Within and Between Firm Changes in Human Capital, Technology, and Productivity

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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

Understanding how the introduction of new technology impacts firms and in turn impacts workers has increasingly become important in the past two decades – particularly understanding the dynamic consequences of firms' decision to invest in advanced technology such as computers. Yet little is known about this interaction - measures of human capital at the firm level have been very limited, detailed firm-level measures of technology are difficult to obtain in general and especially for service sector businesses, and longitudinal data on firms are not widely available. This paper uses new data which remedies many of these deficiencies to provide a detailed examination of these issues for all sectors of the economy: first by documenting how the demand for human capital has changed within and between businesses and then by using firm level data to examine the link between changes in technology and the demand for human capital. We take a broad view of changes in technology in this context – we are interested in observable changes in physical capital with an emphasis on the role of advanced technology such as computers and changes in intangible capital such as organizational and business practices.

Our ability to investigate these issues is due to access to a new longitudinal employer-employee dataset and methods being developed at the U.S. Census Bureau. These data and our approach have a number of advantages relative to the existing literature. First, since we have data on the virtual universe of workers and firms and their associated transitions, we exploit the new techniques pioneered by Abowd and Kramarz (1999) to measures human capital of workers and in turn to measure the human capital at individual firms. In addition, we are able to exploit Economics Census data on firms that includes substantial amount of information about the outputs and inputs used by individual firms which provides a basis for characterizing differences in technology across businesses. Moreover, the data span all sectors of the economy which enables us to test whether the relationship between technology and human capital differ for different types of firms and different types of industries. This can be particularly important in differentiating between the manufacturing and service sectors. In goods producing industries, for example, firms combine a variety of inputs - physical capital, materials, and human capital – in a variety of different ways to produce some physical output. In service industries, the same inputs enter into the production process, but the service is fundamentally delivered by the human capital – and hence human capital differences yield a form of product differentiation. Finally, the longitudinal component of the data enables us to capture the dynamic evolution of the demand for human capital.

Our ability to use such data thus 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 has used 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 forced to use 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 misses 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)). As such, between firm variation is very useful to exploit as it provides a rich source of variation. However, the differences across firms are important beyond providing a source of variation . The differences between firms raise questions about the nature and evolution of the adoption of new technologies and in turn the impact on workers. It has become increasingly clear that the adoption of new technologies is a noisy, complex process at the micro level with considerable trial and error and associated entry and exit of businesses and reallocation of jobs. The churning of businesses and, in turn, workers is thus a critical feature of the relationship between changes in technology and changes in the demand for human capital as there are substantial implications for the allocation of human capital across businesses. Longitudinal matched employer-employee data are required to investigate the nature of these dynamic interactions between firms and workers.

With these introductory remarks in mind, we examine the following key questions in this paper.

- How has the distribution and allocation of human capital changed in the overall economy? Are the observed aggregate change broadly based, or are

[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.

they confined to specific industries or even specific firms within specific industries?

- How do changes occur? Do new firms, with different levels of human capital, supplant old firms? Or do continuing firms adjust their current workforce? Or do high technology firms expand employment, and in the process, "crowd out" employment in lower technology firms?
- Why do changes occur? What types of observable changes in technology are associated drive changes in human capital? Do changes in technology have more than just "first moment effects" on skill intensity – affecting both skill intensity and skill dispersion (Kremer and Maskin (2000))?

2) Background and Conceptual Framework

a) Technology, Organization and the Demand for Skilled Workers

The ideas we pursue here have roots in several literatures but draw heavily upon the recent literatures 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

[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,

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 relationship 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.

b) The Relationship 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:

$$y_{it} = F(Z_{it}, L_{1it}, ..., L_{Kit}) \qquad (1)$$

where y_{it} is output for firm *i* in period *t*, the state of technology including tangible and intangible capital (like organizational capital) indexed by Z_{it}, L_{kit} is the number of workers of type "*k*" where *k* 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 k as given by:

$$M_{kit} = M(Z_{it}, y_{it}, w_{kit} / w_{1it}, ..., w_{kit} / w_{Kit}) \qquad (2)$$

where M_{kit} is the share (or perhaps cost share using a specific functional form for *F*) of type *k* workers and w_{kit} is the appropriate shadow wage rate of type k workers (note that the shadow

Lane and Spletzer (2000), Jovanovic and MacDonald (1994), Juhn, Murphy and Pierce (1993), Kremer and Maskin (2000).

