Brothers in RAMS: Diffusion of the PC and the New Economy[a]

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Abstract – Since the introduction of the modern PC in the workplace in 1981, coupled with the phenomenal doubling of PC technological capacity every two years, the incorporation of PCs into daily work processes has been steadily increasing. This paper examines the role of the computer at the workplace in changing the structure of economic activity, in short the "New Economy". Following Autor, Katz, and Krueger (1998) and using the German Socio-Economic Panel (GSOEP), the diffusion of PC technology throughout the labor market is analyzed. Our data provide year-by-year information spanning 1984 to 1997, thus uniquely covering the complete period starting from the introduction of MS-DOS as the IBM-PC's operating system to today in considerable detail. As current and past PC usage is only asked in the GSOEP retrospectively in 1997, PC usage in past waves is "reconstructed". To impute PC usage which is unobserved due to panel attrition up to 1997, we use a probit model, hotdeck and nearest-neighbor imputation. Based on theoretical considerations along the lines of Aghion and Williamson (1999) we show how PC technology has been differentially incorporated into industries and occupations over time. In particular, we formally confront the idea of a logistic implementation curve for General Purpose Technologies with the data, in attempt at providing evidence for the existence of implementation cycles.

Keywords: Computer, General Purpose Technology, Skill-Biased Technological Change, Implementation Cycles.
JEL classification: J31, 033, C20

[a]This paper continues on from Haisken-DeNew and Schmidt (1999), "Money for Nothing and Your Chips for Free? The Anatomy of the PC Wage Differential", which examines wage premia associated with using a computer at the workplace. Both paper titles (arguably silly) refer to the classic 1985 *Dire Straits* album *Brothers in ARMS* and the single *Money for Nothing and Your CHICKS for Free*. We thank Boris Augurzky, Jochen Kluve and Markus Pannenberg for helpful comments.

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> "In 1965, Gordon Moore was preparing a speech and made a memorable observation. When he started to graph data about the growth in memory chip performance, he realized there was a striking trend. Each new chip contained roughly twice as much capacity as its predecessor, and each chip was released within 18-24 months of the previous chip. If this trend continued, he reasoned, computing power would rise exponentially over relatively brief periods of time. Moore's observation, now known as Moore's Law, described a trend that has continued and is still remarkably accurate. It is the basis for many planners' performance forecasts. In 26 years the number of transistors on a chip has increased more than 3,200 times, from 2,300 on the Intel 4004 in 1971 to 7.5 million on the Intel Pentium II processor." - Intel (1998) on Moore's Law[1]

I. Background

The term "New Economy" is an elusive concept. Even among economists the term carries different connotations, ranging from a concept encompassing everything associated with information technology (henceforth IT) to the very specific notion of the episode of extraordinary productivity growth which has been observed in the US since the end of the 1990's. In stark contrast to the general public's enthusiasm associated with any short-lived economic boom, academic economists seriously discuss whether the advancements in IT the world has witnessed during the last decades have altered the possibilities for economic growth, the nature of any cyclical swings around the growth path, the composition of wages and employment, and market structure in general.

From this analytical perspective, it seems obvious that durable economic principles govern the development of economic activity, and much of what determines business success and failure (e.g. Shapiro and Varian (1998)) in times of rapid technological change. Similarities abound between today's information revolution and the changes induced by advances in communication and transport associated with the steam engine and electricity centuries earlier. Most importantly, it is an overarching theme of most research on the idiosyncrasies of the information revolution and its similarities to other episodes of rapid structural change that technological progress and a supporting infrastructure are both necessary, complementary aspects of this process.

To start with the idiosyncrasies, much is different from previous technological advances. The key ingredient to the current structural change is information, an object of value to its consumers whose generation is typically costly, but whose reproduction is usually inexpensive. An example of which is the $1 Billion Napster legal scuffle where music is freely "shared" over the Internet in small, compressed files, claimed to infringe on the copyrights of the owners. On the demand side, the constant replacement of old by new information makes it difficult for the consumer to assess the value of information accurately before it is consumed. This problem has lead suppliers to devise increasingly innovative ways to allow consumers to gauge first their

[1] See "http://www.intel.com/intel/museum/25anniv/Hof/moore.htm". See also Figure 1.

expected appreciation of the offered product, without "giving the product away" in the process, e.g. shareware, limited license, "try before you buy" setups. In fact, it is more difficult for consumers to filter useful information out of the overwhelming supply of information offered, thus making the appropriate filtering a valuable provision of information on its own. This is the reason behind the popularity of search engines on the Web and the motivation for numerous attempts to established personalized forms of advertisement.

Current structural change is driven by technological advances in the manner in which information can be gathered, stored, processed, and communicated. The major aspect in this process is the speed with which these tasks can be performed, excluding the necessity for labor input and human judgement as much as possible. Since many of the new ways to perform these tasks require substantial initial investment into hardware and software, the formation of strategic alliances and of long-term supplier-customer relationships has become a central issue for businesses, as has the choice between offering widely compatible or proprietary products. The decision for one particular IT solution typically entails a "lock-in" effect. Switching to an alternative solution is costly, since all components of a system will usually have to be replaced by its successor. An important part of the ensuing cost are the cost of retraining to the new system. One need only think of the battle in the last 20 years of the two titan office package makers, MS Word and Word Perfect[2].

In light of these aspects, it is clear that the technological possibility frontier does not determine the prevalence of such a new technology throughout the economy. Yet, while the pace of the development of the technological possibility frontier is breathtaking, this gap between technical potential and utilization is quite a familiar phenomenon. Most importantly, the value of a new technology to potential users can only unfold, if enough users exist. The literature documents that there are substantial network externalities associated with most revolutionary advances in technology. In consequence, it might take considerable time until a new technology is dissipated at a noteworthy scale throughout the economy. Yet, once a critical threshold is passed, this process is typically very rapid and saturation is reached quickly. This observation impinges upon the possible economic impact of any new technology, making an understanding of the dissemination process a crucial ingredient in answering any question about the impact of technological progress. Figure 1 and Table 6 illustrate this for the exploding growth in Intel-CPU power, overwhelmingly dominating the PC market.

