups of workers, it becomes apparent that those workers who have adopted computers gain from the increased productivity of using computer technology. Within the same group, workers who have not adopted computer technology suffer from an increased supply of efficiency units of labor. Between groups, it depends on the degree of substitutability and the amount of overlap between different groups in the labor market. Hence, to understand the wage dynamics of computer technology diffusion it is important to distinguish individual and group effects of computer adoption. Our model indeed shows that it is important to explicitly consider who adopts computer technology at what point in time to help understand the effects of computers on the wage structure. Applying the features that computer adoption is based on cost-benefit considerations, that productivity differentials between and within groups of workers are important in explaining the moment in time of adoption, and the explicit assignment of workers to the computer technology, our model is consistent with both the pattern and timing of the changes in the U.S. wage structure over the past four decades and the changes in the German wage structure since the early 1980s.

There are two main directions for future research. First, our model shows the importance of the distinction between individual and group effects (in the sense that groups of workers produce a similar product) when considering computer technology adoption. It is therefore crucial to distinguish the right groups of homogenous workers in the labor market. An avenue of further investigation would be to look more carefully into which groups of workers substitute each other and which groups do not. Particulary for countries other than the United States (and the United Kingdom) there appears to be a less strong division between skilled and unskilled workers (e.g., Abraham and Houseman (1995) for Germany), which is likely to have an impact on the results in empirical work. Secondly, the model is able to reflect the pattern and timing of wage inequality in the United States and Germany. Crucial distinctions between both countries are the differences in initial (i.e., before computer technology became around) wage inequality between skilled and unskilled workers and the substitutability of both groups of labor. It would be interesting to analyze other countries that vary in initial wage inequality and the substitutability of skilled and unskilled workers. Of interest here are differences between on the one hand the United States and the United Kingdom and on the other hand Germany and France, but also differences between continental European countries, comparing the very equalitarian Scandinavian countries with southern European countries such as France, Spain and Italy that have large wage inequality. Also the comparison between the United States and Canada could be very interesting from this perspective.

Appendix

A March Annual Demographic Supplements to the Current Population Surveys (CPS)

A.1 Skilled and Unskilled Workers

Skilled workers are defined as workers with at least a completed college education and unskilled workers as workers with educational levels below a completed college education. We only use full-time, full-year workers who reported to be employed in the previous year. Full-time, full-year, wage and salary workers are those working at least 35 hours per week and working at least 40 weeks in the previous calendar year.

A.2 Wages

We use annual earnings for four reasons. First, information on weeks worked and usual weekly hours in the previous calendar year is available in the March CPS from 1976 onwards. The 1963-1975 period is only covered by bracketed weeks worked information and hours worked last week. This makes it harder to measure weekly or hourly earnings (e.g., Katz and Autor, 1999 and Lemieux, 2003).[44] Secondly, computer technology can be shared among part-time workers, which induces computer use at lower wage levels as well. Thirdly, since the dispersion in productivity parameters, reflected by wage differentials within the groups of skilled and unskilled workers, is essential to the model, no correction has been made for demographic factors. Finally, computer use is only available on a yearly basis from the October 1984, 1989, 1993, and 1997 School Enrollment Supplements to the CPS. So, a worker makes an annual decision to rent a computer for that year. We only use annual wages between \$1,000 and \$900,000.

A.3 Computer Technology

Individual computer use has been calculated from the October 1984, 1989, 1993, and 1997 School Enrollment Supplements to the CPS as the fraction of currently employed full-time, year-round workers who answered yes to the question, “Do you use a computer directly at work?”. The survey defines a computer as a desktop terminal or PC with keyboard and monitor and does not include an electronic cash register or a hand-held data device. 60,396, 58,401, 59,710, and 52,753 observations were used to calculate these frequencies in 1984, 1989, 1993, and 1997, respectively. We have used full-time, year-round workers only to compute computer use at work because these workers have also been used to calculate wages.

B Germany

For Germany we use the German Socio-Economic Panel (GSOEP) and the Qualification and Career Survey of the German Federal Institute for Vocational Training (BIBB) and

[44] Katz and Murphy (1992), Juhn, Murphy and Pierce (1993) and Autor, Katz and Krueger (1998) discuss several ways in which hours worked can be imputed for the period 1963-1975.

the Federal Employment Service (IAB). The first survey is more precise on wages, while the second provides the best information about the use of computer technology. For analyses in which computer use and wages are combined, we use the BIBB/IAB data.

B.1 Skilled and Unskilled Workers

Skilled workers are defined in both surveys as workers with at least a completed college education (*Fachhochschule*) and unskilled workers as workers with educational levels below a completed college education.

B.2 Wages

Changes in the German wage structure in the period 1984-2001 are illustrated using data on the monthly earnings of full-time, wage and salary workers from the GSOEP. Full-time, full-year, wage and salary workers are those working at least 36 hours per week. Figure 1 reports the figures for between-group wage inequality (Panel A) and within-group wage inequality among skilled and unskilled German workers (Panel B and Panel C). The BIBB/IAB survey asks respondents to report their monthly wages in 500 DM classes. Following DiNardo and Pischke (1997) we assumed the wage to equal the middle of the reported wage class.

B.3 Computer Technology

Individual computer use has been calculated from the 1985, 1992, and 1998 BIBB/IAB surveys as the fraction of currently employed full-time workers who use computer technology at work. The survey defines a computer as a desktop terminal or PC with keyboard and monitor and does not include an electronic cash register or a hand-held data device.

C March CPS versus May and ORG CPS Wage Data

In an interesting paper DiNardo, Fortin and Lemieux (1996) provide evidence from the May CPS data that residual (or within-group) wage inequality has been stable in the 1970s and only increased in the period 1979-1985 (using the Outgoing Rotation Group (ORG)). Thereafter, residual wage inequality grows smoothly. Most recently, Lemieux (2003) compares the wage series from the March Annual Demographic Supplement (ADS) of the CPS with the May (1973-1979) and ORG (from 1979 onwards) Supplements of the CPS. He finds that the timing and extent of the growth in within-group wage inequality depends on the wage measure used. He concludes by contrasting and comparing both series that wages as measured in the MAY/ORG CPS provide a more reliable measure of within-group wage inequality.

Katz and Autor (1999) review the wage changes in residual inequality from 1960 onwards from three different sources: decennial censuses, and March CPSs and May/ORG CPSs. For the 1960s there is no evidence that residual wage inequality is increasing. In the 1970s all three sources show increases in the 90-10 level of residual wage inequality, in which the March CPS data reveal the largest increase and the census the lowest increase. The same holds for the 1980s, although the ORG CPS now shows the largest increase in the overall 90-10 level closely followed by the March CPS series. For the 1990s March and ORG CPS series are comparable. Overall though, they conclude that the relative magnitude and timing of the trends shown in these three data sources are less well understood and less consistent than those for between-group wage inequality. Nevertheless, there is considerable evidence that within-group wage inequality started to increase in the 1970s (see also Acemoglu, 2002).