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 k by a particular firm depends on 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 *k* 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:

$$M_{ket} = \alpha_0 + \sum_i \alpha_{1i} Z_{iet} + \sum_l \alpha_{2l} (w_{kt} / w_{lt}) + \alpha_3 y_{et} + \varepsilon_{et} \qquad (3)$$

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.

In principle, we can use the results of this analysis to analyze changes as well since with coefficient estimates in hand we can ask how much of the observable changes in the distribution of M are due to observable changes in the distribution of Z. While such an

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

approach is an interesting exercise, there are at least two potential limitations with this approach. First, it may be that there are important unmeasured components of Z that imply unmeasured firm heterogeneity and that these unmeasured components of Z are highly correlated with the measured components of Z. For example, it may be that high ability managers are more likely to use the latest advanced technology and implement the best business model on several dimensions including organizational and human resource practices. As such, 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 firm fixed effects can potentially be resolved by estimating this specification in first differences (see, e.g., Berman, Bound and Griliches (1996) and Dunne, Haltiwanger and Troske (1997)):[4]

$$\Delta M_{ket} = \alpha_0 + \sum_i \alpha_1 \Delta Z_{iet} + \sum_l \alpha_{2l} \Delta(w_{kt} / w_{lt}) + \alpha_3 \Delta y_{et} + \varepsilon_{et} \qquad (4)$$

This latter familiar specification permits us to examine more directly within business changes in human capital and how they are related to observable changes in technology and we exploit this specification in the analysis that follows. This first difference specification may still be missing many important aspects of changes in the overall changing 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, this first difference

sharing considerations.

specification only helps us in characterizing the within firm changes for continuing businesses. In the next subsection, we discuss within vs. between changes in the demand for human capital.

c) Within vs. Between Business Changes in the Demand for Human Capital

In the aggregate (total economy or industry level), observed changes in the demand for human capital will reflect within firm changes as well as between firm changes in the demand for human capital. We summarize the relative contribution of within vs. between changes using the following decomposition:

$$\Delta M_{it} = \sum_{e\in C} \omega_{et-1}\Delta M_{et} + \sum_{e\in C}(M_{et-1} - M_{it-1})\Delta\omega_{et} + \sum_{e\in C}\Delta M_{et}\Delta\omega_{it} + \sum_{e\in N}\omega_{et}(M_{et} - M_{it-1}) - \sum_{e\in X}\omega_{et-1}(M_{et-1} - M_{it-1}) \qquad (5)$$

where M_{it} is the human capital index for the industry, M_{et} is the human capital index for an individual business, ω is the share of employment, C refers to continuers, N to entrants and X to exits. This decomposition splits sources of change in the human capital index at an aggregate (e.g., industry) level into four components: that due to within business changes (first term); that due to variations in the composition of employment across businesses (second term); a cross term indicating whether increases in human capital index are positively or negatively related to changes in employment shares; and the change due to net entry. Much of the discussion thus far has referred to the first component of this decomposition: the within firm component.

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[4] We retain a constant even in this first difference specification to capture the possibility of a common time trend. Note that this first difference specification may be subject to various econometric problems as well. The measures of changes in Z and changes in output may be correlated with unmeasured changes in technology.

. The between firm components arise from a number of factors. Perhaps the most interesting is the role of entry and exit. As noted above, the introduction of new technology may be accomplished by changes in technology within existing businesses or may be embodied in new businesses (or both of course). Examining the relative contributions of the within firm changes relative to the contribution of net entry sheds considerable light on the respective role of each for the impact on the demand for human capital. Put differently, an indirect way to assess the impact of technological change on the demand for human capital is to examine the contribution of net entry to the extent that new technology is embodied in new businesses.

