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Technology and Skill: An Analysis of Within and Between Firm Differences

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1. Introduction

> "… the widespread introduction of new technology has brought new employment opportunities and rising relative wages to those with the highest levels of human capital. However, this new technology has also helped to bring about higher than normal job losses, particularly among unskilled workers, and put a premium on being able to adapt to new workplace challenges" Introduction to Chapter 15, Modern Labor Economics, 7th Ed. Ehrenberg and Smith

Quotations like the one above raise a number of empirical questions. How sensitive is the demand for skilled workers to technological change? How sensitive is the demand for unskilled workers? Since skill has different dimensions – partly experience and partly basic ability – how is the demand for different types of skill affected? Progress on quantifying answers to questions like these has been limited due to the presence of substantial empirical challenges. The appropriate unit of analysis is the firm, yet measures of human capital at the firm level are very limited, and certainly not decomposable into experience and ability, detailed firm-level measures of technology are difficult to obtain, and longitudinal data that capture changes in the way in which firms behave over time are very rare.

This paper uses new data which remedies many of these deficiencies. We exploit new measures of human capital that enable us to construct – for the first time – detailed descriptions of multiple measures of the human capital composition of firms' workforces. We match these data with Economic Census data on individual firms that includes substantial amounts of information about the inputs and outputs, including technology. We use these data and measures to directly examine the way in which technology differences across businesses affect the types of workers that are employed, as well as the way in which changes in technology within businesses affect the demand for human capital.

Our contribution to the literature is that we find several key new results. We find a strong empirical relationship between technology and skill in a cross-sectional analysis of firms. We also find that technology interacts with different components of skill quite differently. For example, firm-level high-technology investments in capital such as computers and software are positively linked with individual ability, not to experience. Indeed, we find some evidence that the demand for experience is inversely related to the adoption of advanced technology. Finally, we address in two ways an empirical problem encountered by all related research: the problem of unobserved factors linking the choice of technology to workforce skill demand. First, we use the longitudinal nature of the data to exploit our knowledge of firm survival (which is likely to be linked to these unobserved traits) to control for survival in both our cross sectional and longitudinal analyses. And, to the extent that technology adoption is captured by unobserved fixed or highly persistent characteristics such as managerial ability that drives both technology choice and skill, our analysis of changes in firm behavior controls for such effects.

The paper proceeds as follows. In section 2, we briefly review the recent literature and discuss the underlying conceptual framework. For the latter, we largely adopt the methodology of the recent literature as our contribution is primarily empirical. Section 3 describes the data and the measures of technology and skill we use in the analysis. In section 4, we provide basic facts about technology and skill from our data. Section 5 is the core of the paper including our estimation of the relationship between the demand for skill and technology. Concluding remarks are provided in section 6.

2. Background and Conceptual Framework

Our ability to use longitudinally matched employer-employee data represents a considerable advance over earlier work, since most related work has used either industry level data, typically in manufacturing, and/or very crude measures of human capital at the micro/industry level, and/or data on individuals that has very limited information on the firms at which workers are employed. Berman, Bound and Griliches (1996), for example, used 4-digit manufacturing data to examine changing demand for skills in response to changes in technology, and were limited to using the ratio of non-production to production workers as a measure of skill. Dunne, Haltiwanger and Troske (1997) were also forced to use the same crude measure of skill in exploring similar issues using plant-level data for manufacturing.[1] Data on individuals has been used extensively, of course, to study the impact of technology on the demand for skilled workers (*e.g.,* Autor, Katz and Krueger, 1998) but such data inherently miss some important features of the relationship. For one, the growing literature on firm dynamics makes clear that there is tremendous between-firm heterogeneity in choices of technology (see, *e.g.,* Doms, Dunne and Troske, 1997, Dunne, Haltiwanger, and Troske, 1997, and Haltiwanger, Lane and Spletzer, 2000).

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[1]Our data do have some limitations relative to the data used in these studies. We only have data for the 1990s and for this version of the paper the data are confined to the universe of businesses and workers in one state – Illinois.

Regardless of these limitations, the literature has made a number of important strides in terms of advancing our understanding about the relationship between technology, organization and the demand for skilled workers, measuring technology at the firm level and measuring human capital. In this section we describe both the current state of the literature and how our approach complements and advances previous work.

2.1. Technology, Organization and the Demand for Skilled Workers

The ideas we pursue here have roots in several literatures but draw heavily upon the recent literature on evolution of businesses within industries, technological change and adoption and diffusion of new technologies (broadly defined) and the associated changes in the organization and demand for skilled workers.[2] To begin, a key part of our analysis is distinguishing between vs. within firm changes in human capital and technology. This distinction is important for a variety of reasons. Examining within firm changes and between firm changes permits us to examine in detail how new technologies are implemented and the extent to which adoption of new technologies are embodied in observable within vs. between firm changes. One view of technological change is that it is embodied in new capital – as such, we should be able to observe the changes in capital within vs. between businesses and relate this to within vs. between business changes in human capital. A related but alternative view is that new technology is embodied in new businesses so that by examining the respective differences across continuing, entering and exiting businesses we can investigate the connection between changes in technology and changes in the demand for human capital. In the next section, we begin this characterization by sketching a simple model of the relation between the technology at a business and the demand for human capital at the business. This simple model will be helpful for understanding both the within and between firm changes in the demand for human capital.

2.2. The Relation Between Technology and the Demand for Human Capital at the Firm Level

In this section we sketch a simple model of workforce choice as a function of technology (broadly defined). Suppose firms are faced with a production relationship given by:

[2]Relevant papers include Bartel and Lichtenberg (1987), Berman, Bound and Griliches (1994), Caballero and Hammour (1994), Campbell (1995), Chari and Hopenhyn (1991), Davis and Haltiwanger (1999), Doms, Dunne and Troske (1997), Dunne, Roberts and Samuelson (1989), Dunne, Haltiwanger and Troske (1997), Haltiwanger, Lane and Spletzer (2000), Jovanovic and MacDonald (1994), Juhn, Murphy and Pierce (1993), Kremer and Maskin (2000).

$$y_{jt} = F(Z_{jt}, L_{1jt}, ..., L_{Bjt}) \quad (1)$$

where y_{jt} is output for firm j in period t, the vector Z_{jt}, indexes the state of technology including tangible and intangible capital (like organizational capital), and L_{bjt} is the number of workers of type b, where b indexes both observable and unobservable characteristics of workers. Treating Z as quasi-fixed, cost minimization for a given output level yields (using Shepherd's lemma) the generalized demand for worker of type s as given by:

$$S_{bjt} = S(Z_{jt}, y_{jt}, w_{1jt} / w_{Bjt}, ..., w_{bjt} / w_{Bjt}, ...) \quad (2)$$

where S_{bjt} is the share (or perhaps cost share using a specific functional form for F) of type b workers, $b = 1, \dots, B$, and w_{bjt} is the appropriate shadow wage rate of type b workers (note that the shadow wage may differ from the actual wage due to bargaining, internal labor market and/or rent sharing behavior).[3]

In this framework, the demand for workers of type b by a particular firm depends upon the type of technology adopted (Z), the nature of the firm-worker type complementarities, the scale of operations and the relative shadow wages. In considering the implications, it is important to emphasize that there are many reasons that firms, even within the same industry, adopt different technologies. For example, Z may reflect differences in managerial/entrepreneurial ability, vintage, location, or other aspects of physical and intangible capital. As a result, not only will firms within the same industry exhibit heterogeneity in their demand for workers of type b but this heterogeneity may vary over time as conditions (*e.g.*, available technologies or other cost or demand shocks) change and due to firm life cycle effects.

In the empirical work that follows, we exploit this simple model by estimating specifications like:

$$S_{bjt} = \alpha_0 + \sum_k \alpha_{1k} Z_{kjt} + \sum_\ell \alpha_{2\ell} \ln\left(w_{\ell jt} / w_{Hjt}\right) + \alpha_3 \ln y_{jt} + \varepsilon_{jt} \quad (3)$$

where the coefficients α_{1k} indicate the effect of different types of information technology capital, Z; and the remaining coefficients have the conventional share equation interpretation. The coefficient estimates from cross sectional (or pooled cross sectional data) will shed light on how observable indicators of technology Z are related to human capital across businesses and in what follows we report such estimates.