After carefully comparing March to May/ORG, we prefer to use the March CPSs for our analysis of the U.S. wage structure in the period 1963-2000. There are a number of reasons to believe that the March series are more reliable for the purpose of our analysis.

First, a major reason for conducting the Annual Demographic Supplement (ADS) around the month of March is to obtain better income data on an annual basis. It is thought that since March is the month before the deadline for filing federal income tax returns, respondents are likely to have recently prepared tax returns or be in the midst of preparing such returns and are able report their income more accurately than at any other time of the year. Since the goal of our paper is to compare annual wage series of regular (full-time, full-year) workers, these series seem to be the most appropriate for our purpose. In addition, the March CPS data are available since 1963 while the May/ORG series start only in the 1970s.

Secondly, we have compared the wage series of March 1999 with March, April, May and June from the 1998 MORG.[45] In matching the two files we obtain that 20,490 individuals have reported to have a wage in both surveys. In addition, 4,520 respondents do report to have earned a wage last week in May but do not report a wage in the March survey. Finally, 1,291 respondents report wages in the March survey but do not in the May survey. For the comparison of the two surveys we only include those workers reporting a wage in both surveys. We made two comparisons to investigate both differences in average wages between both surveys and the standard deviation of the differences, controlling for important characteristics of the person and the date of the interview. First, we regressed the log of the difference between the March and ORG wages on the month of the ORG interview, the periodicity of wages, the log of the weeks worked, and the number of hours worked. In addition, we included dummies for 15 levels of education, 50 age dummies (ages 15 to 65), and nine 1-digit occupational and industrial classification dummies. The results of this regression analysis are reported in the first column of Table A1; a positive sign indicates that the March wages are higher and a negative sign means that the ORG wages are higher. Secondly, we took the absolute value of the residual of the first regression and regressed this residual on the same set of variables, to investigate how the standard deviation of the difference between March and ORG depends on these characteristics.

Although average wages in the March data are higher than average wages in the ORG data, the intercept of the regression is negative, indicating that for the reference person (ORG interview in March, annual income, varying number of hours per week, part time job and male) the mean ORG wage is above the mean March wage. The standard deviation differs with the month of the interview. The results in May come closest to the March ADS, suggesting that the old custom to ask for income in May was an appropriate choice, and suggesting that the shift from May supplements to ORG in the early 1980s might

[45] The month of interview of each household for the ORG is such that in each month 25 percent of the sample has been surveyed.

have caused an increase in measured wage inequality.

Lemieux (2003) claims that the periodicity at which workers feel most comfortable reporting their earnings is likely to be an important source of difference between the two series, and that especially people paid by the hour might provide inaccurate information about their annual wages. Although the March supplement aims to measure the annual income, this is done with great care. The CAPI program available at the NBER website about the March interviews shows that respondents are first allowed to indicate their income on a frequency that suits them best. Based on this information, combined with the number of periods in which this income has been received, an annual wage is calculated and the respondent is asked to indicate whether this outcome sounds likely. Furthermore, the initial question not only asks to include bonuses, but also an additional question is asked whether the respondent did indeed include bonuses. If not, these bonuses are added. In our sample the periodicity of earnings is such that 45.1 percent of the workers is paid by the hour, 15.0 percent is paid weekly, 6.9 percent bi-weekly, 1.9 percent twice monthly, 5.6 percent monthly, 24.3 percent annually, and 1.1 percent otherwise. In contrast to the findings of Lemieux (2003) we find that significant differences in the average income are not found for workers paid by the hour, but that those who are paid on a weekly basis report relative high wages in the ORG, while workers paid on a bi-weekly, twice monthly or monthly basis report relatively high March incomes. According to the estimated standard deviation especially for those paid on a weekly or twice monthly basis the differences between both surveys are large. A possible explanation for these differences is that workers who are paid on a weekly basis over report their income because they do not take into account the weeks they do not get paid (e.g., holidays and unpaid leave of absence). Underestimations of people with other non-annual frequencies of pay might indicate that annual bonuses are often not included in the ORG income. The large average difference between ORG and March for workers paid on a bi-monthly basis might also be caused by a confusion between bi-monthly and two-weekly payments. In our view there is more reason to believe that the weekly earnings as measured in the ORG files do not take into account all income sources that make up the annual income, than that it is likely that measurement error in March is much higher.

This impression is supported by the finding that differences in the number of hours and weeks worked is a source of difference between the March and May surveys. Particularly the entries of people in irregular jobs (part-time, part-year) differ strongly between March and ORG. Although annual incomes in March seem to be more accurate from this perspective we only use full-time, full-year workers in our empirical analysis, to avoid any problem with part-time or part-year work.

Insert Table A1 over here

Furthermore, Figure A1 shows the age profile of the differences between ORG and March wages. The figure suggests that particularly the young workers make mistakes in reporting their earnings by overestimating their ORG wages relative to their March wages. For the other workers there does not seem to be a large difference between the two series.

Insert Figure A1 over here

Finally, plotting the 90th - 10th wage differential for both skilled and unskilled workers shows that there are much larger year to year fluctuations in the May series compared to the March series; see Figure A2. Nevertheless, the timing of the increase in within-group inequality for unskilled workers around 1980 is still present, but there is a rather implausible drop in within-group wage inequality for the unskilled in the 1990s. The series for the skilled workers show a pattern with such large year-to-year fluctuations that it becomes hard to construct a clear picture. Our reading of this latter line is that the pattern of within-group wage inequality among skilled workers has been rising during all three decades and is therefore consistent with the much clearer picture that is provided by using the March data.

Insert Figure A2 over here

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Table 1
Relative Wages in Efficiency Units in Each of the Five Stages of Computer Technology Diffusion

Stage	Relative wages ($\frac{w_s^{eu}}{w_u^{eu}}$) in efficiency units
No computer technology	$\left(\frac{\psi U^e p^u(\overline{\beta}^{\sigma}-\underline{\beta}^{\sigma})}{\chi S^e p^s(\overline{\alpha}^{\sigma}-\underline{\alpha}^{\sigma})}\right)^{\frac{1}{\sigma}}$
Productive skilled adopt	$\left(\frac{\psi U^e p^u(\overline{\beta}^{\sigma}-\underline{\beta}^{\sigma})}{\chi S^e p^s(\theta^s\overline{\alpha}^{\sigma}-\underline{\alpha}^{\sigma})}+\frac{(\theta^s-1)^{1-\sigma}V^{\sigma}}{\theta^s\overline{\alpha}^{\sigma}-\underline{\alpha}^{\sigma}}\right)^{\frac{1}{\sigma}}$
Both types adopt	$\left(\frac{\psi U^e p^u(\theta^u\overline{\beta}^{\sigma}+(\chi S^e p^s(\theta^s-1)^{1-\sigma}-\psi U^e p^u(\theta^u-1)^{1-\sigma})V^{\sigma}}{\chi S^e p^s(\theta^s\overline{\alpha}^{\sigma}-\underline{\alpha}^{\sigma})}\right)^{\frac{1}{\sigma}}$
All skilled adopt	$\left(\frac{\psi U^e p^u\left((\theta^u\overline{\beta}^{\sigma}-\underline{\beta}^{\sigma})-(\theta^u-1)^{1-\sigma}V^{\sigma}\right)}{\chi S^e p^s\theta^s(\overline{\alpha}^{\sigma}-\underline{\alpha}^{\sigma})}\right)^{\frac{1}{\sigma}}$
All workers adopt	$\left(\frac{\psi U^e p^u\theta^u(\overline{\beta}^{\sigma}-\underline{\beta}^{\sigma})}{\chi S^e p^s\theta^s(\overline{\alpha}^{\sigma}-\underline{\alpha}^{\sigma})}\right)^{\frac{1}{\sigma}}$