The process of technology adoption can lead to important contributions of the other terms in the above decomposition. The process of technology adoption may be closely linked to the observed patterns of employment reallocation across continuing businesses. For example, if technology adoption is skill biased and adoption is associated with the downsizing of overall employment then these combined effects can lead to a negative covariance. More generally, the adoption of technology will have industry and general equilibrium effects that generate both within and between firm changes in the demand for human capital. Relative wage changes induced by systematic changes in the demand for human capital induced by technological changes will induce within and between firm changes in the mix and share of employment. Analogously, technological change will interact with industry demand to yield changes in relative product prices that in turn yield within and between firm changes as employment is reallocated to the highest valued use.

To sum up, we are interested in exploring the factors underlying changes in the distribution of human capital between and within businesses. We are especially interested in using observable indicators of changes in technology. Such changes might be evidenced by the turnover of businesses via entry and exit and/or by within business changes in the type of technology being used. In the remainder of this section, we describe how we plan to measure human capital and technology.

d) 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, from firm level data the measures used are quite crude – the ratio of production to non-production workers. Even for household datasets, the usual suspects (e.g., education and experience) only capture limited and imperfect dimensions of skill. As such, many studies conclude (e.g., Juhn, Murphy 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 and Kramarz (1999) along with very rich matched longitudinal data on both firms and workers to identify the unobserved components of worker skill..

Briefly, we use the Abowd and Kramarz decomposition of (log) wages for individuals:

$$w_{ijt} = \theta_i + X_{it}^{'}\beta + \psi_{j(i,t)} + \varepsilon_{it}$$

Here the dependent variable is the log wage rate of an individual i working for employer j at time t. while the function J(*i,t*) indicates the employer of *i* at date *t*. The first component is the time invariant person effect, the second the contribution of time varying observable individual characteristics, the third is the firm effect and the fourth component is the statistical residual, orthogonal to all other effects in the model.

We use the worker fixed effect θ plus the experience component of $X'\beta$ as the core measure of human capital, called "M".[5] It is worth noting that the specification is in logs, and hence the human capital measure should be thought of in relative as opposed to absolute terms. That is, in comparing two workers with differences in M by .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 used in this paper are discussed and described in detail in Abowd et. al (2001).

c) Measuring Technology at the Firm Level

A second challenge is developing direct measures of technology, particularly ones that are comparable across sectors. As suggested above, an indirect measure of the change in technology within an industry is evidenced by the entry and exit process itself. That is, the observation of new businesses that organize their workforces in systematically different ways than the exiting businesses they displace is a useful means of gauging the link between changes in technology and changes in demand for human capital. Thus, in the analysis that follows we use the decomposition (5) and associated components to characterize the role of the changing composition of businesses (particularly via entry and exit) on changes in the demand for human capital.

However, we are also interested in exploiting observable indicators of technology. Clearly, physical capital intensity is a natural candidate, as are direct measures of the use of

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[5] X has a number of other controls including time effects and full quarter employment adjustments. Data limitations restrict the usefulness of studying changes in the overall average growth of experience (as it will by construction increase over the sample).

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 change management. An indicator of the latter might be changes in the relationship between inventory to 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, $\varphi_{J(I,t)}$ is the component of the wage that is due to 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, M, 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 measure of difficult to measure components of the technology of a business and so we are interested in this as a potential control for such components.