[3]Our proposed analysis of earnings dynamics described below will shed light on internal labor market and rent sharing considerations.

In principle, we can also analyze changes in the demand for different types of labor—asking how much of the observable change in the distribution of *S* is due to observable changes in the distribution of *Z*. While such an approach is an interesting exercise, there are at least two potential limitations. First, there may be important unmeasured components of *Z* that imply unmeasured firm heterogeneity. Second, these unmeasured components of *Z* may be correlated with the measured components of *Z*. For example, high ability managers may be more likely to use the latest technology and implement the best business model on several dimensions including organizational and human resource practices. Thus, our coefficient estimates for a particular component of measured *Z* (*e.g.*, computers) from the level specification may reflect such difficult to measure firm effects rather than the independent contribution from the measured Z itself.

This common problem of fixed firm effects can potentially be resolved by estimating equation (3) in first differences (see, e.g., Berman, Bound and Griliches (1996) and Dunne, Haltiwanger and Troske (1997)):

$$\Delta S_{sjt} = \alpha_0^* + \sum_{\ell} \alpha_{1\ell} \Delta Z_{\ell jt} + \sum_{\ell} \alpha_{2\ell} \Delta \ln\left(w_{\ell jt} / w_{Hjt}\right) + \alpha_3 \Delta \ln y_{jt} + \Delta \varepsilon_{jt} \tag{4}$$

where α_0^* is the intercept of the first difference equation which has the interpretation of capturing the possibility of a common time trend in the skill bias of technological change. The specification in equation (4) permits us to examine more directly within business changes in human capital and how they are related to observable changes in technology.

The first difference specification may still be missing many important aspects of changes in the demand for skilled workers at the industry or economy-wide level since the latter may be driven by both within-business and between-business effects. Put differently, the first difference specification only helps us to characterize the within-firm changes for continuing businesses. We use our cross-sectional analysis in levels to gain insights into between business differences in technology (with the associated limitations).

The first difference specification generates another limitation since it relies on businesses that are continuers over the period that the differencing is calculated. Estimation of equation (4) as is yields inferences on the impact of changes in technology on the demand for skills conditional on the business being a continuer. As such, there is a selection bias that in this dynamic labor setting is analogous to the issues considered in Abowd, Crepon and Kramarz

(2001). In what follows, we estimate (4) using OLS but also consider a selection corrected version in a manner similar to Abowd, Crepon and Kramarz (2001).

The issue of selection is potentially relevant not only in the first difference specification (4) but also in the level equation (3). As noted, one substantial limitation of (3) is that unobserved heterogeneity that is correlated with both the level of skills and the level of technology may be biasing the results. In the absence of suitable plant-level instruments, we pursue an approach in the spirit of Olley and Pakes (1996) who estimated production functions in levels and were concerned with problems of unobserved heterogeneity. In particular, we note that the unobserved heterogeneity is likely to be correlated with selection. That is, exiting businesses may have characteristics and/or made decisions that influence the level of skills and technology that are inherently different than the businesses that are continuers. Accordingly, we estimate (3) using a selection correction as well to control for such unobserved heterogeneity that is correlated with survival.

2.3. Measuring Human Capital at the Firm Level

One of the limitations of the existing literature relating changes in technology to skill is that the measures of skill are quite limited. As noted above, the measures used from firm-level data are quite crude—the ratio of production to non-production workers. Even for household-level data, the usual skill variables (*e.g.,* education and experience) capture only limited and imperfect dimensions of skill. Thus, many studies conclude (e.g., Juhn, Murphy and Pierce, 1993) that it is the unobserved dimensions of skill that are most important for understanding the changing demand for skills in the workplace. For our purposes, we exploit the new techniques developed by Abowd, Kramarz and Margolis (1999, hereafter AKM) along with very rich matched longitudinal data on both firms and workers to identify the unobserved components of worker skill.

Briefly, we use the AKM decomposition of (log) wages for individuals:[4]

$$\ln w_{it} = \theta_i + \psi_{\mathrm{J}(i,t)} + x_{it}\beta + \varepsilon_{it} \tag{6}$$

where the dependent variable is the log fulltime, full year wage rate of an individual *i* working for employer *j* at time *t* and the function J(*i*,*t*) indicates the employer *j* of individual *i* at date *t*. The first component of equation (6) is the time invariant person effect, the second component is

[4]The vector *x* has a number of other controls including time effects and full quarter employment adjustments.

the time-invariant firm effect, the third component is the contribution of time varying observable individual characteristics, and the fourth component is the statistical residual, orthogonal to all other effects in the model.

We use the fixed worker effect θ plus the experience component of $x\beta$ as the core measure of human capital, called "*H*". In addition, in what follows, we take advantage of the decomposition of human capital into its components, the person effect and the experience effects. It is worth noting that because the specification is in logs the human capital measure is relative, not absolute. That is, in comparing two workers who differ in *H* by 0.1 we would say that the two workers differ in human capital by 10 log points (approximately 10 percent).

The econometric methodology and estimates of human capital, H and its components, used in this paper are discussed and described in detail in Abowd, Lengermann and McKinney (hereafter, ALM 2003). Briefly, ALM find that the new measures capture a much broader array of skills than do traditional measures. The proportion of earnings variation that is able to be explained using this type of approach is about 84%. And, in matches to the Current Population Survey – the basis for much analysis of earnings and employment outcomes – they find that only small fraction of the person specific effects can be explained by education, sex, and race. In addition, when they examine changes in the human capital distribution over time, they find that the overall distribution of human capital shifted to the right over the five year period of 1992-1997. They note that a substantial portion of this shift is due to the fact that while exiting workers were highly experienced and equally as educated as both entering and continuing workers, the unobservable component of their human capital was much lower. Entering workers, by contrast, while generally less experienced than continuing workers, were otherwise more highly skilled. In addition, they found a marked tendency for firms –both economy-wide and within the same industry -- to hire either relatively high skilled workers or low skilled workers, rather than hire large amounts of workers in the middle part of the distribution.

These interesting results lead us to explore the relationship between technology and the separate components of human capital as well as an over all measure. It may very well be that technology interacts differently with these components particularly as we seek to examine different measures of technology including measures of advanced technology. In proceeding, we need to consider how to translate the measures of "*H*" (and components) at the person level with the measures of skill mix that are present in empirical specifications (3) and (4). For this purpose, we follow ALM by first generating firm-level kernel density estimates of the distribution of each skill measure. In turn, using economy-wide thresholds, we compute the proportion of the firm-level workforce that is, for example, above the economy-wide 75th percentile. We use such firm-level proportions as our measures of *S* in what follows.

2.4. Measuring Technology at the Firm Level

A second challenge is developing direct measures of technology, particularly ones that are comparable across sectors. Clearly, physical capital intensity is a natural candidate, as are direct measures of the use of information technology such as computers or computer software. In addition, changes in other observable dimensions of a firm's activity may prove useful. For example, information technology has been associated with a variety of changes in the manner of doing business such as changes in supply chain management. An indicator of the latter might be changes in the relation between inventory and sales.

As will become clear in what follows, we have some quite interesting direct measures of technology that we can use for this analysis. While these measures are very interesting, they undoubtedly leave much unmeasured, especially with regard to the intangible capital components of technology. An indirect means of capturing some of this firm heterogeneity is to exploit the firm effects from the estimated wage decomposition above. That is, $\psi_{J(i,t)}$ is the component of the wage that is due to the firm effects. Such firm effects presumably reflect many factors. One factor is rent sharing—that is, firms may share rents from high levels of profitability/productivity. The latter are, in turn, presumably related to the type of technology (broadly defined) that has been implemented at a business. Thus, in what follows we also investigate the connection between our measures of human capital at the businesses, *S*, and the estimated firm effects. This latter connection is interesting in its own right as we are interested in whether high human capital businesses also have high firm effects. However, this also provides us with an indirect assessment of difficult to measure components of the technology of a business, for which the firm effects serve as a potential control for such components.