Table 2

Individual Workers' Wages at Different Stages of Computer Technology Diffusion Relative to Worker j with Productivity $\underline{\beta}$[a]

Stage	Worker 1 with productivity parameter a_1
1	$\frac{a_1}{\underline{\beta}}\left(\frac{\psi U^e p^u(\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s(\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
2a	$\frac{a_1}{\underline{\beta}}\left(\frac{\psi U^e p^u(\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s(\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)} + \frac{(\theta^s-1)^{1-\sigma}V^\sigma}{\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma}\right)^{\frac{1}{\sigma}}$
2b	$\frac{a_1\theta^s - V}{\underline{\beta}}\left(\frac{\psi U^e p^u(\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s(\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)} + \frac{(\theta^s-1)^{1-\sigma}V^\sigma}{\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma}\right)^{\frac{1}{\sigma}}$
3	$\frac{a_1\theta^s - V}{\underline{\beta}}\left(\frac{\psi U^e p^u(\theta^u\overline{\beta}^\sigma + (\chi S^e p^s(\theta^s-1)^{1-\sigma} - \psi U^e p^u(\theta^u-1)^{1-\sigma})V^\sigma}{\chi S^e p^s(\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
4	$\frac{a_1\theta^s - V}{\underline{\beta}}\left(\frac{\psi U^e p^u\big((\theta^u\overline{\beta}^\sigma - \underline{\beta}^\sigma) - (\theta^u-1)^{1-\sigma}V^\sigma\big)}{\chi S^e p^s\theta^s(\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
5	$\frac{a_1\theta^s - V}{\underline{\beta}\theta^u - V}\left(\frac{\psi U^e p^u\theta^u(\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s\theta^s(\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
6	$\frac{a_1\theta^s}{\underline{\beta}\theta^u}\left(\frac{\psi U^e p^u\theta^u(\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s\theta^s(\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
	Worker 2 with productivity parameter a_2
1	$\frac{a_2}{\underline{\beta}}\left(\frac{\psi U^e p^u(\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s(\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
2	$\frac{a_2}{\underline{\beta}}\left(\frac{\psi U^e p^u(\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s(\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)} + \frac{(\theta^s-1)^{1-\sigma}V^\sigma}{\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma}\right)^{\frac{1}{\sigma}}$
3a	$\frac{a_2}{\underline{\beta}}\left(\frac{\psi U^e p^u(\theta^u\overline{\beta}^\sigma + (\chi S^e p^s(\theta^s-1)^{1-\sigma} - \psi U^e p^u(\theta^u-1)^{1-\sigma})V^\sigma}{\chi S^e p^s(\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
3b	$\frac{a_2\theta^s - V}{\underline{\beta}}\left(\frac{\psi U^e p^u(\theta^u\overline{\beta}^\sigma + (\chi S^e p^s(\theta^s-1)^{1-\sigma} - \psi U^e p^u(\theta^u-1)^{1-\sigma})V^\sigma}{\chi S^e p^s(\theta^s\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
4	$\frac{a_2\theta^s - V}{\underline{\beta}}\left(\frac{\psi U^e p^u\big((\theta^u\overline{\beta}^\sigma - \underline{\beta}^\sigma) - (\theta^u-1)^{1-\sigma}V^\sigma\big)}{\chi S^e p^s\theta^s(\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
5	$\frac{a_2\theta^s - V}{\underline{\beta}\theta^u - V}\left(\frac{\psi U^e p^u\theta^u(\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s\theta^s(\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$
6	$\frac{a_2\theta^s}{\underline{\beta}\theta^u}\left(\frac{\psi U^e p^u\theta^u(\overline{\beta}^\sigma - \underline{\beta}^\sigma)}{\chi S^e p^s\theta^s(\overline{\alpha}^\sigma - \underline{\alpha}^\sigma)}\right)^{\frac{1}{\sigma}}$

[a]Note: Computer adoption is assumed to occur in the following order: $\overline{\alpha}, a_1, \overline{\beta}, \underline{\alpha}, \underline{\beta}$ and $\overline{\alpha}, \overline{\beta}, a_2, \underline{\alpha}, \underline{\beta}$. Stage 1: No computer use; Stage 2a: Most productive skilled worker adopts; Stage 2b: Worker 1 adopts; Stage 3a: Most productive unskilled worker adopts; Stage 3b: Worker 2 adopts; Stage 4: All skilled workers have adopted; and Stage 5: All workers have adopted, but $V > 0$. Stage 6: $V = 0$. Wages for Worker 2 remain the same in stages 2a and 2b, hence only one equation for stage 2 is reported. The same holds for Worker 1 in stages 3a and 3b.

Table 3

Computer Technology Use in the United States and Germany[a]

	Year	Skilled	Unskilled
United States	1984	.452	.216
	1989	.628	.331
	1993	.704	.376
	1997	.766	.428
Germany	1985	.300	.161
	1989	..	..
	1992	.589	.302
	1998	.834	.462
Difference (United States − Germany)	1984	.152	.056
	1993	.115	.074
	1997	−.068	−.034

[a]Note: Computer technology use in the United States is available from the October Supplements to the CPS. For Germany the numbers are referring to 1985, 1992 and 1998 and are taken from the Qualification and Career Survey of the German Federal Institute for Vocational Training (BIBB) and the Federal Employment Service (IAB). The data refer to workers employed on a full-time and full-year basis. .. indicates no observations available.

Table 4

Computer Technology Adoption and the Wage Distribution[a]

	Year	Computer use	Computer use subject to distr. $t-1$
United States	1984	.261	
	1993	.463	.309
	1997	.540	.492
U.S. changes	1984-1993	.202	.048
	1993-1997	.077	.029
Germany	1985	.187	
	1992	.359	.226
	1998	.537	.404
German changes	1985-1992	.172	.039
	1992-1998	.178	.045

[a]Note: Note: Computer technology use in the United States is available from the October Supplements to the CPS. For Germany the numbers are referring to 1985, 1992 and 1998 and are taken from the Qualification and Career Survey of the German Federal Institute for Vocational Training (BIBB) and the Federal Employment Service (IAB). The data refer to workers employed on a full-time and full-year basis.