3. Data

We exploit a new Census Bureau data-set[6], (part of the Longitudinal Employer-Household program) that integrates information from state Unemployment Insurance data and Census Bureau economic and demographic data that permit the construction of longitudinal information on workforce composition at the firm level. The LEHD project 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 elsewhere (see xxx). Every state in the U.S. collects quarterly employment and earnings information through its State Employment Security Agency to manage its unemployment compensation program., enabling 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. Virtually all business employment is covered. The advantages of UI wage record databases are numerous. The data are frequent, longitudinal, and potentially universal. The sample size is generous and reporting is more accurate than survey based data. Longitudinal earnings and employer files can be constructed for individuals at quarterly intervals. The advantage of having the universe of the data set is that movements of individuals to different employers and the consequences on earnings can be tracked. It is also possible to construct longitudinal data sets using the employer as the unit of analysis. In this analysis, we use data from the state of Illinois. In the two years, 1992 and 1997, that we analyze there are roughly 5 million workers and two hundred thousand firms.

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[6] 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 initative

Perhaps the main drawback to the UI wage records data is the lack of even the most basic demographic information on workers. The links to Census Bureau data overcome this for two reasons. First, the micro-data can be linked to administrative data at the Census Bureau containing information such as date of birth, place of birth, and gender for almost all the workers in the dataset. Second, as discussed in the previous section, staff at the LEHD program at the Census Bureau have exploited the longitudinal and universal nature of the dataset to estimate both worker and firm fixed effects.

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). The analytical dataset that we construct from these merged files has the employer as the unit of analysis, and our rich dataset permits us to measure many key variables. These include 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 are measured using the methodology described in section 2.

In addition, because we are particularly interested in differences within and between industries, we examine several major sectors in some detail: manufacturing, services, retail trade and the financial sector. Then, in turn, we examine several industries within each of those sectors in yet more detail: within manufacturing, the primary metal industry, within services, the computer and business services industries, and within the financial sector, the financial services industry.

For the measures of Z (i.e., observable measures of technology) we use information collected from the Economic Censuses. The nature of the availability of such measures varies by sector and by year. One of our two primary sources for this information are the subset of businesses in the Manufacturing Economic Census who are also in the Annual Survey of Manufactures (ASM). Such ASM businesses are asked a set of detailed questions that are useful in this regard. In a like manner, 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 roughly 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, expenditures on equipment investment as a fraction of total investment, the ratio of inventories to sales, and the ratio of purchases of computer software and data processing services 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.

4. Basic Facts about the Within and Between Firm Differences in the Demand for Human Capital

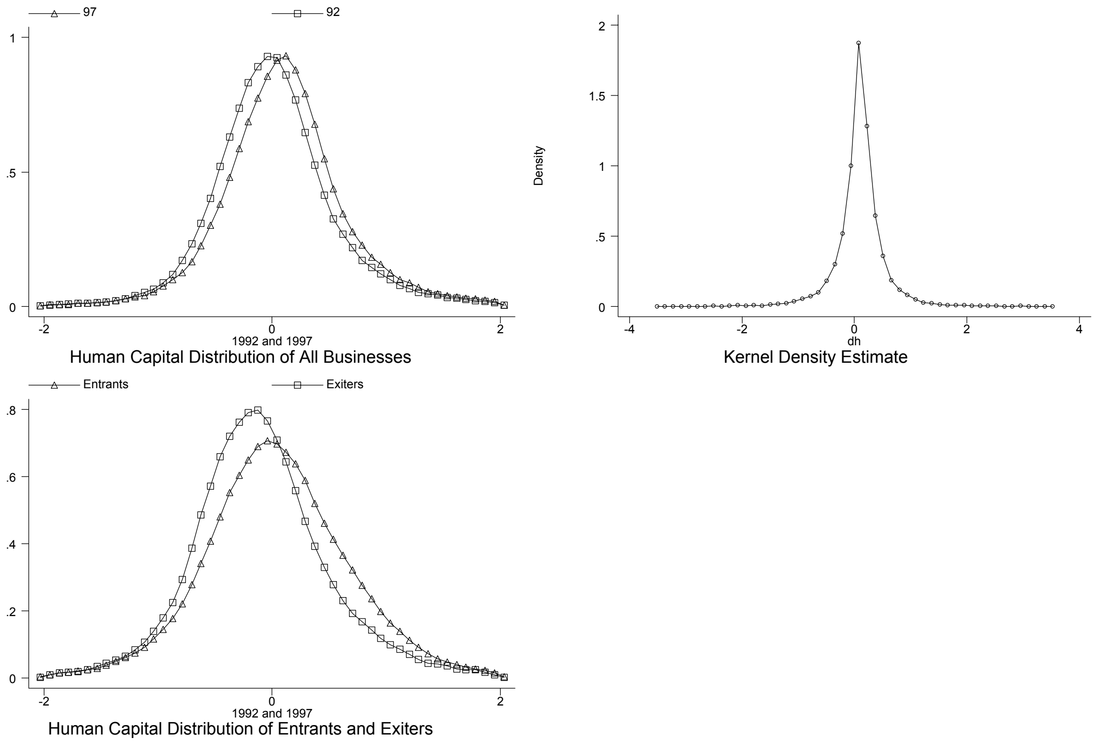
a) Levels and Changes in the distribution of human capital