3. Data

We exploit a new Census Bureau data-set[5], (part of the Longitudinal Employer-Household Dynamics Program, LEHD) that integrates information from state unemployment insurance data with Census Bureau economic and demographic data. thus permitting the construction of longitudinal information on workforce composition at the firm level. The LEHD program represents a substantial investment made by the Census Bureau in order to permit direct linking of its demographic surveys (household-based instruments) with its economic censuses and surveys (business and business unit-based surveys).

The unemployment insurance (UI) wage records are discussed in more detail in the Data Appendix. Every state in the U.S. collects quarterly employment and earnings information through its State Employment Security Agency to manage its unemployment compensation program. The quarterly wage reports, which contain a record for every employer-employee pair, enable us to construct a quarterly longitudinal data set on employers. The employer's four digit Standard Industrial Classification is then added from another administrative file collected as a part of the state's employment security program. According to the BLS, which cooperates with the states to develop coding standards for the some of these reports, 98% of all employment is covered by the employer reports. The advantages of the UI wage record database are numerous. The data are frequent, longitudinal, and potentially universal. The sample size is generous and earnings reports are more accurate than survey-based data. The advantage of having the universal coverage is that movements of individuals to different employers and the consequences on earnings can be tracked. It is also possible to do longitudinal analysis using the employer as the unit. We accomplish this by selecting businesses that qualify for a particular analysis, then reconstructing their complete employee rosters at every point in time during the analysis period that the firm had positive employment.

In the empirical analysis for this paper, we use LEHD data from three states for the period 1992 and 1997. We focus on these two years since 1992 and 1997 are Economic Census years. We use the LEHD data for the states for which we have human capital data estimated at the firm level from 1992 and 1997 drawing upon the human capital estimates from ALM (2003).

An important limitation of the UI wage records as they are maintained by the individual states is the lack of any demographic information on the employees. The links to Census Bureau data overcome this limitation in two distinct ways. First, the micro-data are linked to administrative data at the Census Bureau containing information such as date of birth, place of

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[5]This has been generously supported by both the National Science Foundation and the National Institute on Aging as part of a social science database infrastructure initiative

birth, and sex for almost all the workers in the dataset. Second, as discussed in the previous section, the staff at the LEHD program have exploited the longitudinal and universal nature of the data to estimate fixed worker and firm effects, according to an exact least squares solution of representation in equation (6).The information in the UI wage records is also quite limited with regard to characteristics of the employer. We overcome this by linking the UI data to detailed information on individual firms available in each of two economic Census years (1992 and 1997). See the Data Appendix for details. The analytical dataset that we construct from these merged files has the employer as the unit of analysis, and our rich data permit us to measure many key variables, including output, the distribution of human capital within a business, workers, wages, entry, exit, and also some proxies for Z (see below). The measures of human capital within the business were constructed using the methodology described in section 2.

For the measures of Z (*i.e.*, observable measures of technology) we also use information collected from the Economic Censuses. The availability of such measures varies by sector and by year. One of our two primary sources for this information is the subset of businesses in the Manufacturing Economic Census who are also in the Annual Survey of Manufactures (ASM). ASM businesses are asked a set of detailed questions that enhance the basic information covered in the census. Similarly, a subset of nonmanufacturing (*i.e.*, retail, wholesale and services) businesses in the Economic Censuses are sampled in the Business Expenditures Survey (BES). The questions in the BES are similar to those asked in the ASM.

For our purposes, we focus on the following measures. In the 1992 Economic Census for Manufacturing, ASM plants were asked questions that permit us to generate a measure of physical capital intensity (capital per worker), expenditures on computer investment as a fraction of total equipment investment, the ratio of inventories to sales, and the ratio of purchases of computer software to sales. In the 1992 Economic Censuses for non-manufacturing, BES businesses were asked questions that permit us to generate all of these same measures. For the 1997 Economic Census of Manufacturing we can generate all of these measures for ASM plants except for the computer investment measure. For the non-manufacturing Economic Census in 1997, we can generate all of these measures for BES businesses except for the computer investment and capital intensity measures. The lack of computer investment data in 1997 is a substantial limitation for our analysis and is the primary reason that our cross-sectional analysis focuses on 1992. Our first-difference within firm analysis is also limited by this omitted data item in 1997 but, as will become clear, some of our other proxies for adoption of advanced technology yield striking results even with this limitation.

A major technical issue that is raised by this approach is that our analytical sample is based upon human capital measures, based on ES202 data, for a selected number of states (3) and aggregated to a unit that can be used in the cross walk to the Census Business Register. This crosswalk – which is based on aggregating establishments within each EIN that have the same state, county, and industry identifier – and which is our unit of observations. This cross walk issue, plus the fact that we match a variety of different surveys and censuses -- Economic censuses, Annual Survey of Manufactures and Business Establishment Survey mean that our matched sample will not be representative. To correct for the non-representativeness of our sample, we construct weights (ex post) as follows. We begin by computing the fraction of units, employment and payroll in the universe of business units using our ES202 based data[6] by industry and size. We then calculate the same statistics by industry and size class for our matched units. We then chose weights that are the inverse of the ratio in the industry size class of the employment in the matched sample to the universe matched employment. Such weights have the property that the weighted size distribution of employment by industry in our matched sample matches the universe weighted size distribution.

Finally, although the above approach is appropriate for our cross sectional dataset, a very different approach is needed for first difference specifications, which, by definition, are based on continuing firms. For continuers, we compute these same statistics for the fraction of payroll, employment and firms in the universe file of continuers and matched sample. The weights are such that the two sample average fraction of activity in the weighted continuer panel is the same as in universe in the industry-size cell.

Structuring the weights in this fashion means that we can make our nonrepresentative sample of continuers a weighted representative sample of continuers. Note, however, that incorporating such weights only makes the results representative for continuers and thus the first difference specifications still need to control for selection in the estimation.

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[6] The universe is all businesses in the ES202 based data sample in the in scope industries with more than 5 employees. We exclude the latter from our analysis since we cannot compute within firm distributions of skill reliably for such businesses (i.e., no KDE estimates for the smallest units).

4. The Link between Human Capital and Technology: Basic Facts

We now turn to the main point of the paper: exploring the influence of a firm's use of technology on its demand for human capital. Our analysis contains the following features: (i) we treat businesses in the more traditional manufacturing sector separately from businesses in the "new" (more service oriented) economy; (ii). we characterize the proportion of a firm's workforce in terms of the proportion of worker in each quartile of the earnings distribution, (iii) we decompose the overall measure of human capital into both the person effect and the experience component (iv) we distinguish between more conventional measures of technology (such as capital per worker) and indicators of newer, more computer-oriented technologies, and (v) we conduct our analysis both with and without selection correction adjustments.

4.1. Variable Measurement

In developing our measures of human capital, we note that is possible that technology investment affects the demand for both various skill groups and for different types of skill differently. We therefore construct, for each firm, the share of their workforce that is drawn from each quartile of the economy-wide human capital distribution. These four measures are constructed for the overall measure of human capital, the person effect and experience.

We construct several different measures of technology. Three measures reflect the use of newer, more computer-oriented technologies: investment in computers as a proportion of overall equipment investment, spending on computer software and data processing services as a proportion of annual sales[7], and total inventories as a proportion of sales[8]. We also include more traditional measures of technology use such as the capital stock per worker. Finally, in spite of the diversity of technology measures that we do observe and include in this exploration, there remain many aspects of technology use that we are not able quantify. One possibility is that many of these unobserved traits are correlated with the time-invariant fixed firm effect, $\psi_{J(i,t)}$. For this reason, we include $\psi_{J(i,t)}$ as a proxy for technology that we cannot directly measure.

[7]The measure of computer investment is the same as used in Autor, Katz and Krueger (1998) at an aggregate, industry level and by Dunne, Foster, Haltiwanger and Troske (2000) at a micro level.

[8] Inventory holdings act as a proxy for integration of information technology, which we do not observer directly. One advantage enjoyed by businesses with access to more sophisticated information technology (IT) networks is an enhanced ability (lower cost) to engage in more synchronized delivery of both inputs and outputs. Such scheduling abilities reduce the firm's need to hold costly inventories.