Table 5

The Relationship Between the Rising Use of Computer Technology and Wage Differentials Between Groups of Skilled and Unskilled Workers in the United States and Germany[a]

United States	Δ Wage diff. 40th $S-$ 75.5th U	Δ Wage diff. 50th $S-$ 83.9th U	Δ CU $U-$ Δ CU S	$\Delta S/U$
1984-89	.045	.076	.164	.040
1989-93	$-.063$	$-.061$	.009	.036
1993-97	.034	.029	.064	.037
Germany	Δ Wage diff. 40th $S-$ 76.9th U	Δ Wage diff. 50th $S-$ 85.7th U	Δ CU $U-$ Δ CU S	$\Delta S/U$
1985-92	$-.087$	$-.062$	$-.089$	.043
1992-98	.006	$-.015$	.116	.037

[a]Note: *CU* is computer use. The first two columns report the changes in the log wage differential between two percentiles in the wage distribution of the skilled and unskilled workers for the relevant years. The third column reports the change in the use of computer technology among unskilled workers minus the change in the use of computer technology among skilled workers for the relevant time periods. The final column shows the change in the relative supply of skilled and unskilled workers. Computer technology use in the United States is available from the October Supplements to the CPS. For Germany the numbers are referring to 1985, 1992 and 1998 and are taken from the Qualification and Career Survey of the German Federal Institute for Vocational Training (BIBB) and the Federal Employment Service (IAB). The wage data for the United States are taken from the March Current Population Surveys and the German data from the Qualification and Career Survey of the German Federal Institute for Vocational Training (BIBB) and the Federal Employment Service (IAB). The data refer to workers employed on a full-time and full-year basis.

Table A1

Comparing March and May CPS Wages[a]

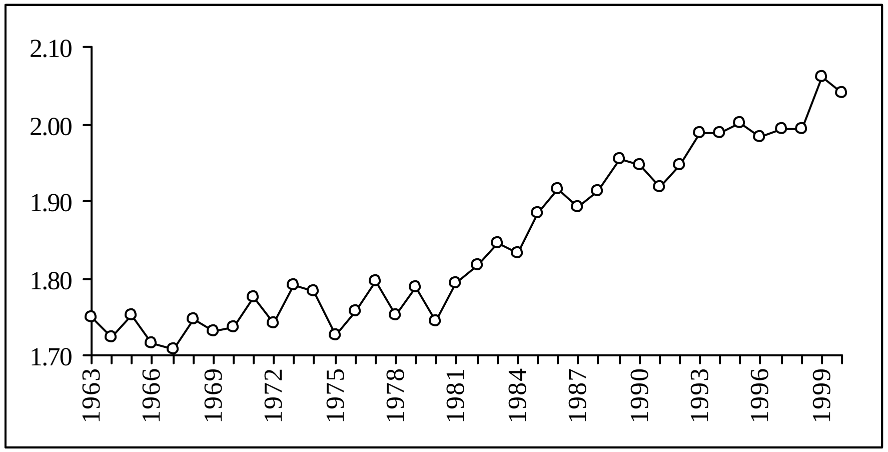
Dependent variable	ln(March) −	ln(MORG)	Standard	deviation
	β	S.E.	β	S.E.
Constant	-0.724	0.065***	1.181	0.048***
Month of ORG				
March (reference)				
April	-0.007	0.014	-0.010	0.010
May	-0.003	0.014	-0.029	0.010***
June	-0.013	0.014	-0.010	0.010
Frequency of payment				
Hourly	0.009	0.014	0.067	0.011***
Weekly	-0.039	0.017**	0.161	0.013***
Bi-weekly	0.058	0.021***	0.059	0.016***
Twice monthly	0.169	0.037***	0.157	0.027***
Monthly	0.081	0.023***	0.036	0.017**
Annual (reference)				
Other	-0.040	0.049	0.278	0.036***
ln(weeks work per year)	0.018	0.010*	-0.133	0.007***
0-20 hours	0.085	0.041**	-0.108	0.030***
21-34 hours	-0.108	0.041***	-0.211	0.031***
35-39 hours	-0.330	0.043***	-0.311	0.032***
40 hours	-0.403	0.039***	-0.283	0.029***
41-49 hours	-0.458	0.043***	-0.345	0.032***
50 or more hours	-0.471	0.042***	-0.262	0.031***
Varies, full time	-0.368	0.045***	-0.188	0.033***
Varies, part-time (ref.)				
Female	-0.044	0.012***	-0.030	0.009***

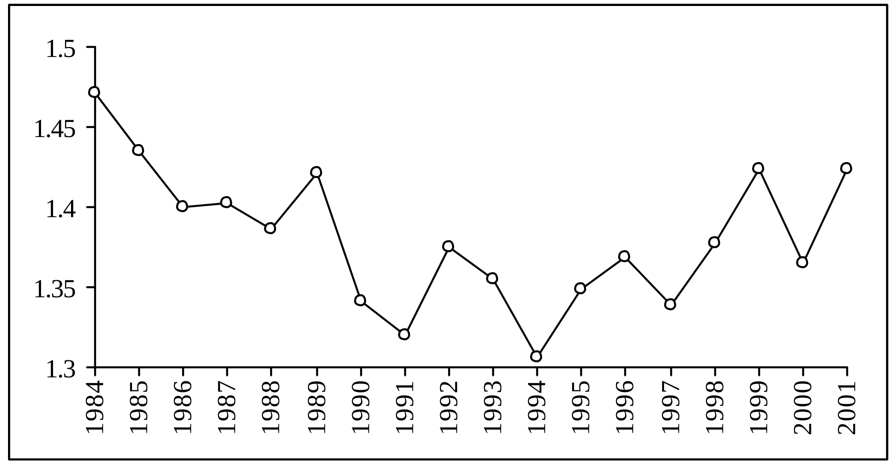
[a]Note: The regression equations also include unreported dummies for 15 levels of education, 50 ages, and nine 1-digit occupational and industrial classification dummies. March is the reference month for the Month of ORG; annually payment is the reference group for the frequency of payment and part-time workers with varying hours are the reference group for the number of hours worked. * is significant at the 10 percent level; ** is significant at the 5 percent level and *** is significant at the 1 percent level. The data are taken from the March 1999 and MORG 1998 CPS. See Appendix C for details.