Reflecting this prominence, the dissemination of new general purpose technologies (GPTs) is a matter of deep theoretical interest in economics. In particular, the literature on endogenous growth characterizes this dissemination process as typically relatively moderate at the begin-

[2]All tradenames are used here in a generic sense for illustrative purposes only.

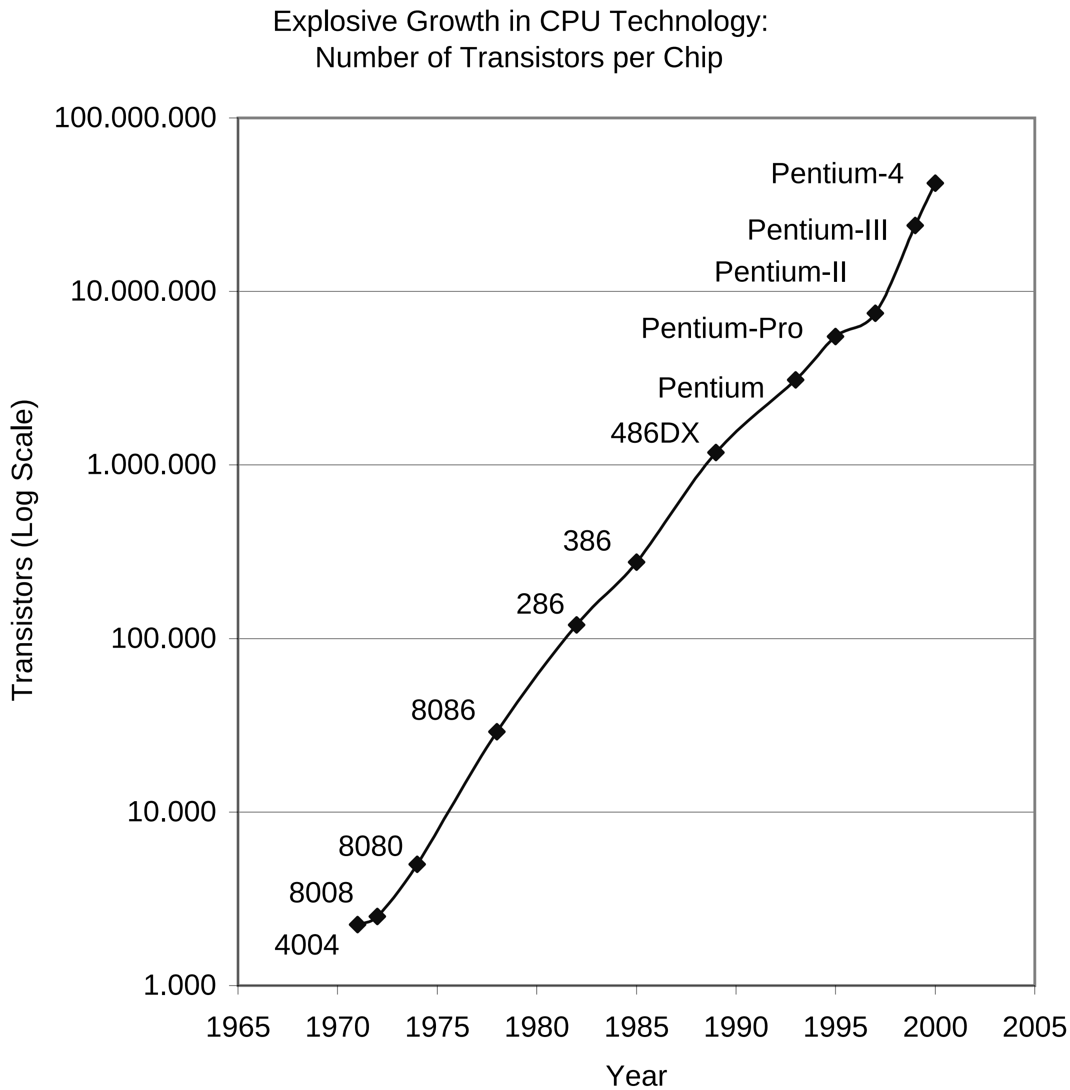

Figure 1: Technological Change

ning, then leading to a brief phase of rapid dissemination, followed by a maturation period in which the market converges to a saturated stake. Structural theoretical models supporting such a pattern are the models by Shleifer (1986) or by Aghion and Williamson (1999) building on the idea of "blueprints" being necessary for the exploitation of any GPT's potential. See also Autor, Katz, and Krueger (1998) looking at the PC and skill-biased technological change and Autor (2001) for the impact of the Internet.

Basically, the existence of the GPT by itself does not suffice warranting its implementation into a specific line of business. Instead, so the argument goes, for its adaptation to the specific demands of any line of business, an initial user has to make the investment to develop a "blueprint", a detailed plan how to proceed in using the GPT. Once this blueprint is available, dissemination of the GPT in this industry can proceed very rapidly. An example of this is the bundling of PC's from IBM (a market giant at the time) with Intel CPU's and the MS-DOS operating system in 1984, thereby setting a defacto standard for many other hardware and software producers. Similar predictions hold for the across-industry pattern of dissemination: once one or some industries demonstrate how to exploit the GPT, it is very inexpensive for the others to follow suit.

While the intuitive appeal of these considerations is obvious, this process is described scarcely at the empirical level. Most of the existing literature concerns the industry or firm level. In our empirical analysis, we deviate from this literature and characterize the speed of dissemination also at the level of the economy. Specifically, we develop an index of the speed of dissemination and apply this concept to the level of industry-occupation-skill cells, to industry-occupation strata, and to industries.

This paper uses individual-level data on German workers between 1984 and 1997 to characterize the dissemination of computer technology at the workplace in a major European economy. To this end, it exploits unique interview information derived in the 1997 wave of the major German panel data set, the German Socio-Economic Panel (GSOEP). In 1997, employed respondents were asked whether they use a computer at the workplace and, in addition, in which year they were working with a PC for the first time.