We begin by characterizing the distribution of human capital and the changes in this distribution. In Figure 1, we depict the distribution across years and the distribution of changes within continuing businesses using the average human capital in each business in

1992 and in 1997. The first panel overlays the human capital distribution of all businesses that exist in 1992 with the human capital distribution of those that exist in 1997, and reveals that between 1992 and 1997 the average level of human capital in the Illinois economy increased, with little change in dispersion – in other words, the economy up-skilled [7]. This could have happened in a number of ways – continuing firms might have systematically increased the human capital of their workforce, or new, skill intensive firms could have replaced older firms. In a first effort to determine what has occurred, we turn to examining how firms that existed in both periods (continuing firms) changed their human capital. We calculate the difference in human capital in the two periods, and graph the distribution of these differences in the second panel. Interestingly, the upskilling that we observed in the first panel was NOT because all firms upskilled, which would have meant that the distribution of changes was all in the positive range. What we do observe is that while the mean change is clearly positive, some firms downskilled (the change in average human capital is negative) and others upskilled. The third panel compares the skill distribution of new firms and exiting firms and finds the same phenomenon. Clearly the typical entering firm is more skill intensive than the typical exiting firm, but the distributions clearly overlay each other: some entering firms employ a less skilled workforce than some exiting firms.

[7] The graph is truncated at ±2 for ease of presentation. The figures represents the distribution of mean human capital at all businesses, equally weighted: employment weighted estimates reveal similar patterns.

Figure 1



Because we are interested in whether the distributional change is broadly based, we calculate the quartiles of the human capital for each of the key industries we identified in the previous section. In addition, so that we both characterize the experience of individual workers and that of individual businesses, we calculate both the employment weighted and the unweighted distributions.

The summary statistics for the overall economy reported in Table 1 bear out the graphical rendition. The median business in 1992 employed a workforce with an average human capital level of -.045; by 1997 the median business had an average human capital level of .073 – a gain of some 13 log points.[8] On the other hand, the median worker in 1992 worked in an business with a mean human capital of -.026; by 1997 the median worker

[8] The level of the human capital measures are arbitrary since the human capital is measured from the wage equation in (6) which includes a variety of controls including time dummies. What matters here are the differences across businesses and within businesses over time.

worked in a business with workforce mean human capital of .069. Although the median increased substantially between the two years, the spread of the distribution increased only slightly: the unweighted interquartile range increased from .64 to .679; the weighted from .405 to .434.