4.2 Descriptive Statistics

We report two different sets of results: the first describes how technology and human capital vary across sectors and types of firms; the second how they vary over time within firms. The first set—namely statistics describing the manufacturing and non-manufacturing distributions of human capital and our different measures of technology—are reported in Table 1.a[9]. In order to capture the heterogeneity across businesses, we rank each business by their position in the distribution of the relevant measure, and then report the mean of each measure for firms in the 10th, 50th and 90th percentile of that distribution.

The results indicate substantial variation across businesses in both the distributions of skill and of technology. For example, in the manufacturing sector, the business at the 90th percentile of the person effect distribution in terms of the proportion of workers in the upper quartile has almost 40 percent of its workers in the upper quartile while the 10th percentile business only has about 7 percent). There is also evidence of substantial variation in computer intensity across businesses. The 90th percentile firm in both manufacturing and service sectors is about sixty percent of equipment investment in computers while that for the 10th percentile business is zero. This suggests that some businesses are actively upgrading to advanced technology while others are not.

One limitation of the data is the absence of a computer investment expenditures in 1997. As noted, this drives our focus in the cross sectional analysis on 1992 and limits our analysis of first differences (specification (4)) to alternative measures of advanced technology. One of the primary measures that we do measure consistently in 1992 and 1997 is expenditures on software. To gain some insight into the relationship between hardware and software spending, Figure 1 contrasts the distribution of 1992 computer spending share for two groups of businesses: those with zero software spending in 1992 (roughly fifty percent of businesses) and those with positive software spending. It is clear form the graph that the majority of businesses that spent nothing on software in 1992 also had zero computer hardware investment. In contrast, the share of businesses with zero hardware investment in 1992 is markedly smaller among those with positive software spending in 1992. This finding is not surprising but is important for at least two reasons. First, in the cross sectional analysis when we explore the role of several different

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[9] The results are weighted to be representative of the typical **firm** in the economy. Because the biggest firms employ by far the largest number of workers, this is very different from an **employment** weighted sample.

measures of technology simultaneously, we need to be careful to acknowledge the covariation across technology measures. In this regard, we may be more interested in the combined influence of our technology measures rather than the individual influence of any specific measure since even with multiple measures our measures are presumably proxying for a host of other possible measures of technology. Second, and perhaps more importantly, this finding suggests our software measure may be a reasonable proxy for other measures of advanced technology which is important since it is one of the key measures we have in both 1992 and 1997.

As we have noted, ALM (2003) found that the distributions of human capital are quite different across businesses that are continuers, exiting businesses and entering businesses. For our purposes, these differences in human capital on this dimension are of particular interest to the extent they are correlated with differences in the adoption of technology across businesses. In the next section, we control formally for selection but for now we simply examine whether there are observably different patterns in the technology and skill mixes across businesses in the 1992 cross-section as a function of survival. Table 1.b presents the share of businesses in each sector that survive (overall, about 48 percent), and we report summary statistics for exiters versus continuers in Table 1.c. From Table 1.c, it is clear that exiting businesses look substantially different than continuing businesses. In particular, they tend to be smaller, less skill intensive (overall) and less technology intensive (particularly in computer and software investment in the manufacturing sector. Of particular interest is the fact that different components of skill work somewhat differently in the two sectors. Although exiting firms uniformly are less skill intensive (using the person effect measure), manufacturing firms have both higher shares of lower quartile workers and of top quartile workers in terms of their person effects. The experience characteristics of the workforce are much less systematically related to exit. Technology measures also work differently in the two sectors in that manufacturing exiters have much higher measures of the firm effect—ψ—than do continuing firms, while the opposite is true in the service sector. The results in Table 1.c provide *prima facie* evidence that controlling for selection is likely to be important.

Now turning to basic facts about within-firm changes, Table 2 presents summary statistics for continuing businesses for the first differences in our measures. The evidence suggests that the median continuing firm in both the manufacturing and service sectors is substantially upskilling in terms of not only the overall component of human capital but also in the separate person and experience components. Firms are also becoming more technology intensive in all of our measures: more capital intensive, more software intensive and less inventory intensive (all of these measures are only available for both years in manufacturing). We also find substantial variation across businesses. For example, in the computer software measure, the evidence is that 90th percentile manufacturing and services businesses increased their software spending substantially while the 10th percentile business in both sectors actually experienced a decrease.[10]

5. The Link between Technology and Human Capital: Specification and Estimation

5.1 Empirical Strategy

Because our estimation sample is subject to two distinct kinds of selection we use both weighting adjustments and selection corrections in our estimates of specification (3) in levels and (4) in first differences. First, we must correct for the fact that in either 1992 or 1997 our sample of businesses is based on the multistage probability sampling scheme implemented in the ASM and BES, respectively, for manufacturing and non-manufacturing establishments. The procedure for developing *ex post* weights for establishments (or EIN county SIC pseudo-establishments in the case of multiunits) from the ES-202 data associated with the UI wage records is discussed above. For the cross-sections in 1992 and 1997 the *ex post* weights render the estimation sample representative of the same population that the ASM and BES represent.

The dynamic modeling is more troublesome. For specification (4) the *ex post* weights make the estimation sample representative of the population of continuers in the combined ES-202 data for 1992 and 1997. There are a variety of reasons why this might be problematic but the most important among them is that the original ASM and BES samples were multistage with many self-representing units (large establishments). To the extent that establishment size is serially correlated, the same large units are sampled in both 1992 and 1997; however, the probability samples of the smaller units do not include a dynamic component. Hence, smaller units occur in the combined 1992/1997 sample of continuers with probabilities well-approximated by the product of their original sampling probabilities in the ASM and BES,

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[10] The share of software expenditures as a share of total sales is intrinsically a small number. In terms of percentage increases, the changes are quite large. For example the change for the 90th percentile business is as high as 50 percent increase even if that business started at the 90th percentile in terms of levels in 1992.

respectively. The primary benefit associated with our re-weighting scheme is that it lets us distinguish true exits from sample exits because the ES-202 universes are essentially complete in both 1992 and 1997 and the LEHD data editing procedures correct for both the BLS's successor/predecessor relations and establishment recombinations (mergers and divestitures) that can be inferred from the movements of workers (see Benedetto *et al.*, 2004). In principle, our *ex post* weights correct for the differential sampling of large and small businesses and eliminate the problem of false exits, but one should remain circumspect about potential biases arising from the combination of these several samples since there is no independent method of validating our weights.

Of course, re-weighting the observations will not correct for behaviorial consequences of exiting. To capture these effects we estimate an exit selection equation using the sample of all pseudo-establishments that were active in 1992, whether they were sampled in 1997 or not. Hence, an exit is a true exit not a sample exit. We handled the problem of measuring the conditioning variables for the exit equation comparably for establishments that were sampled in the 1992/1997 ASM/BES and those that were not. All of the conditioning information for the exit selection equation is available for all the 1992 active establishments.

In principle, we could also have constructed a selection equation for new entrants in 1997; however, this is a significantly more complicated modeling exercise that we have not undertaken at this time.

We begin by reporting estimates using weighted least squares using the weights constructed in the manner described in section 3 and using the matched sample described in section 3. We have estimated these specifications with and without industry effects and find results are quite similar whether or not industry effects are included. We report the results without industry effects since in our view this specification is slightly preferred as it exploits variation in human capital and technology within and between industries. ALM (2003) report substantial variation in the human capital distributions across industries and in principle we are interested in exploiting such variation.

After reporting the weighted least squares results, we then report estimates of both of these specifications controlling for selection (and also using weighted least squares). We model the latter using a probit specification. For the estimation of this selection probit, we use the entire universe of businesses in the EC-202 in 1992 that are in scope in industries covered by the

ASM and the BES (and that have five or more employees since these are the only businesses for which we have human capital measures). We are not restricted to using only the matched ASM and BES cases for this analysis since we do not model selection to be directly a function of the observed technology. Instead, the likelihood of exit from the ES-202 from 1992 to 1997 is specified to be a function of log labor productivity, the log change in population of the county in which the business is located between 1992 and 1997, the log change in sales in the two digit SIC industry in that county between 1992 and 1997, and indicators for firm size, firm location (whether the business is located in a suburb, rural area , or central city in 1992), legal form of organization (whether the firm is a sole proprietorship, partnership or corporation). In addition, we interact all variables with an industry effect so that the impact of, say, size on exit is permitted to vary by industry (industry effects are at a major industry level of aggregation). While we do not report the results from this selection analysis, the selection results are sensible. For example, as is common in the firm dynamics selection literature, we find that low labor productivity businesses are more likely to exit as are businesses in areas with increasing market demand.