Figure 1
Wage Inequality in the United States and Germany

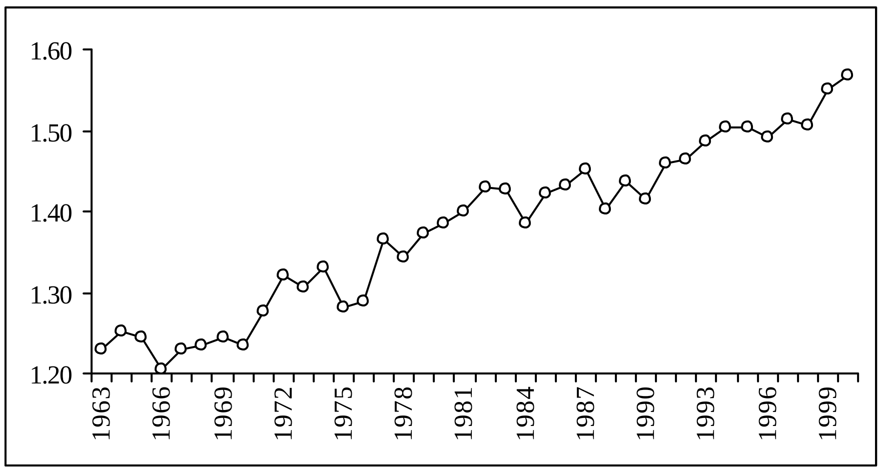
United States **Germany**

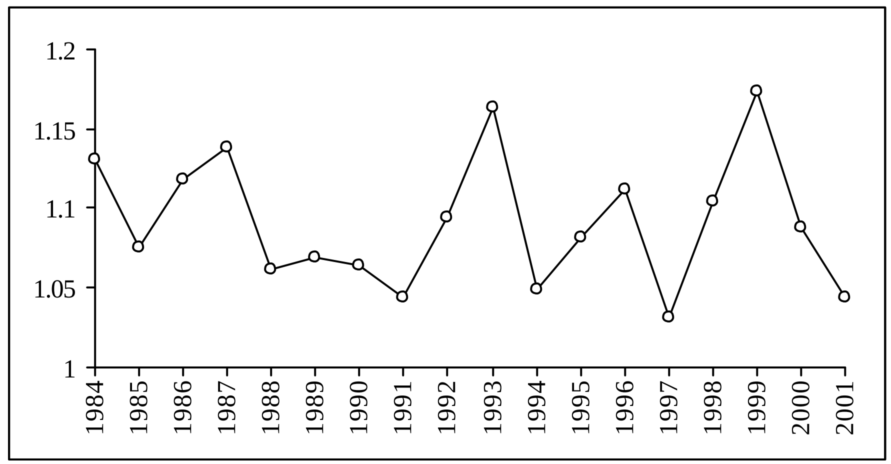
Panel A: ln (90th Percentile Skilled) – ln (10th Percentile Unskilled)



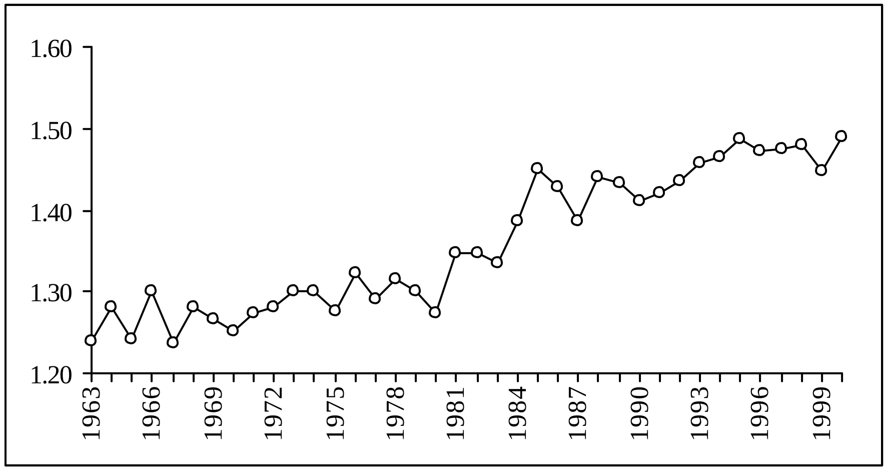


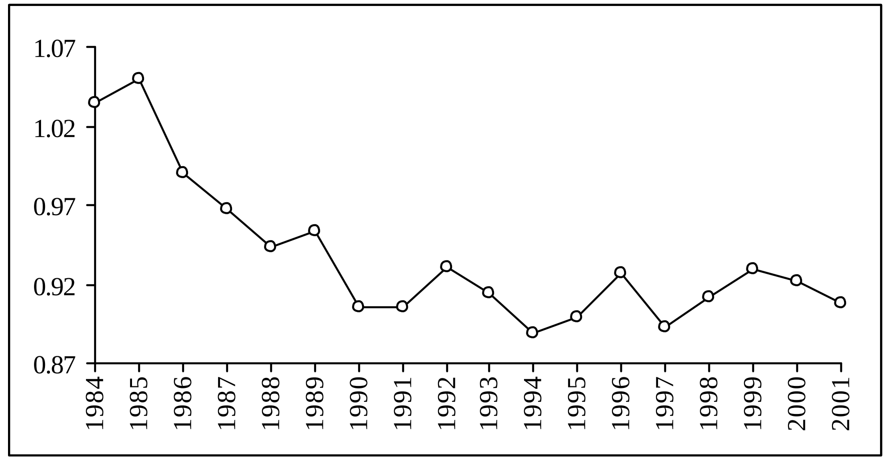
Panel B: ln (90th Percentile Skilled) – ln (10th Percentile Skilled)





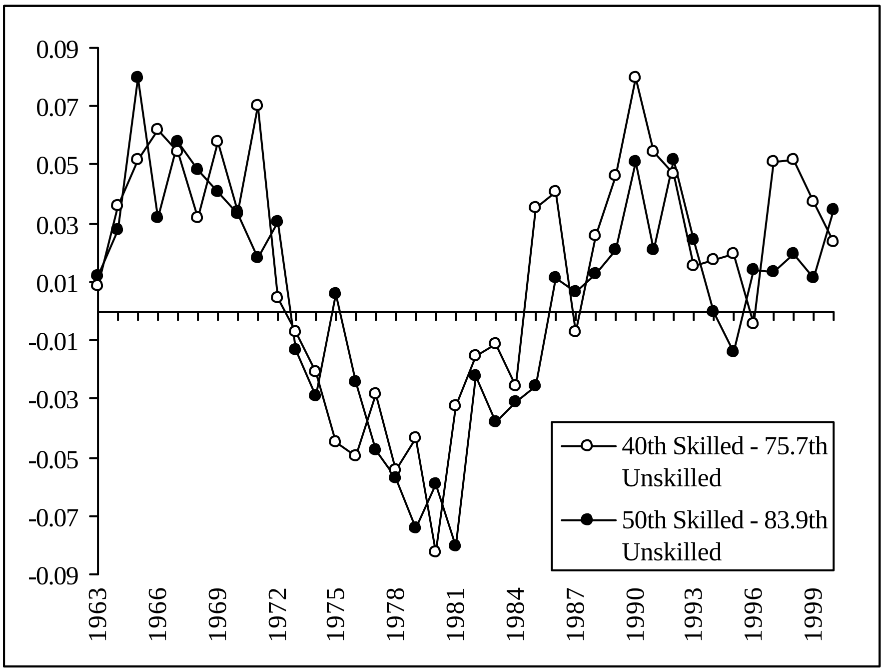
Panel C: ln (90th Percentile Unskilled) – ln (10th Percentile Unskilled)





Note: Data are for the United States taken from the March CPS, 1964-2001. Skilled workers are college graduates and higher; unskilled workers are the remaining ones. See Appendix A for details about the U.S. data. The data for Germany are taken from the GSOEP, 1984-2001. Skilled workers are those with at least college education (*Fachhochschule*); unskilled workers are the remaining ones. See Appendix B for details about the German data.