This information allows the construction of individual PC histories between 1984 and 1997, under the relatively mild assumption that somebody once working with a PC would not stop using a PC in later years and pick PC usage up again before the interview. The entries in this history can be linked with contemporaneous information from the respective panel waves of the GSOEP to characterize the dissemination process. A principal aspect of the analysis will be the question whether the more able workers *ceteris paribus* receive faster access to new technology.

The major methodological obstacle, that our analysis needs to address, lies in the nature of the data. Since the questions of PC usage were asked only in 1997, the sample is only representative of the state of the dissemination of PCs throughout the work force in that particular year. For all preceding years, not only must respondents be employed to be candidates for PC usage at the workplace, they must also remain in the sample until 1997 where they have to be employed as well. In its methodological part, the paper develops various strategies to deal with the ensuing selectivity problems, mainly based on the contemporaneous availability of observable characteristics. These include probit imputation, hotdeck and nearest neighbor matching methods.

The setup of the paper is as follows. Section II. describes the data base, with particular emphasis on the balance of observable covariates across the different samples, those with and those without the information on PC usage. Section III. analyzes the sub-sample of individuals observable as employed in 1997 - for these workers information on PC usage and its duration is available. Section IV. translates these results to the representative sample of workers via an imputation exercise. Finally, Section V. draws some conclusions and works out the agenda for further research about dissemination issues.

II. The Data

The German Socio-Economic Panel (GSOEP) is panel dataset from 1984 to the present consisting of some 13,500 individuals and roughly 7,000 households living in West Germany (the "old" states) and East Germany (the "new states"). Foreigners and recent migrants are also included in the sample. The data analyzed here stem from the 1984 to 1997 waves of the GSOEP.

In 1997 for the first time, the following question was asked of all adult [employed] respondents in the household: *Do you use a computer at home and/or at work, and if so, since what year at home, and since what year at work? What is meant here are PC's or terminals to mainframes but not dedicated game computers.*[3]

Due to the longitudinal structure of the GSOEP, we are able to reconstruct for these workers their individual history of PC usage, and link this information to contemporaneous observable characteristics in each preceding wave, provided that the worker was interviewed in that wave.

The sample containing all respondents for any of the years 1984 to 1997, for whom the PC usage question was asked in the 1997 wave, is termed the "PC sample" in the remainder of the paper.

[3]The original German text from the 1997 personal questionnaire is: *"Q4. Benutzen Sie privat oder beruflich (bzw. in Ihrer Ausbildung) einen Computer? Gemeint sind hier Personal-Computer (PC) aber auch Grossrechneranlagen, jedoch nicht reine Spielcomputer! [Ja/Nein], ich benutze [einen/keinen] Computer [privat/beruflich] und zwar seit ..."*

In addition to workers in the PC sample, we observe in each of the panel years a number of employed workers who are not interviewed in the 1997 wave, either because they are not observed in that wave at all or because they are not employed in 1997. For these workers, a valid wage observation is available for other years, though, and we term this sample the “wage sample”. The PC sample is a subset of the wage sample.

As a consequence of the particular situation in the 1997 wave, for these workers the PC usage question was never asked, and we cannot reconstruct PC usage for the preceding years directly from the interview information. Instead, we might be able to use the information from the PC sample to infer PC usage at the workplace in other years for the complete wage sample. To prepare this analysis, we investigate in a first step whether and to what extent the PC sample is representative of the wage sample. As a final, and more encompassing data set, we have a full sample at our disposal, containing all the individual-level observations for all panel years, that is for any given wave also on those individuals who are not employed at that time.

Table 1 documents that the sampling criteria determine quite heavily the distribution of available cases in the three different samples. Since the PC sample is constructed for each year under the requirement of a valid observation on employed workers in 1997, and on availability of information in that particular year, it is to be expected that the early years of the GSOEP are fairly modestly represented. This is illustrated by Figure 2, where the left half of the diagram clearly shows the large amount of person-year observations, where information is missing. By contrast, both the wage sample and the full sample display a relatively uniform distribution of cases across panel waves. Based on this evidence we will maintain the assumption that the wage sample is not plagued by severe attrition problems.

Table 1: How representative is the PC sample ? (in %)

Year	PC Sample	Wage Sample	Full Sample
1984	3.89	7.57	7.40
1985	3.77	6.20	6.86
1986	4.24	6.13	6.82
1987	4.66	6.39	6.96
1988	4.79	6.23	6.79
1989	6.12	7.66	6.85
1990	6.69	7.65	6.95
1991	6.76	7.15	7.10
1992	7.08	6.99	7.19
1993	8.65	7.86	7.34
1994	8.90	7.27	7.39
1995	10.54	7.84	7.43
1996	10.89	7.30	7.45
1997	13.02	7.79	7.48
Total	12481	26492	77338