Using these probit estimates, we construct inverse Mills Ratios and include the latter in our estimation of equations (3) and (4). The role the selection correction plays in the level and first difference specification is somewhat different. For the latter, the selection correction is a direct control for the sample selection induced by the use of continuers in the estimation of the first difference specification. For the former, the selection correction is included as a control for unobserved heterogeneity that may be simultaneously correlated with survival, human capital and technology. It should be noted that while we estimated the selection correction in two steps that we have corrected the standard errors appropriately for this two step procedure.

5.2 Empirical Estimation

Our empirical analysis of the relation between technology and human capital focuses on 1992 and 1997, which are the Economic Census years. In 1992, we have especially rich data on technology. As noted above, we use twelve different measures for the dependent variable in equation (3)– the share of workers at the business from each quartile of the economy-wide human capital distribution using three different measures of human capital.

One of the most difficult challenges in estimating the pure relationship between technology adoption and the demand for human capital is the fact that it is likely that the same factors that drive the adoption of technology – like the characteristics of the entrepreneur – also drive the selection of a high-skill workforce. Thus, any parameter estimates are likely to be upwardly biased to the degree that the two factors are driven by the same unobservable. In order to correct for this, we adjust our estimates for selection bias, on the rationale that the same unobservable that would act to correlate the adoption of high skill and technology would be highly correlated with the probability of a firm exiting.

We capture the between-firm relationship between technology adoption and workforce human capital by means of estimating equation (3) using cross-sectional data for a sample of businesses. In the estimation for the manufacturing sector, we use the technology measures from the ASM, and for a sample of service sector businesses (retail trade, wholesale trade and services) we use the technology measures from the BES. We capture the within-firm relationship by estimating equation (4) for continuing businesses between 1992 and 1997. In this estimation, all variables are measured as before, but the specification means that the measures are converted to first differences, and the 1997 dollar denominated measures such as sales are converted to 1992 dollars using BLS price deflators. Unfortunately, not all technology measures available in both years, and hence the specification is limited to including such changes in technology measures as: capital intensity per worker (ASM sample only), inventory to sales ratio, the ratio of computer software and data processing expenditures to sales, and the ratio of equipment investment to total investment (ASM only). Notably we do not measure computer investment in 1997 as the Economic Censuses did not include questions on this type of expenditure[11].

5.3 Between Firm Variation: Findings from Cross Section Model

The results from the cross section model are reported in Tables 3a (without selection controls) and 3b (with selection controls). A brief perusal of these results demonstrates that there is a strong empirical relationship between technology and skill. By and large, firms that use more technology employ a lower proportion of low-skill workers and a higher proportion of high-skill workers than do their non-technology using counterparts. The strongest and most robust set of

[11] In principle, for both the level and the change specification we would have preferred a measure of the stock of computer capital (and then the change in the stock for the first difference specification) as opposed to the flow. However, in line with other studies that have used this Census data (*e.g.*, Autor, Katz, and Krueger, 1998 and Dunne *et al.*, 2000) we use the computer intensity variable as a proxy for this. However, since we only observe this in 1992 we do not include a computer intensity variable in the first difference specification.

results are those associated with computer intensity, which shows a monotonically increasing relationship between technology use and the skill level of the workforce. This relationship is evident in both the regressions for manufacturing and for services, and both with and without correction for selection.

A repeated theme in the reported results is that the relationship between technology and skill differs substantially depending on what measure of skill is used. For example, when we examine the relationship between computer intensity and human capital in manufacturing, the relationship is monotonic for both the overall and the person effect measure . This consistency is quite the opposite when the dependent variable is the experience measure of human capital: here not only is the relationship nonmonotonic, but in some cases (such as the firms in the fourth quartile of the manufacturing distribution), firms that have higher computer usage have lower proportions of highly experienced workers.

The reported results on the relationship between high tech capital and skill are both economically and statistically significant. For example, combining the summary statistics from Table 1a with the results from Table 3b on the difference in computer intensity between the 90th percentile business shows that the implied difference in share of workers in the highest quartile of the person effect distribution is about 3 percent higher at the 90th percentile business. The analogous computation yields a 4 percent higher share of high person effect workers in services.

We find similarly strong results for capital intensity in manufacturing and computer software in services – firms with greater levels of each of these measures are more likely to have highly skilled and less likely to have less skilled workforces – using both the overall and person effect measures of human capital. Again, and most interestingly, the reverse is true for firms with higher proportions of computer software – they are actually less likely to employ highly experienced workers.[12]

Finally, we also find that the relationship between our unmeasured technology variable -- ψ and human capital use is positive in the simple least squares regression, but negatively related in the selection corrected specification. One possibility for this result is that PSI serves as proxy for unobserved heterogeneity, in that it capture the wage premium or discount associated with

[12] In manufacturing, the results in the cross section on software are less systematic although there is evidence that, for example, higher software intensity is associated with a higher share of the highest quartile of the person effect. It is our sense that the software measure has more information content in the first difference relative to the cross section since software usage increased dramatically over the period.

every firm, and may also capture the entrepreneurial or managerial ability that we speculated might simultaneously drive the adoption of new technology and the employment of highly skilled workers.

In sum, our cross-sectional results with respect to the relationship between firm level technology adoption and the skill level of the workforce as captured by the overall and person effect measures are completely consistent with a priori expectations. While these results are new in the sense that it has never before been possible to directly link at the firm level such complex measures of human capital and complex measures of technology, we also uncovered a very different and negative relationship between technology adoption and experience. In subsequent research which analyses the dynamics of the composition of the workforce, we will examine whether this is truly a worker experience effect, or simply a firm vintage effect – in that older firms are simultaneously less likely to adopt technology and more likely to have experienced workers.

5.4 Within Firm Variation: Findings from First Difference Model

A major strength of our dataset is that we can also examine within firm changes in technology use and the skill level of the workforce, which permits us to control for unobserved heterogeneity and in turn selection. Although this approach is intuitively appealing, there are two reasons to expect the results to be less robust than in the previous section. First, unfortunately, some key technology questions were dropped between 1992 and 1997, and we are therefore unable to capture the effect of changes in some of the measures. In addition, in other work (Haltiwanger, Lane and Spletzer, 2001), we have found that firms are both remarkably heterogeneous in the ways in which they organize themselves and remarkably persistent. Much change occurs not because existing firms reorganize their existing production, but rather because new firms enter and displace old firms, or because firms with successful production techniques expand at the cost of their less successful, contracting, counterparts (Foster, *et al*. 2002).

The results of our estimation of equation (4) are provided in Tables 4a and 4b. As before, the relationships confirm a prior expectations. In particular, firms – in both manufacturing and services -- that increase their investment in computer software tend to reduce their share of low skill workers. This effect is ALL driven by the person effect of the workforce: as before, those firms increasing computer software between the two periods tend to increase their share of less experienced workers and reduce their share of more experienced workers. The magnitude of the estimated effects is not only statistically important but also quantitatively important. For example, combining the summary statistics from Table 2 with the estimated results from Table 4.b suggests that the 90^{th} percentile business relative to the 10^{th} percentile business in terms of changing the software share has more than 1 percent smaller share of the bottom quartile person effect workers in both manufacturing and services.

The results are more mixed for our other technology measures. We would expect firms that reduce their inventory holdings (suggesting more investment in technology) to increase the skill level of their workforces, and this is certainly the case in manufacturing especially for the overall human capital measure and the experience component of human capital. There is also some evidence (for manufacturing) that changes in firm-level capital intensity affects the demand for skilled workers.