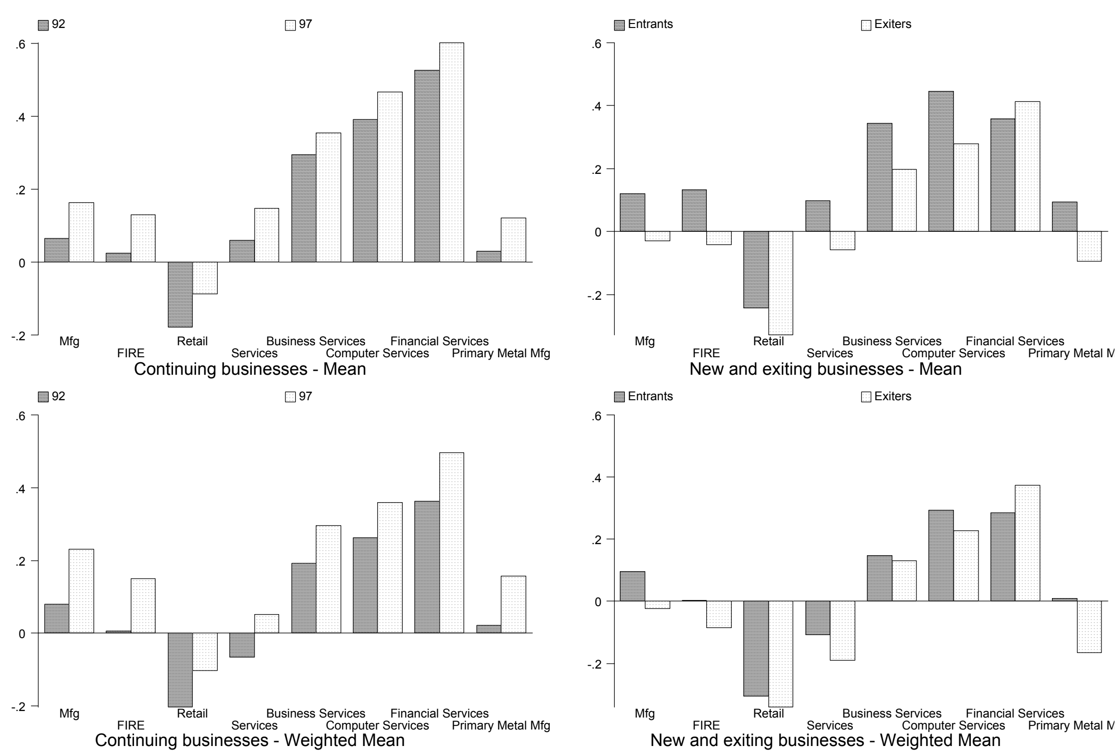
Interestingly, while the increase in human capital was indeed broadly based, it was by no means completely uniform. In fact, the median business in financial services actually down-skilled between the two periods, and the median business in retail trade increased its median human capital only one third as much as did its counterpart in the primary metal sector. Some industries, such as wholesale trade, moved the entire distribution of businesses up by almost exactly the same amount, others, such as transportation flattened out without changing the median very much at all.

The differences between the experience of the median worker and the median business are also highlighted by examining the weighted and unweighted panels of Table 1. The human capital distribution of businesses in the financial services became slightly more compressed in 1997 than in 1992, while the employment weighted distribution actually became more spread out in the period.