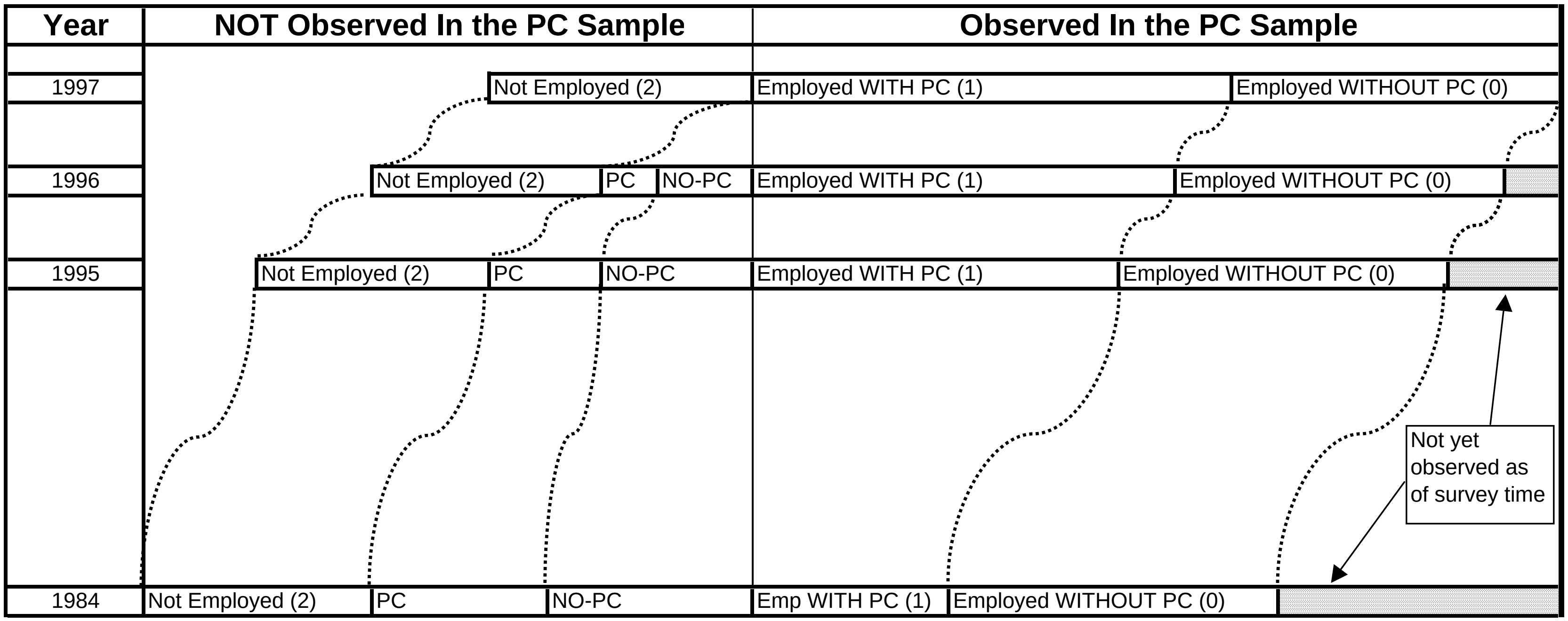

Figure 2: Structure of the Sample: PC vs. Wage

A careful comparison (not in the tables) of the developments of observable worker and firm characteristics over time demonstrates that these inter-temporal movements are similar in nature across the PC sample and the wage sample, apart from some selected variables. For both samples, workers' contract hours decline continuously, as do actual hours, albeit less clearly. The share of white collar workers in both samples increases continuously, from roughly 1/3 to approximately 1/2. For both samples, the average education in the PC sample rises only slightly over the observation period. For the PC sample, the share of female workers rises substantially over time, from less than 1/5 to approximately 30%, whereas it increases only slightly in the wage sample. That is, it is particularly women working with PCs who are present in the 1997 sample wave.

Over time, the share of foreign workers declines substantially in both samples, mainly due to the sampling frame of the GSOEP. It explicitly oversamples workers from the five main sending countries of the guest worker era, Spain, Italy, Greece, Yugoslavia, and Turkey. Over time, the nature of immigration to Germany, specifically the mix of origin countries, has changed substantially, with now much larger shares of each immigrant wave originating in developing countries or countries in transition in Eastern Europe. Moreover, the original immigrant population reflected in the GSOEP has experienced substantial return migration.

The development of the age structure in the PC sample depends heavily on our selection criteria, since we generally exclude workers born before 1937 from the analysis. In consequence, while the youngest age category represents a stable share of the sample, the importance of the second category declines rapidly, and that of the third category rises continuously. The oldest category only becomes relevant in the early 1990s, representing slightly more than a 10% share of the sample in 1997. We adjust our sampling criteria to receive corresponding results in the wage sample. The share of married workers declines drastically over the sample period, in both PC and wage sample.

The regional distribution of the workers is relatively stable in both samples. Also, many of the industry shares are stable over time. The manufacturing industries "plastics", "wood", and "textiles", but particularly the metal industry decline in importance over time, as does the construction sector. By contrast, "trade", "transport" and particularly "other services" increase in importance over the sample period. Regarding firm size, larger firms gain somewhat in importance in the PC sample over time. Finally, in terms of the occupational distribution, it is the science, management and office workers whose share rises at the expense of manufacturing positions in both samples.

III. Results in the PC Sample

In this section, we discuss the dissemination of PC usage at the workplace, as it can be extracted directly from the PC sample. If using or not using a PC in earlier waves did not impinge upon the likelihood of being observed as an employed worker in the private sector in the 1997 wave, then the PC sample would allow accurate reconstruction of the extent of dissemination of PCs in these earlier years. In the following section, we will consider how to react to violations of this very restrictive identification assumption.

Perhaps the most striking aspect of PC dissemination at the workplace is the distinct pattern of dissemination by age. Table 2 demonstrates that the increase in the average extent of PC usage increased from a mere 14% in 1984 to almost 59% by 1997. The overwhelming part of this overall pattern is carried by skilled workers, though. For those with high education (12 or more years of education), the corresponding increase was from 19% to 74%. The table displays a smooth pattern of dissemination in all three skill groups, with most of the implementation occurring before 1993.

Table 2: Dissemination by Education Class

Year	All Levels	Low Education (7-9 Yrs)	Medium Education (10-11 Yrs)	High Education (12+ Yrs)
1984	0.1394	0.0483	0.1384	0.1867
1985	0.2447	0.0664	0.2448	0.3214
1986	0.1678	0.0201	0.2422	0.3333
1987	0.2565	0.0471	0.2457	0.3639
1988	0.2827	0.0441	0.2594	0.4212
1989	0.2923	0.0847	0.2673	0.4289
1990	0.3540	0.1403	0.3260	0.5137
1991	0.3992	0.1282	0.3679	0.5680
1992	0.4277	0.1441	0.3948	0.6110
1993	0.4450	0.1429	0.4144	0.6212
1994	0.4944	0.2202	0.4583	0.6601
1995	0.5352	0.2011	0.5162	0.6995
1996	0.5880	0.2345	0.5682	0.7466
1997	0.5873	0.2954	0.5608	0.7395

The data from the PC sample also demonstrate (not in the tables) that in the beginning of the sample period, in 1984, not only do few workers have a PC at the office, but those who use a PC at the workplace typically do so only there (i.e. not at home). Corresponding to the steady increase of PC usage at the workplace documented in the table, there one can detect at first a moderate, then rapid decline in office-only users, though.