In sum, although, as expected, the effects of within-firm changes in technology on the demand for skilled workers are much more mixed, the evidence by and large supports the results in the previous section. This is particularly evident with the software measure, which also evidenced the same differential relationship between it and the two separate measures of human capital: the person effect and experience.

6. Concluding Remarks

We began by raising a number of empirical questions. How sensitive is the demand for skilled workers to technological change? How sensitive is the demand for unskilled workers? Since skill has different dimensions – partly experience and partly basic ability – how is the demand for different types of skill affected?

In this paper we began to provide answers to some of these questions by using new measures of human capital matched to multiple measures of technology derived from substantial amounts of information about the inputs and outputs, including technology. We used these data and measures to directly examine the way in which technology differences across businesses affect the types of workers that are employed, as well as the way in which changes in technology within businesses affect the demand for human capital.

We found several key new results. We found a strong empirical relationship between technology and skill in a cross-sectional analysis of firms. We also found that technology interacts with different components of skill quite differently: firms that use technology are more likely to use high ability workers, but less likely to use high experience workers. These results, by and large, held even when we controlled for unobservable heterogeneity by means of both selection correction and by first differencing our measures.

In sum, observable differences in technology across businesses are closely related to the differences in human capital across businesses. The capital intensity of a business, the computer investment of a business, the equipment investment intensity of a business and the computer software expenditure intensity of a business are all positively related to the level of human capital at a business. We also find that unobservable measures of technology – the firm effect – is positively correlated with the skill of the workforce at a firm. One interpretation of this finding is that the firm effects are proxies for (or positively correlated with) unobserved components of the technology (*e.g.*, intangible capital, managerial ability) and thus this finding is supportive of the view that high tech businesses on these unmeasured dimensions are also more likely to employ high skilled workers.

Accounting for changes in the demand for human capital across businesses is more difficult. This difficultly stems in part from data limitations in terms of being able to measure changes in technology consistently across businesses, and in part from the persistence with which firms organize themselves. However, the pattern for the level results holds for the change results for the most part – that is, businesses that upgrade their technology are also observed to upgrade their skills.

As always, more work remains to be done. The evidence suggesting that firms that adopt more technology are less likely to employ experienced workers has clear implications for the future as the workforce ages. We would like to explore further the extent to which the result in the cross section is a firm vintage effect, or a true relationship between technology and experience. Our current first difference results that also go in the same way suggest it is a technology effect since the vintage effects are differenced out in that specification. Because our potential sample is now augmented as more states have entered the LEHD program, we can investigate within and across detailed industries to tease out the importance of our different measures.

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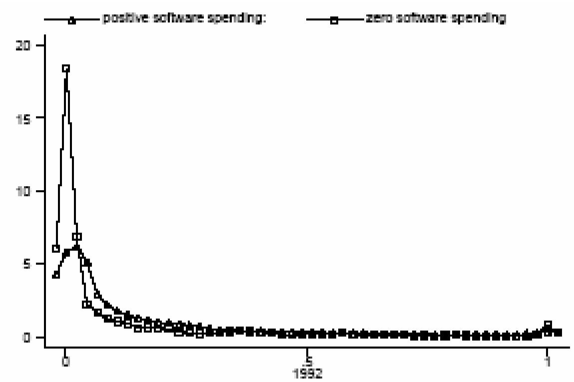
Figure 1: 1992 Computer Spending Share Distributions for Zero and Positive 1992 Software Spending



Share Computer Spending: High and Low Software Spending

Table 1a: 1992 Summary Statistics for Human Capital and Technology Measures

	Annual Survey of Manufactures			Business Establishment Survey		
	10th percentile	50th percentile	90th percentile	10th percentile	50th percentile	90th percentile
Proportion of workforce in bottom quartile of human capital (overall)	0.051	0.198	0.475	0.082	0.309	0.602
Proportion of workforce in second quartile of human capital (overall)	0.134	0.24	0.375	0.138	0.236	0.353
Proportion of workforce in third quartile of human capital (overall)	0.127	0.254	0.405	0.092	0.204	0.353
Proportion of workforce in fourth quartile of human capital (overall)	0.075	0.233	0.47	0.032	0.173	0.455
Proportion of workforce in bottom quartile of human capital (person effect)	0.107	0.294	0.517	0.042	0.211	0.436
Proportion of workforce in second quartile of human capital (person effect)	0.176	0.263	0.365	0.119	0.217	0.317
Proportion of workforce in third quartile of human capital (person effect)	0.125	0.21	0.322	0.138	0.229	0.357
Proportion of workforce in fourth quartile of human capital (person effect)	0.067	0.188	0.371	0.128	0.29	0.518
Proportion of workforce in bottom quartile of human capital (experience)	0.066	0.184	0.339	0.136	0.341	0.65
Proportion of workforce in second quartile of human capital (experience)	0.146	0.235	0.327	0.135	0.231	0.336
Proportion of workforce in third quartile of human capital (experience)	0.171	0.244	0.325	0.082	0.189	0.297
Proportion of workforce in fourth quartile of human capital (experience)	0.148	0.294	0.491	0.032	0.171	0.364
Log Sales	6.69	8.251	10.224	5.982	7.439	9.362
Computer Investment Share	0	0.019	0.553	0	0.033	0.601
Software Share (x100)	0	0.018	0.393	0	0	0.047
Log Capital Intensity	2.438	3.981	5.207	1.969	3.429	10.027
Inventory/Sales	0.023	0.093	0.286	0	0.008	0.206
Psi	-0.145	0.146	0.391	-0.51	-0.024	0.335

Notes: Percentiles are based upon matched samples (match between ECF and ASM and ECF and BES) and using ex post sample weights. 4643 firms in manufacturing; 9460 in services. Percentiles reported in this and subsequent tables reflect weighted average of value in the three percentiles centered on the reported percentile.

Table 1b: Share of Businesses (by Sector) from ES-202
that Exit between 1992 and 1997

Sector	Share Exiting Businesses
Manufacturing	0.445
Retail	0.505
Services	0.478
Wholesale	0.473

Table 1c: 1992 Summary Statistics for Continuing and Exiting Businesses

	Manufacturing 50th percentile		Services 50th percentile	
	Continuers	Exiters	Continuers	Exiters
Proportion of workforce in bottom quartile of human capital (overall)	0.188	0.211	0.287	0.338
Proportion of workforce in second quartile of human capital (overall)	0.24	0.239	0.236	0.236
Proportion of workforce in third quartile of human capital (overall)	0.255	0.253	0.209	0.199
Proportion of workforce in fourth quartile of human capital (overall)	0.244	0.215	0.182	0.161
Proportion of workforce in bottom quartile of human capital (person effect)	0.285	0.309	0.206	0.218
Proportion of workforce in second quartile of human capital (person effect)	0.264	0.261	0.218	0.217
Proportion of workforce in third quartile of human capital (person effect)	0.213	0.207	0.233	0.225
Proportion of workforce in fourth quartile of human capital (person effect)	0.193	0.18	0.296	0.284
Proportion of workforce in bottom quartile of human capital (experience)	0.187	0.181	0.339	0.344
Proportion of workforce in second quartile of human capital (experience)	0.235	0.236	0.231	0.23
Proportion of workforce in third quartile of human capital (experience)	0.243	0.246	0.192	0.186
Proportion of workforce in fourth quartile of human capital (experience)	0.295	0.293	0.176	0.165
Log Sales	8.31	8.175	7.613	7.189
Computer Investment Share	0.024	0.014	0.033	0.034
Software Share (x100)	0.025	0.012	0	0
Log Capital Intensity	3.975	3.98	3.634	3.273
Inventory/Sales	0.092	0.094	0.006	0.009
Psi	0.124	0.174	-0.009	-0.037

Notes: Percentiles are based upon matched samples and using ex post sample weights.