Table 1:								
	92				97			
Weighted								
Industry	25th	Median	75th	Interquartile Range	25th	Median	75th	Interquartile Range
Finance	-0.133	0.03	0.221	0.354	-0.024	0.154	0.364	0.388
Manufacturing	-0.16	0.004	0.141	0.301	-0.05	0.129	0.255	0.305
Retail	-0.414	-0.246	-0.039	0.375	-0.373	-0.203	0.007	0.38
Services	-0.349	-0.071	0.122	0.471	-0.296	-0.002	0.204	0.5
Transportation	-0.04	0.13	0.264	0.304	0.008	0.149	0.347	0.339
Wholesale	-0.093	0.077	0.227	0.32	0.015	0.184	0.336	0.321
Business Services	-0.006	0.165	0.293	0.299	0.035	0.221	0.382	0.347
Computer Services	0.087	0.247	0.428	0.341	0.112	0.317	0.48	0.368
Financial Services	0.126	0.414	0.519	0.393	0.15	0.413	0.613	0.463
Primary Metal Mfg	-0.113	0.011	0.104	0.217	0.053	0.151	0.252	0.199
Total |	-0.245	-0.026	0.16	0.405	-0.181	0.069	0.253	0.434
Unweighted								
Finance	-0.315	-0.028	0.328	0.643	-0.227	0.094	0.481	0.708
Manufacturing	-0.24	-0.015	0.219	0.459	-0.127	0.107	0.361	0.488
Retail	-0.533	-0.254	0.045	0.578	-0.471	-0.158	0.158	0.629
Services	-0.373	-0.035	0.337	0.71	-0.274	0.09	0.478	0.752
Transportation	-0.277	-0.029	0.215	0.492	-0.193	0.07	0.319	0.512
Wholesale	-0.119	0.169	0.53	0.649	-0.001	0.295	0.662	0.663
Business Services	-0.113	0.213	0.585	0.698	-0.046	0.315	0.719	0.765
Computer Services	0.031	0.36	0.662	0.631	0.148	0.48	0.771	0.623
Financial Services	-0.002	0.364	0.862	0.864	-0.035	0.383	0.853	0.888
Primary Metal Mfg	-0.184	0.044	0.14	0.324	-0.079	0.077	0.267	0.346
Total |	-0.358	-0.045	0.282	0.64	-0.263	0.073	0.416	0.679

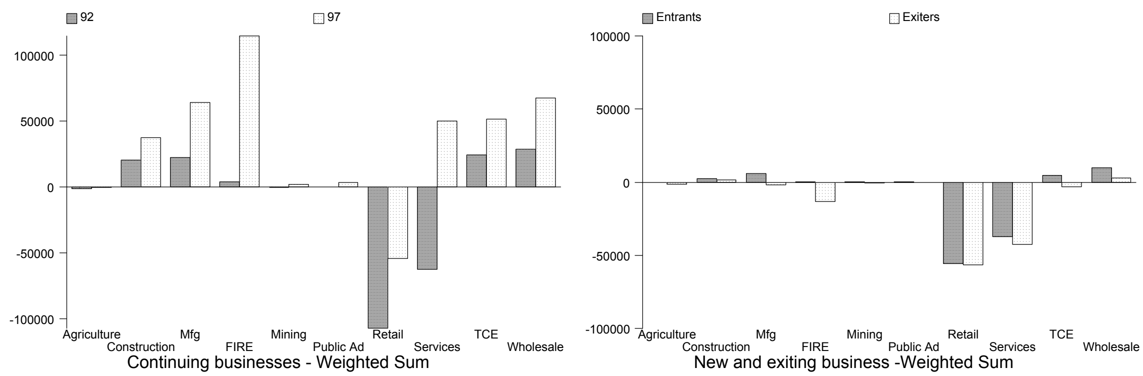
This leads to the next set of questions: how important are continuing businesses versus new and exiting businesses in contributing to changes in human capital - and how broadly based are these patterns across industries? In order to address this, we first calculate, by industry, the average human capital in both continuing and entering/exiting businesses in both of the two years - 1992 and 1997. The results clearly indicate that there are quite large differences in the average human capital in businesses across industries – and that up-skilling is by no means uniform. In particular, an examination of the first and third panels of Figure 2 makes it clear not only that the average continuing business in retail trade has a workforce with much lower human capital than does one in business services, but that the average employee in retail trade works in a workplace with low human capital. It is also, clear, however, that average continuing business has increased its mean level of human capital over time – and that this effect holds across the board for all industries. The second and fourth panel describe the same information for entering and exiting firm, but paint a slightly different picture. Although it is still true that the average entering business had higher human capital than the average exiting business, this result is not nearly as uniform across industries as for continuing businesses. In particular, the workforce in new firms in financial services were less skilled on average than in the businesses they replaced – and this is true even when the results are employment weighted.