IV. Reconstructing the Past By Imputation

If the usage of PCs at the workplace in earlier years impinges upon the possibility of observing a worker in private employment in 1997 - and, thus, extracting contemporaneous and retrospective information from his or her response, the construction of the extent of dissemination requires additional identification assumptions. While the data might not provide a representative picture of the aggregate, a re-weighted version of the sample might do so. The required empirical effort is the construction of a representative figure from the selected information available in the data.

For instance, individual-level data are very much affected by participation decisions and employment success which, in turn, might be the result of underlying observable characteristics such as education. For instance, it might well be that highly educated workers are more prevalent in the data with PC information than in the economy. Then, a sensible identification assumption might be that, conditional on education level, the share of workers in the data and in the economy are equal. A re-weighted average of the sample information will therefore reveal the true extent of IT dissemination in the aggregate.

In our basic imputation, we follow exactly this idea of the statistical control of observable components of heterogeneity, worker and firm information, which characterize the individuals *before* IT is introduced, and which are likely to influence both IT introduction and individual-level labor market outcomes. For a detailed discussion of imputation procedures, see Little and Rubin (1987).

A. Imputation by Probit Estimation

Specifically, we run (weighted) probit estimates for selected years, 1984, 1990, and 1997, with marginal effects and corresponding t−values reported in Table 3. This year-by-year specification allows for inter-temporal changes in the impact of the various determinants on PC usage. For instance, in all three years, highly educated workers (there is no overall constant in this specification) are more likely to use a PC at the workplace, as are white collar workers. Both determinants display an increase over time, reflecting the average increase in PC dissemination. Yet, between education groups, the changes seem minor.

Female workers are less likely to use PC technology throughout, albeit with decreasing intensity. It is the young workers who are more likely to work with a PC, yet as PCs disseminate throughout the economy over time, age becomes less important as a determinant. Interestingly, small firms apparently introduce PCs at a lower pace, and it is clearly the manufacturing occupations, which miss out the most as the usage of the new technology increases.

Table 3: Probit Estimates of Computer Usage (Marginal Effects with t's)

Year	1984	1990	1997
Low Education	-0.165 (-6.190)	-0.231 (-3.420)	0.057 (0.600)
Medium Education	-0.406 (-3.740)	-0.164 (-1.870)	0.223 (3.010)
High Education	-0.186 (-5.750)	-0.146 (-1.830)	0.243 (3.000)
White Collar Worker	0.260 (2.430)	0.325 (4.070)	0.318 (5.420)
Female	-0.035 (-0.950)	-0.024 (-0.460)	-0.051 (-0.900)
Age 25-34	0.042 (0.620)	0.104 (1.780)	0.043 (0.800)
Age 35-44	-0.001 (-0.020)	0.056 (0.970)	0.020 (0.400)
Transport and Services	-0.031 (-1.020)	-0.163 (-3.630)	-0.239 (-4.590)
Small Firm	-0.018 (-0.550)	-0.147 (-3.550)	-0.141 (-3.290)
Manufacturing Occupation	0.049 (0.780)	-0.180 (-2.170)	-0.340 (-5.140)
N	532	913	1803
Log Likelihood	-198.21	-481.49	-950.04

Finally, we use the probit estimates derived from the PC sample to impute the dissemination of PC usage throughout the economy, as reflected by the workers found employed in the wage sample. That is, for the three selected years discussed above, we impute the extent of PC dissemination in the aggregate, and separately for the three major education groups, respectively, by evaluating the probit coefficients with the sample weights of the corresponding characteristics in the wage sample. The corresponding results are reported in Table 4 (See also Figure 3). Clearly, due to the sampling frame explained above one should expect near identity for the figures for 1997, which is indeed the case. For the earlier years, though, the consideration of imputing the desired figures from the wage sample seems to matter. In particular, the figures directly extracted from the PC sample overstate the dissemination of PCs in the workplace somewhat, as apparently workers with particularly favorable characteristics for stable employment (and inclusion into the PC sample) are also more likely to work with a PC

Table 4: PC Usage Predictions: Share with Standard Deviation

Year Sample	1984 PC	 Wage	1990 PC	 Wage	1997 PC	 Wage
All	0.1469 (0.0046)	0.1394 (0.0022)	0.3702 (0.0079)	0.3540 (0.0052)	0.5908 (0.0061)	0.5873 (0.0057)
Low Education (7-9 Yrs)	0.0476 (0.0039)	0.0483 (0.0025)	0.1238 (0.0095)	0.1403 (0.0072)	0.2657 (0.0110)	0.2954 (0.0114)
Medium Education (10-11 Yrs)	0.1411 (0.0058)	0.1384 (0.0030)	0.3347 (0.0090)	0.3260 (0.0062)	0.5686 (0.0076)	0.5608 (0.0071)
High Education (12+ Yrs)	0.2135 (0.0082)	0.1867 (0.0037)	0.5496 (0.0140)	0.5137 (0.0092)	0.7442 (0.0081)	0.7395 (0.0077)

Note: See also Figure 3.

in earlier years.

B. Imputation by Hotdeck

We use the "hotdeck" procedure from Mander and Clayton (2000) which fills missing values in a multiple-imputation framework. One "matches" recipient (missing) observations to donor (valid) observations, based on certain characteristics that must be matched *exactly*, or no match is made. In our case, the group of variables listed in Table 3 is used.