Table 2: First Difference Summary Statistics for 1992-97 Changes for Continuing Businesses

	Annual Survey of Manufactures			Business Establishment Survey		
	10th percentile	50th percentile	90th percentile	10th percentile	50th percentile	90th percentile
Proportion of workforce in bottom quartile of human capital (overall)	-0.246	-0.102	-0.001	-0.245	-0.086	0.04
Proportion of workforce in second quartile of human capital (overall)	-0.172	-0.052	0.095	-0.152	-0.037	0.093
Proportion of workforce in third quartile of human capital (overall)	-0.093	0.031	0.16	-0.106	0.031	0.146
Proportion of workforce in fourth quartile of human capital (overall)	-0.005	0.127	0.261	-0.033	0.091	0.237
Proportion of workforce in bottom quartile of human capital (person effect)	-0.2	-0.064	0.031	-0.173	-0.036	0.091
Proportion of workforce in second quartile of human capital (person effect)	-0.079	-0.007	0.055	-0.09	-0.002	0.084
Proportion of workforce in third quartile of human capital (person effect)	-0.043	0.015	0.1	-0.082	0.007	0.106
Proportion of workforce in fourth quartile of human capital (person effect)	-0.045	0.053	0.169	-0.12	0.028	0.185
Proportion of workforce in bottom quartile of human capital (experience)	-0.148	-0.03	0.065	-0.204	-0.045	0.101
Proportion of workforce in second quartile of human capital (experience)	-0.11	-0.022	0.039	-0.109	-0.002	0.117
Proportion of workforce in third quartile of human capital (experience)	-0.051	0.017	0.106	-0.073	0.019	0.12
Proportion of workforce in fourth quartile of human capital (experience)	-0.091	0.041	0.141	-0.085	0.033	0.159
Log Sales	-0.793	0.123	0.965	-1.315	0.087	0.764
Software Share (x100)	-0.304	0	0.193	-0.088	0.003	0.165
Log Capital Intensity	-0.686	0.216	1.422			
Inventory/Sales	-0.116	-0.011	0.08	-0.014	0	0.014

Note: Percentiles computed using ex post sample weights for continuing businesses; 1516 firms in manufacturing; 1709 in services

Table 3a: Regression of Skill Mix on Technology --1992, Cross-section, No Selection Control

	First_Quartile		Second_Quartile		Third_Quartile		Fourth_Quartile	
	Manufacturing	Services	Manufacturing	Services	Manufacturing	Services	Manufacturing	Services
Total Human Capital								
Capital Intensity	-0.0531*	-0.0064*	-0.0145*	-0.0006*	0.0286*	0.0012*	0.0380*	0.0062*
	0.0021	0.0005	0.0014	0.0003	0.0015	0.0003	0.0022	0.0005
Computer Investment Share	-0.0396*	-0.0769*	-0.0213*	-0.0136*	0.0017	0.0186*	0.0683*	0.0788*
	0.0084	0.0062	0.0055	0.0037	0.0060	0.0038	0.0087	0.0060
Inventory/Sales	-0.0446*	-0.1109*	-0.0069	0.0291*	-0.0057	0.0839*	0.0292*	0.0002
	0.0141	0.0139	0.0093	0.0084	0.0101	0.0086	0.0146	0.0133
Software Share	-0.6468	-0.0205	-0.9356*	0.3566*	-0.5762	-0.2486	2.5608*	-0.0614
	0.4481	0.2473	0.2967	0.1490	0.3228	0.1529	0.4648	0.2377
Psi	-0.1286*	-0.2633*	0.0366*	0.0023	0.1078*	0.1149*	0.0205	0.1570*
	0.0111	0.0051	0.0074	0.0031	0.0080	0.0032	0.0115	0.0049
Person Effect								
Capital Intensity	-0.0320*	-0.0014*	-0.0032*	-0.0004	0.0121*	-0.0008*	0.0250*	0.0021*
	0.0021	0.0004	0.0012	0.0003	0.0011	0.0003	0.0018	0.0005
Computer Investment Share	-0.0729*	-0.0379*	-0.0015	-0.0295*	0.0262*	-0.0065	0.0463*	0.0702*
	0.0082	0.0058	0.0045	0.0034	0.0044	0.0035	0.0070	0.0063
Inventory/Sales	0.0377*	0.0052	0.0174*	0.0283*	-0.0105	0.0303*	-0.0455*	-0.0619*
	0.0137	0.0129	0.0076	0.0075	0.0074	0.0079	0.0117	0.0140
Software Share	-0.2151	-0.8053*	-1.2326*	-0.1504	-0.1164	-0.1318	1.7709*	0.9834*
	0.4363	0.2304	0.2435	0.1336	0.2347	0.1408	0.3734	0.2497
Psi	0.0497*	-0.0083	0.0440*	0.0256*	0.0088	0.0003	-0.0935*	-0.0188*
	0.0108	0.0048	0.0060	0.0028	0.0058	0.0029	0.0093	0.0052
Experience								
Capital Intensity	-0.0063*	-0.0060*	-0.0073*	0.0005	-0.0013	0.0021*	0.0136*	0.0031*
	0.0015	0.0005	0.0011	0.0003	0.0010	0.0003	0.0019	0.0004
Computer Investment Share	0.0001	-0.0208*	0.0226*	0.0132*	0.0086*	0.0071*	-0.0278*	0.0028
	0.0061	0.0071	0.0043	0.0033	0.0037	0.0034	0.0076	0.0052
Inventory/Sales	-0.0850*	-0.0753*	-0.0210*	-0.0508*	0.0407*	0.0170	0.0700*	0.1000*
	0.0101	0.0159	0.0072	0.0075	0.0063	0.0076	0.0127	0.0116
Software Share	-0.6216*	1.0488*	-0.0208	-0.1692	-0.2008	-0.3498*	0.9432*	-0.4766*
	0.3235	0.2842	0.2281	0.1332	0.2001	0.1351	0.4048	0.2071
Psi	-0.1016*	-0.2370*	-0.0250*	0.0746*	0.0358	0.0854*	0.0937*	0.0821*
	0.0080	0.0059	0.0056	0.0028	0.0049	0.0028	0.0100	0.0043

Note: All level regressions control for log(sales) and county relative wage for skill mix in question. Regressions are estimated using ex post sample weights. Coefficients that are statistically significant at the 5 percent level are starred and coefficient and standard error are shade in grey.

Table 3b: Regression of Skill Mix on Technology --1992, Cross-section, With Selection Control

	First_Quartile		Second_Quartile		Third_Quartile		Fourth_Quartile	
	Manufacturing	Services	Manufacturing	Services	Manuf.	Services	Manuf.	Services
Total Human Capital								
Capital Intensity	-0.0506*	-0.0059	-0.0154	-0.0007	0.0247*	0.0010	0.0391	0.0061
	0.0203	0.0146	0.0114	0.0066	0.0114	0.0056	0.0284	0.0164
Computer Investment Share	-0.0499*	-0.0761*	-0.0216*	-0.0143*	0.0063*	0.0171*	0.0696*	0.0799*
	0.0014	0.0009	0.0010	0.0006	0.0011	0.0006	0.0015	0.0009
Inventory/Sales	0.0003	-0.0004	-0.0073*	-0.0002	-0.0082*	0.0003	0.0118*	0.0002
	0.0020	0.0005	0.0014	0.0003	0.0015	0.0003	0.0021	0.0005
Software Share	-0.2278*	0.0250*	-0.1685*	0.3444*	0.0649*	-0.2965*	1.1311*	-0.0491*
	0.0023	0.0017	0.0016	0.0010	0.0017	0.0011	0.0024	0.0017
Mills Ratio	-0.0191	-0.0074	0.0038	0.0016	0.0105	0.0009	0.0080	0.0047
	0.0106	0.0049	0.0076	0.0030	0.0081	0.0030	0.0112	0.0047
Psi	-0.1458*	-0.2626*	0.0302*	0.0022	0.1118*	0.1138*	0.0438	0.1576*
	0.0257	0.0176	0.0103	0.0052	0.0110	0.0054	0.0355	0.0192
Capital Intensity	-0.0269*	-0.0013	-0.0050	-0.0005	0.0103	-0.0010	0.0240	0.0022
	0.0127	0.0067	0.0095	0.0050	0.0149	0.0087	0.0151	0.0113
Computer Investment Share	-0.0701*	-0.0389*	-0.0085*	-0.0299*	0.0227*	-0.0066*	0.0549*	0.0716*
	0.0014	0.0009	0.0008	0.0005	0.0008	0.0005	0.0012	0.0010
Inventory/Sales	0.0107*	-0.0001	-0.0025*	0.0001	-0.0010	-0.0000	-0.0052*	-0.0000
	0.0020	0.0005	0.0011	0.0003	0.0011	0.0003	0.0017	0.0005
Software Share	0.6915*	-0.8257*	-0.9255*	-0.1717*	0.0745*	-0.1425*	0.3515*	1.0369*
	0.0023	0.0017	0.0013	0.0009	0.0012	0.0010	0.0019	0.0019
Mills Ratio	-0.0036	-0.0059	0.0070	-0.0013	0.0030	0.0027	-0.0063	0.0053
	0.0106	0.0048	0.0058	0.0027	0.0057	0.0027	0.0088	0.0053
Psi	0.0171	-0.0092	0.0507*	0.0250*	0.0155*	0.0002	-0.0754*	-0.0172
	0.0155	0.0090	0.0074	0.0045	0.0077	0.0048	0.0133	0.0101
Capital Intensity	-0.0100	-0.0057	-0.0069	0.0007	0.0016	0.0020	0.0142	0.0028
	0.0193	0.0227	0.0256	0.0182	0.0264	0.0223	0.0346	0.0209
Computer Investment Share	-0.0049*	-0.0204*	0.0218*	0.0143*	0.0160*	0.0073*	-0.0285*	0.0015*
	0.0010	0.0011	0.0007	0.0005	0.0006	0.0005	0.0013	0.0008
Inventory/Sales	-0.0164*	-0.0002	-0.0061*	-0.0000	0.0057*	0.0001	0.0178*	0.0002
	0.0014	0.0006	0.0010	0.0003	0.0008	0.0003	0.0019	0.0004
Software Share	-0.5737*	1.0912*	-0.0481*	-0.1365*	-0.1791*	-0.3576*	0.7629*	-0.5353*