Figure 2
Log Wage Differentials for U.S. Workers in Different Groups
Earning the Same Wages in 1963



Note: Data are taken from the March CPS, 1964-2001. Skilled workers are college graduates and higher; unskilled workers are the remaining ones. The comparison of wages is such that the wage of the skilled workers at the 40^{th} and 50^{th} percentile of the skilled wage distribution corresponds to the wages of the 75.7^{th} and 83.9^{th} percentile of the unskilled wage distribution in 1963. Because the wages do no perfectly match in 1963, the actual difference, in logarithmic terms, is not zero in 1963 but a small deviation can be observed from the figure. See Appendix A for further details about the data.

Figure 3

Within-Group Wage Inequality over Time

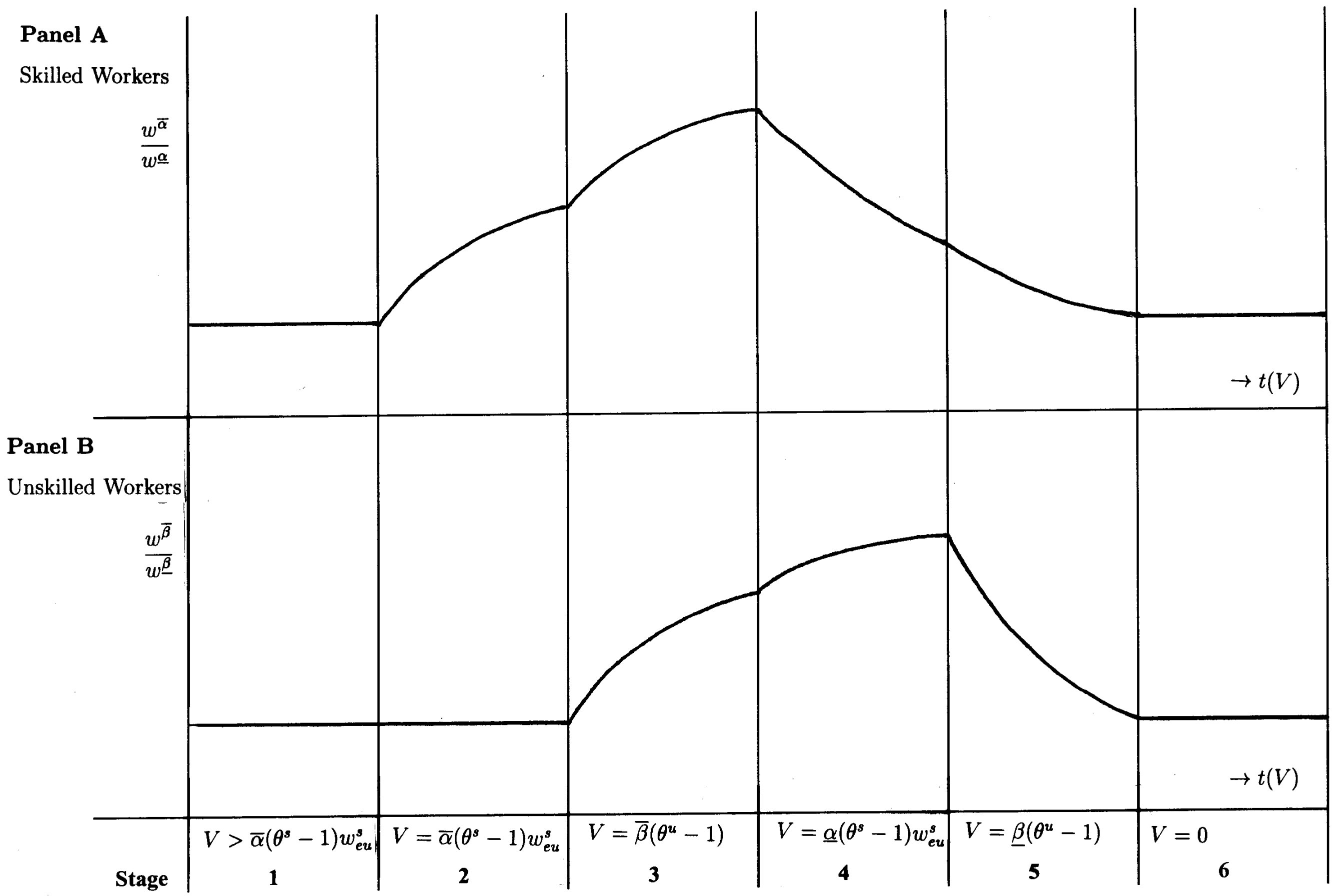


Figure 4

Between-Group Wage Inequality Over Time

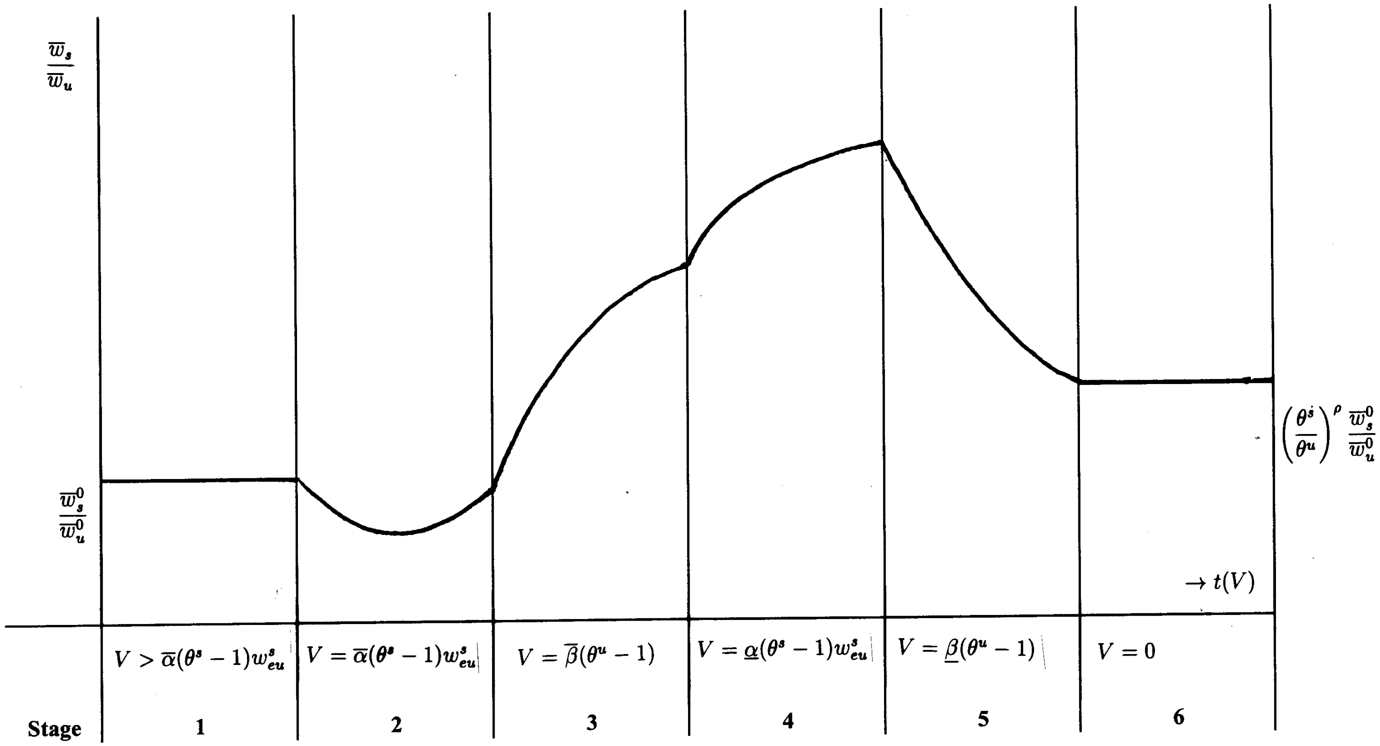
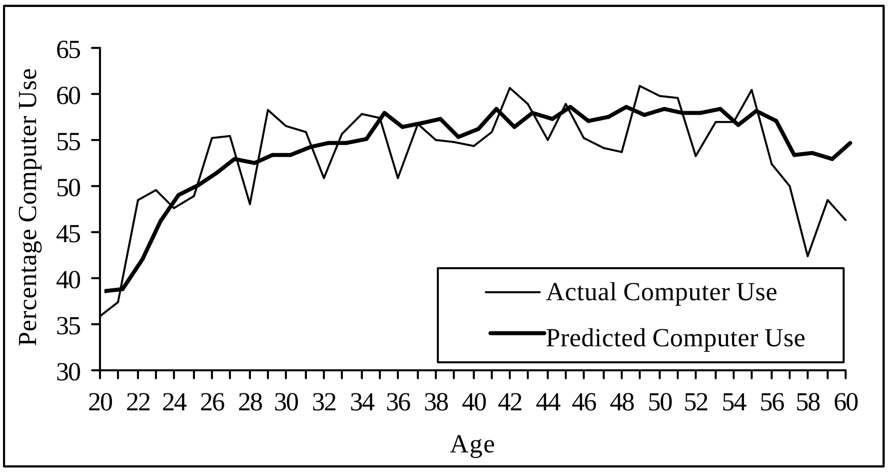
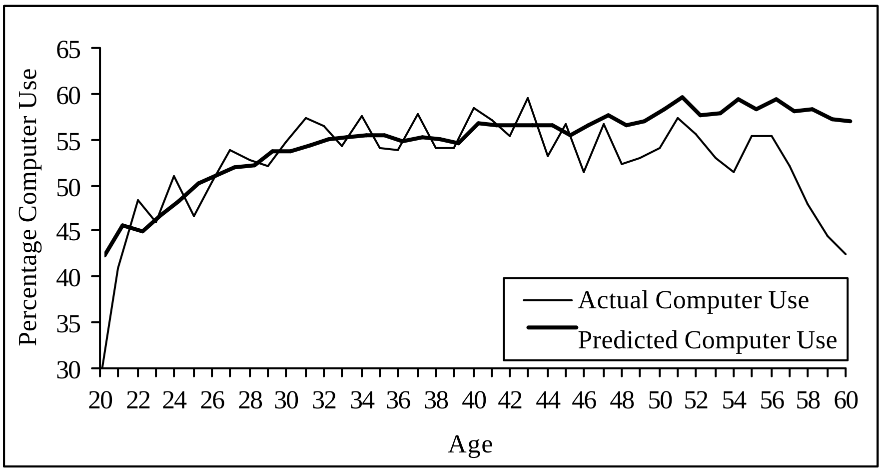


Figure 5
Actual and Predicted Computer Technology Use by Age in the United States (1997) and Germany (1998)

Panel A: United States



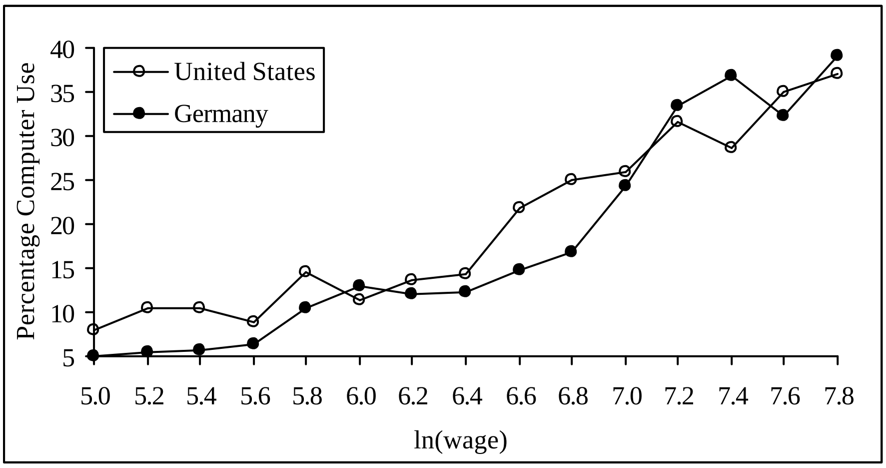
Panel B: Germany



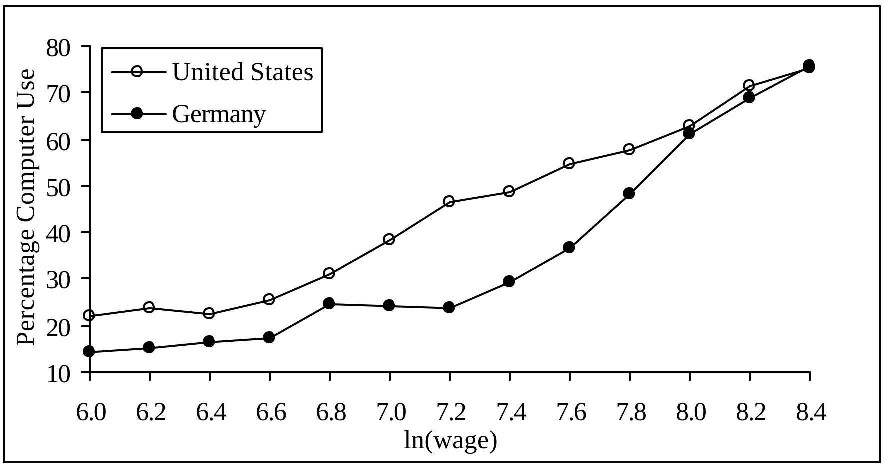
Note: See the text for details.