Given that valid donors are found, a single value is chose at random (with replacement) from the selected donor(s) using the approximate Bayesian bootstrap method of Rubin and Schenker (1986). Then, a data set is created containing the valid and (now) imputed information and a regression is run. In our case this is simply a regression of the PC usage variable on a constant, i.e. we are interested in calculating the mean. This is then repeated, say 10 times[4], allowing us to calculate an average of the 10 different estimates and an overall estimate of the variance (comprised of "within" and "between" variance components). We do this for each and every year separately, starting in 1984. The results are presented in Table 5 and Figure 4.

C. Imputation by Nearest-Neighbor Matching

Another potential method of imputing is to use "nearest-neighbor" matching. Various matching methods are outlined in Heckman, Ichimura, and Todd (1997) and Heckman, Ichimura, and

[4] "Data, if tortured long enough, will always confess"-*Unknown*

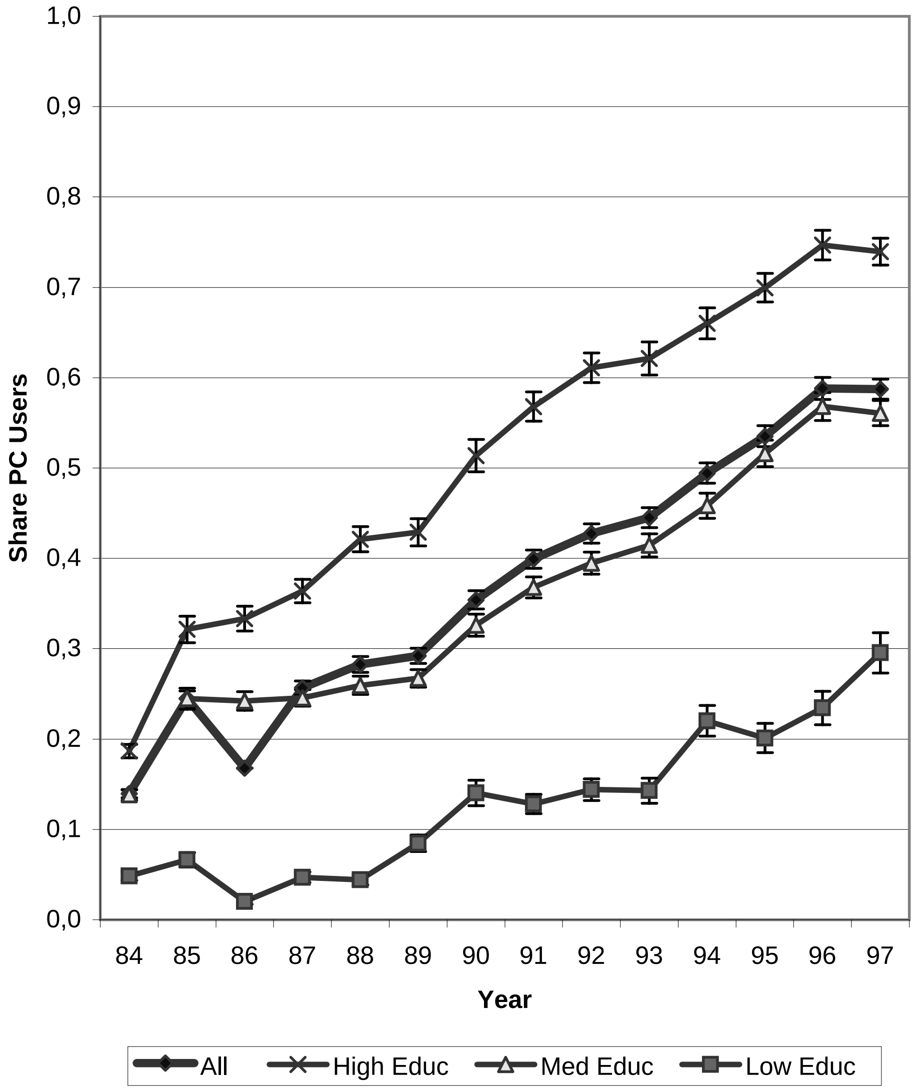

Figure 3: PC Usage Predictions: Imputation by Probit

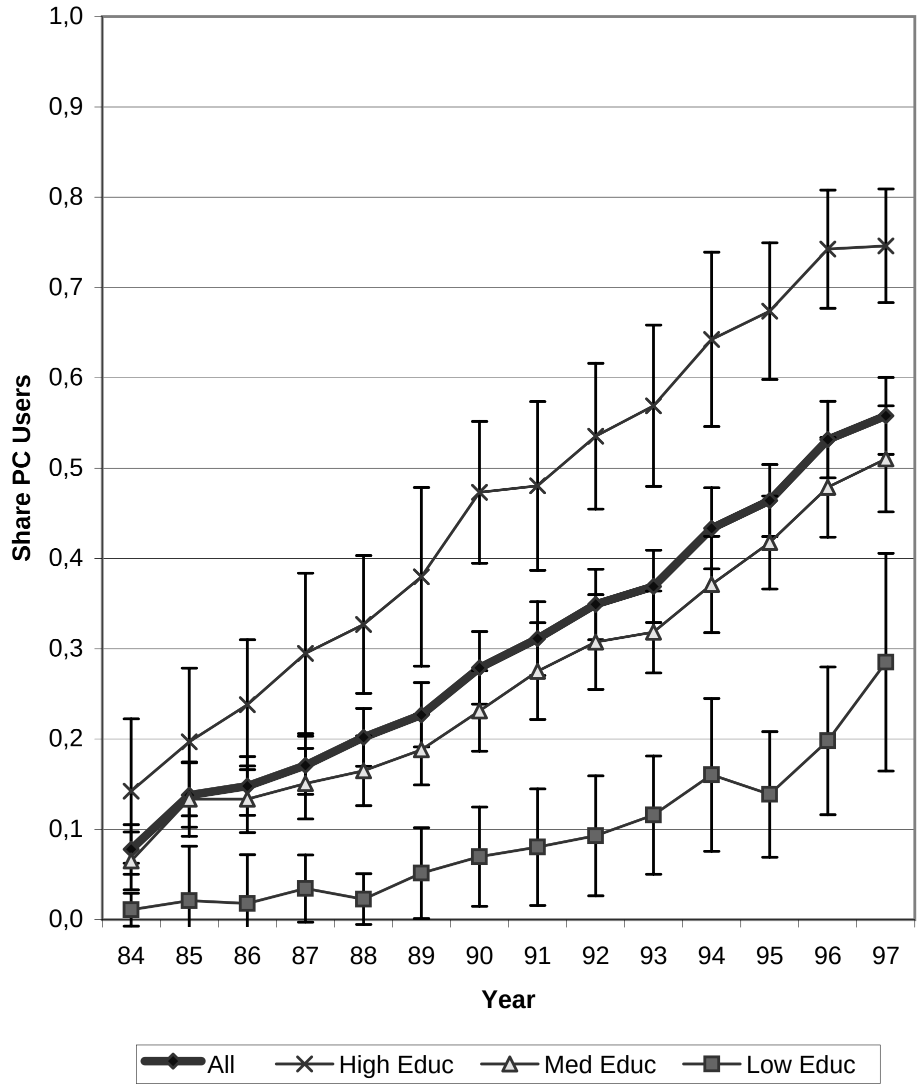

Figure 4: PC Usage Predictions: Imputation by Hotdeck

Todd (1998). In the first stage, we would estimate the probability of having *missing* PC information using a probit model, assuming that the information is *missing at random*. We use the explanatory variables listed in Table 3. The resulting *predicted probability* for *all* observations (valid and otherwise) is then used as a propensity score index.

In the second stage, we sort all observations by this index, and try to find suitable "donors" for the missing value "recipients", based on the proximity of the donor's index to that of the recipient's. Based on the explanatory variables chosen in the first step, a clustering of propensity scores can be observed, based on the combination and permutations available (if only two binary explanatory variables are used in the first stage, then there are obviously at most four clusters of propensity scores).

If valid donors for a missing observation can be found within a propensity score group (PSG), then it at random (with replacement), a particular donor's valid value is donated to the recipient. If however, there are no valid donors within the PSG, then one finds the next nearest PSG up or down, and so on. We force a caliper of 0.01, i.e. a nearest neighbor donor must have a propensity score difference of less than or equal to 0.01, or no match is made. (In fact, all recipients have successfully found valid donors.)