	0.0016	0.0021	0.0011	0.0009	0.0009	0.0009	0.0021	0.0015
Mills Ratio	-0.0072	-0.0015	-0.0030	0.0007	-0.0008	0.0010	0.0121	0.0008
	0.0075	0.0061	0.0052	0.0026	0.0044	0.0027	0.0098	0.0042
Psi	-0.0894*	-0.2360*	-0.0240*	0.0755*	0.0184*	0.0853*	0.0955*	0.0807*
	0.0143	0.0162	0.0069	0.0043	0.0084	0.0071	0.0156	0.0090

Note: All level regressions control for log(sales) and county relative wage for skill mix in question. Regressions are estimated using ex post sample weights. Coefficients that are statistically significant at the 5 percent level are starred and coefficient and standard error are shade in grey.

Table 4a: Regression of Change in Skill Mix on Change in Technology --1992-97, No Selection Controls

	First_Quartile		Second_Quartile		Third_Quartile		Fourth_Quartile	
	Manufacturing	Services	Manufacturing	Services	Manufacturing	Services	Manufacturing	Services
Overall Effect								
Capital Intensity	-0.0269*		0.0225*		0.0068*		-0.0025	
	0.0031		0.0033		0.0028		0.0033	
Inventory/Sales	0.0678*	0.0444*	0.0366	-0.0018	-0.0296	-0.0268	-0.0712*	-0.0153
	0.0234	0.0260	0.0245	0.0220	0.0210	0.0240	0.0252	0.0262
Software Share	-3.8733*	-1.4525*	1.8655	1.1515*	2.4827*	0.1032	-0.3148	0.0620
	0.9270	0.3025	0.9760	0.2554	0.8344	0.2787	1.0024	0.3047
Person Effect								
Capital Intensity	0.0001		-0.0008		-0.0031		0.0025	
	0.0025		0.0015		0.0016		0.0025	
Inventory/Sales	-0.0274	0.0066	0.0367*	-0.0001	-0.0539*	-0.0073	0.0402*	0.0022
	0.0194	0.0241	0.0114	0.0166	0.0119	0.0172	0.0189	0.0269
Software Share	-2.7971*	-2.0438*	0.6457	-0.5394*	0.6682	0.8655*	1.5905*	1.6536*
	0.7664	0.2813	0.4541	0.1931	0.4714	0.2001	0.7456	0.3136
Experience Effect								
Capital Intensity	-0.0100*		-0.0008		0.0019		0.0092*	
	0.0022		0.0016		0.0016		0.0024	
Inventory/Sales	0.0705*	0.0306	0.0311*	0.0035	-0.0061	-0.0092	-0.0867*	-0.0270
	0.0167	0.0282	0.0125	0.0216	0.0125	0.0175	0.0181	0.0215
Software Share	-0.6436	0.9545*	1.3067*	0.0257	-0.0519	-0.0859	-0.4312	-0.8680*
	0.6614	0.3273	0.4957	0.2515	0.4956	0.2030	0.7177	0.2501

Note: Controls also include change in log (real sales) and change in county relative wage. Estimated equation also includes a constant. Coefficients that are statistically significant at the 5 percent level are starred and coefficient and standard error are shade in grey.

Table 4b: Regression of Change in Skill Mix on Change in Technology --1992-97, Selection Controls

	First Quartile		Second Quartile		Third Quartile		Fourth Quartile	
	Manufacturing	Services	Manufacturing	Services	Manufacturing	Services	Manufacturing	Services
Overall Effect								
Capital Intensity	-0.0261		0.0220		0.0075		-0.0035	
	0.5298		0.5805		0.6353		0.5836	
Inventory/Sales	-0.0136	-0.0001	0.0224	0.0002	0.0003	-0.0000	-0.0095	-0.0001
	0.0304	0.0099	0.0331	0.0085	0.0371	0.0093	0.0366	0.0097
Software Share	-4.0627*	-1.4069*	1.8324*	1.0550*	2.4803*	0.0583*	-0.0623	0.1611*
	0.0343	0.0120	0.0386	0.0115	0.0439	0.0132	0.0407	0.0112
Mills Ratio	-0.0472*	0.0243	-0.0225*	-0.0473	-0.0919*	-0.0231	0.1615*	0.0491
	0.0103	0.3332	0.0113	0.3104	0.0123	0.3134	0.0110	0.3490
Person Effect								
Capital Intensity	-0.0000		-0.0009		-0.0029		0.0027	
	0.3940		0.2704		0.2439		0.3727	
Inventory/Sales	0.0046	0.0003	-0.0007	0.0001	-0.0183	-0.0001	0.0124	-0.0003
	0.0223	0.0085	0.0153	0.0060	0.0140	0.0064	0.0213	0.0094
Software Share	-2.7323*	-2.0743*	0.5104*	-0.6016*	0.7776*	0.8486*	1.5464*	1.7655*
	0.0252	0.0109	0.0168	0.0074	0.0154	0.0073	0.0234	0.0114
Mills Ratio	-0.0195*	-0.0153	0.0074	-0.0306	-0.0145*	-0.0082	0.0332*	0.0557
	0.0077	0.2849	0.0053	0.2167	0.0047	0.2135	0.0072	0.3467
Experience Effect								
Capital Intensity	-0.0095		0.0001		0.0019		0.0080	
	0.3890		0.2827		0.2962		0.4262	
Inventory/Sales	-0.0051	-0.0003	0.0042	0.0001	0.0084	0.0001	-0.0039	0.0001
	0.0228	0.0102	0.0175	0.0065	0.0169	0.0064	0.0254	0.0082
Software Share	-0.8541*	1.0304*	1.2124*	-0.0637*	-0.0158	-0.0839*	-0.1887*	-0.8614*
	0.0253	0.0119	0.0195	0.0079	0.0185	0.0072	0.0280	0.0093
Mills Ratio	-0.0660*	0.0383	-0.0679*	-0.0452	0.0295*	0.0007	0.0864*	0.0030
	0.0075	0.3531	0.0054	0.2504	0.0057	0.2116	0.0082	0.2711

Note: Controls also include change in log (real sales) and change in county relative wage. Estimated equation also includes a constant. Coefficients that are statistically significant at the 5 percent level are starred and coefficient and standard error are shade in grey.