Figure 6
Computer Technology Use Conditional on Wages in the United States and Germany

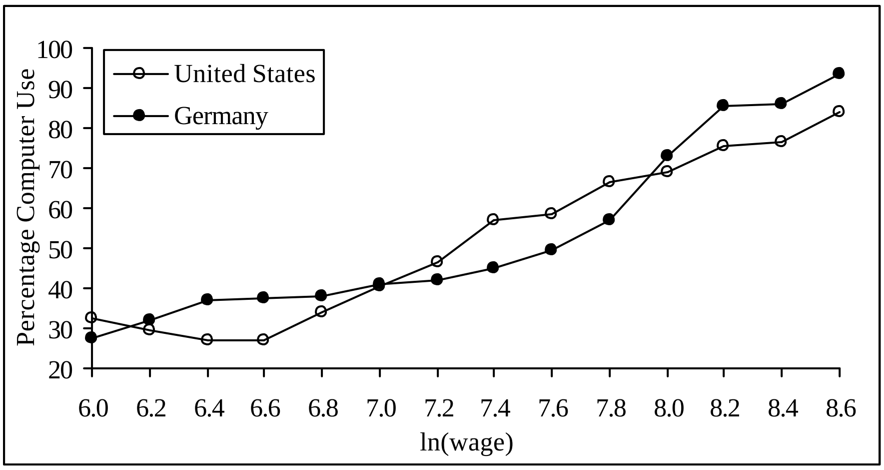
Panel A: 1984/5



Panel B: 1992/3

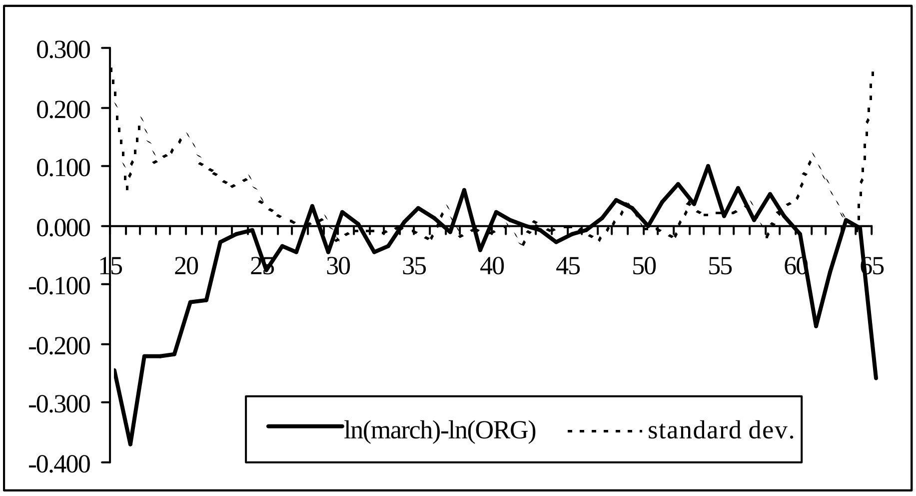


Panel C: 1997/8



Note: See the text for details.

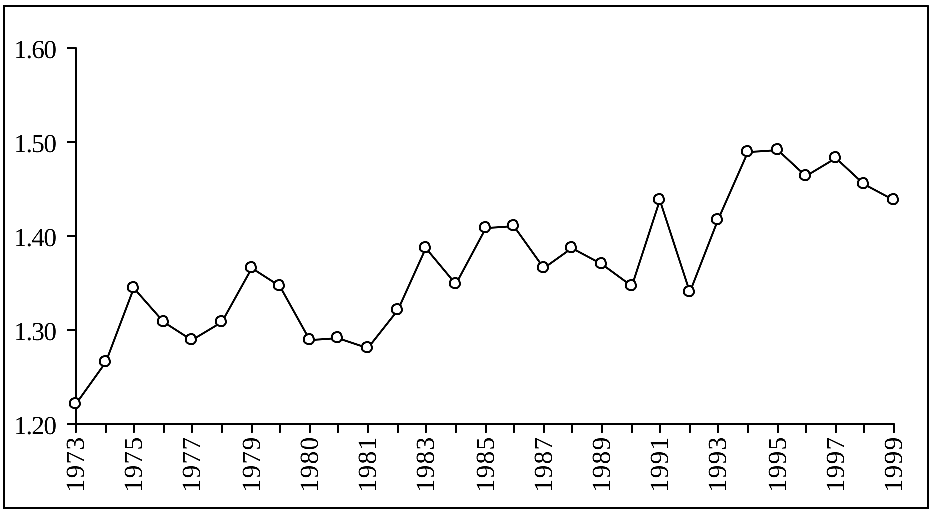
Figure A1
The Age Profile of the Difference Between ORG and March Wages



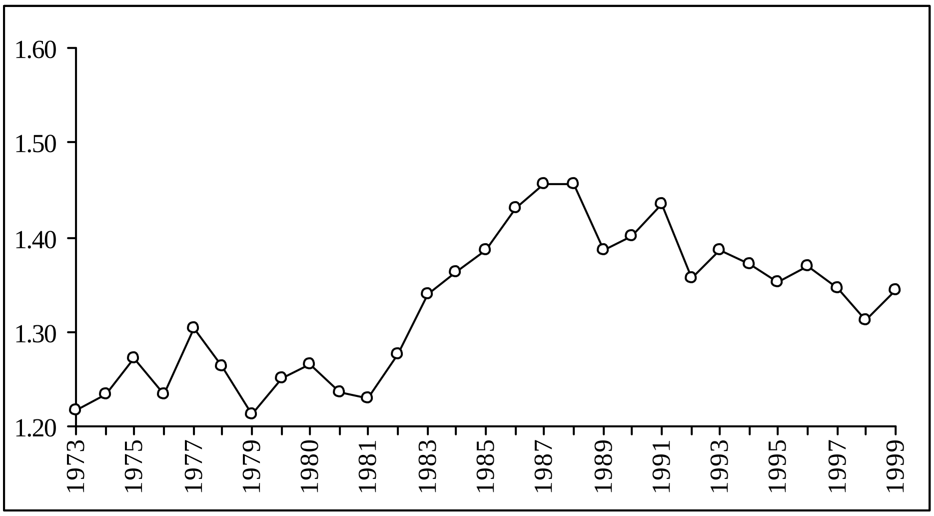
Note: Data are taken from the March 1999 and May/ORG 1998 CPS. See Appendix C for details.

Figure A2
Within-Group Wage Inequality Using May/ORG Data

Panel A: ln (90th Percentile Skilled) – ln (10th Percentile Skilled)



Panel B: ln (90th Percentile Unskilled) – ln (10th Percentile Unskilled)



Note: Data are taken from the May/ORG CPS, 1973-1999. Skilled workers are college graduates and higher; unskilled workers are the remaining ones. See Appendix C for details.