Then, a data set is created containing the valid and (now) imputed information and a regression is run. In our case this is simply a regression of the PC usage variable on a constant, i.e. we are interested in calculating the mean. This is then repeated, say 10 times, allowing us to calculate an average of the 10 different estimates and an overall estimate of the variance (comprised of "within" and "between" variances). We do this for every year separately, starting in 1984. The results are presented in Table 5.

D. Discussion

We find very similar results when using the Nearest Neighbor (NNM) and the Hotdeck matching methods. In fact, for an overall average of PC usage, they delivered almost *identical* results, as shown in Table 5. Probit imputation predicts higher usage rates in the earlier years (1984) and slightly higher rates towards the end of the observation period 1997. Further, the probit model has the advantage of having smaller standard errors. We do find the high-skilled dominating all other skill levels for PC usage at the workplace, both absolutely and relatively, with the exception of the last three years (in which the low skilled seem to "catch up" somewhat). We find some evidence for increased skill-technology specialization as discussed in Autor (2001). It is very difficult to observe a plateau effect (top right of the "S"-curve) of the implementation cycle that one might expect according to Shleifer (1986) for the highly skilled (already at 75% in 1997), considering that the 1990's were a time of sustained worldwide economic growth.

Table 5: PC Usage Predictions: Share with Standard Deviation

	Nearest Neighbor	Hot Deck			
Year	All Levels	All Levels	Low Education (7-9 Yrs)	Medium Education (10-11 Yrs)	High Education (12+ Yrs)
1984	0.0756 (0.0100)	0.0778 (0.0120)	0.0111 (0.0080)	0.0650 (0.0140)	0.1423 (0.0340)
1985	0.1290 (0.0180)	0.1379 (0.0150)	0.0211 (0.0260)	0.1334 (0.0180)	0.1968 (0.0350)
1986	0.1483 (0.0130)	0.1480 (0.0140)	0.0179 (0.0230)	0.1333 (0.0160)	0.2379 (0.0320)
1987	0.1789 (0.0160)	0.1709 (0.0140)	0.0344 (0.0170)	0.1506 (0.0170)	0.2948 (0.0390)
1988	0.2004 (0.0150)	0.2019 (0.0140)	0.0227 (0.0120)	0.1648 (0.0170)	0.3267 (0.0340)
1989	0.2267 (0.0160)	0.2268 (0.0160)	0.0515 (0.0220)	0.1882 (0.0170)	0.3796 (0.0430)
1990	0.2801 (0.0160)	0.2788 (0.0180)	0.0697 (0.0240)	0.2312 (0.0200)	0.4731 (0.0350)
1991	0.3028 (0.0190)	0.3111 (0.0180)	0.0803 (0.0290)	0.2751 (0.0230)	0.4803 (0.0410)
1992	0.3458 (0.0170)	0.3491 (0.0170)	0.0928 (0.0300)	0.3075 (0.0230)	0.5353 (0.0360)
1993	0.3661 (0.0190)	0.3690 (0.0180)	0.1157 (0.0290)	0.3185 (0.0200)	0.5690 (0.0400)
1994	0.4303 (0.0210)	0.4333 (0.0200)	0.1603 (0.0380)	0.3711 (0.0240)	0.6425 (0.0430)
1995	0.4652 (0.0190)	0.4640 (0.0180)	0.1387 (0.0310)	0.4176 (0.0230)	0.6739 (0.0340)
1996	0.5300 (0.0180)	0.5316 (0.0190)	0.1980 (0.0370)	0.4788 (0.0250)	0.7424 (0.0290)
1997	0.5614 (0.0200)	0.5578 (0.0190)	0.2851 (0.0540)	0.5102 (0.0260)	0.7461 (0.0280)

Note: See also Figure 4.

V. Conclusions

In contrast to many other studies using firm-level data, we use a large household panel data set with individual-level information, containing detailed human capital indicators. Based on the characteristics of employees in 1997, we are able to reconstruct past PC "take-up" using imputation methods based on a probit imputation model, "hotdeck" and "nearest-neighbor" matching methods. All in all we find similar results using the different methods, although the predictions of the probit model have the advantage of smaller standard errors.

Examining the absolute levels of PC usage rates at the workplace, we conclude that highly educated employees at all time periods dominate all others. Further, *usage growth* over time is also dominated by the highly educated. Thus, there seems to be the prevalence of complementarity between high levels of education (perhaps computer skills) and computer usage. This is further pushed by the steady movement into services, where PC's are an integral part of the office "production function", and away from manufacturing.

Yet, the possible presence of remaining aspects such as motivation or cognitive ability might necessitate additional effort at the identification of the genuine extent of dissemination. For instance, if workers with high unobserved motivation are more likely to be in stable employment, and are also more likely to receive early access to the new technology at their employing firm, the figures in Table 4 and Table 5 might still overstate the extent of dissemination. This issue will be addressed as our work in this area develops.

Similarly, the construction of an appropriate index of dissemination is an important further step. Clearly, the choice of appropriate stratification of the sample is the crucial ingredient of this task. On the one extreme, Table 4 and Table 5 already provide the information on the extent of dissemination in the aggregate. On the other extreme, a saturated stratification of the sample along the lines of age, gender, industry, occupation is likely to produce only observations with ones or zeros. Once a sensible stratification of the sample is found, though, it will be interesting to find out, if the pattern of dissemination within the detailed population cells tends to follow the S-shaped curve predicted by the theoretical models of new growth theory.

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Table 6: Major Hardware and Software Events in PC History

Date	Event
76-11	The tradename “Microsoft” is registered
78-06	8086 XT : 5-10 MHz, 29K Transistors
79-06	8088 XT : 5-8 MHz, 29K Transistors
81-08	IBM introduces its Personal Computer with MS-DOS 1.0
82-02	80286 AT : 6-12 MHz, 134K Transistors
83-09	Microsoft Word for MS-DOS 1.00
84-00	Apple Macintosh (MAC)
84-00	MS-DOS 3.0
84-01	Microsoft makes software for Apple MAC
84-08	IBM chooses Microsoft MS-DOS for operating system
85-00	256KB DRAM Memory Chip
85-10	Intel386 DX : 16 MHz, 275K Transistors
85-11	Microsoft Windows 1.0
86-00	MS-DOS 3.2
86-00	WordPerfect 4.2
87-00	MS-DOS 3.3
87-02	Intel386 DX : 20 MHz, 275K Transistors
87-04	Microsoft Windows 2.0
88-00	1MB DRAM Memory Chip
88-00	MS-DOS 4.0
88-04	Intel386 DX : 25 MHz, 275K Transistors
88-06	Intel386 SX : 16 MHz, 275K Transistors
89-00	WordPerfect 5.1
89-01	Intel386 SX : 20-25 MHz, 275K Transistors
89-04	Intel386 DX : 33 MHz, 275K Transistors
89-04	Intel486 DX : 25 MHz, 1.2M Transistors
89-08	Microsoft Office announced
90-05	Intel486 DX : 33 MHz, 1.2M Transistors
90-05	Microsoft Windows 3.0
90-10	Intel386 SL : 20 MHz, 855K Transistors
91-00	MS-DOS 5.0
91-06	Intel486 DX : 50 MHz, 1.2M Transistors
91-09	Intel386 SL : 25 MHz, 855K Transistors
91-09	Intel486 SX : 16-20 MHz, 1.2M Transistors
91-09	Intel486 SX : 25 MHz, 1.2M Transistors
92-00	4MB DRAM Memory Chip
92-03	IntelDX2 : 50 MHz, 1.2M Transistors
92-04	Microsoft Windows 3.1
92-08	IntelDX2 : 66 MHz, 1.2M Transistors
92-09	Intel486 SX : 33 MHz, 1.2M Transistors
92-10	Intel386 SX : 33 MHz, 275K Transistors
92-10	Microsoft Windows for Workgroups 3.1
92-11	Intel486 SL : 20-33 MHz, 1.4M Transistors
93-03	Pentium : 60-66 MHz, 3.1M Transistors
93-03	MSDOS 6.0
93-05	Microsoft Windows NT
93-11	Microsoft Windows for Workgroups 3.11.
94-00	Netscape 1.0 WWW Browser
94-00	MSDOS 6.22
94-00	“Pentium Bug”: 2 million units with FPU bug
94-03	IntelDX4 : 75-100 MHz, 1.6M Transistors
94-03	Intel Pentium : 90-100 MHz, 3.2M Transistors
94-10	Intel Pentium : 75 MHz, 3.2M Transistors
95-00	16MB DRAM Memory Chip
95-03	Intel Pentium : 120 MHz, 3.2M Transistors
95-06	Intel Pentium : 133 MHz, 3.3M Transistors
95-08	Windows 95
95-10	Microsoft Internet Explorer 2.0 for Windows 95
95-11	Intel Pentium Pro : 150-200 MHz, 5.5M Transistors
96-00	32MB DRAM Memory Chip
96-00	Microsoft Windows NT 3.0
96-01	Intel Pentium : 150-166 MHz, 3.3M Transistors
96-06	Intel Pentium : 200 MHz, 3.3M Transistors
97-00	64MB DRAM Memory Chip
97-00	Netscape Browser 4.0
97-01	Microsoft Office 97
97-01	Intel Pentium MMX : 166-200 MHz, 4.5M Transistors
97-06	Intel Pentium MMX : 233 MHz, 4.5M Transistors
97-09	Microsoft Internet Explorer 4.0

NOTE:

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