Figure 2



We are also interested in finding out how important these changes are in total, and hence calculate the total human capital contributed by each industry in each of the two years – for both continuing and entering/exiting firms. It is clear from an examination of figure 3 that there are marked differences across industries, as well as differences by type of business. In particular, most of human capital adjustment is accounted for by continuing firms in very few sectors: retail trade, services, and FIRE. Although new and exiting business had, by and large, very little to contribute to aggregate human capital change, the two important exceptions were the retail trade and service sectors.

Figure 3



These exploratory results reveal that while the economy increased its skill level between 1992 and 1997, there appear to be quite marked differences not only within and between industries but also between continuing firms and new and exiting firms. We now turn to examining this in more detail.

b) Sources of human capital change: A decomposition of the contribution of new, exiting and continuing firms

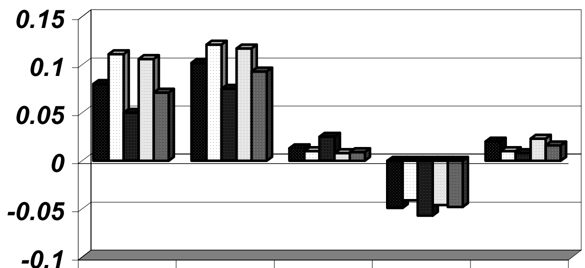
The prior subsection found that two key factors contribute to the increase in central tendency of the distribution of mean human capital   The first is that, on average, continuing businesses are up-skilling. The second is that net entry yields a systematic change in human capital; that is exiters have lower mean human capital.   In this section we examine the importance of the different sources by means of the decomposition outlined in Section 2.

Figure 4 summarizes the decomposition both for the overall Illinois economy and for some key industries. The Illinois economy up-skilled by an average 8% which is striking over a five year horizon. The contribution of the terms of the decomposition reveal a complex and interesting set of dynamics.   The within business component is very large suggesting that in the absence of entry and exit and reallocation amongst continuing businesses the upskilling would have even be larger (10%). Interestingly, the contribution of net entry is also positive with entrants having substantially higher human capital than the exits they displaced. The contribution of net entry is 2% suggesting that about a quarter of the overall change can be accounted for by net entry. However, in combination the within component plus net entry account for roughly 150% of the overall change. The reason for this is that there is a large offsetting negative cross term of almost 5%. The large negative cross term is consistent with the view that downsizing businesses exhibit substantial upskilling – thus part of the reallocation process across businesses appears to be associated with businesses shedding their less skilled workers. It should also be noted that the between effect is positive but relatively small suggesting that there is some tendency for businesses that were initially high in the human capital distribution to expand.

The differences across industries in terms of levels is just as marked here as in the earlier discussion - for example, manufacturing up-skilled by twice as much as retail trade - but the decomposition into the various effects is similar across the industries – a large within effect, a substantial contribution from net entry and a large negative cross term.

Figure 4

Human Capital Decomposition

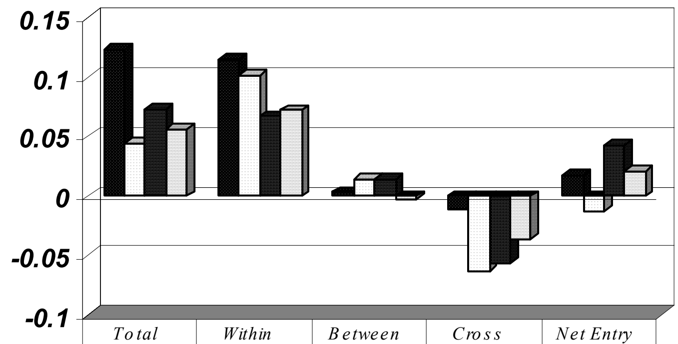


	Total	*Within*	*Between*	*Cross*	*Net Entry*
Overall	0.08	0.102	0.013	-0.049	0.02
Manufacturing	0.111	0.121	0.01	-0.041	0.01
Retail Tade	0.05	0.075	0.025	-0.057	0.008
FIRE	0.106	0.117	0.008	-0.046	0.023
Services	0.071	0.093	0.009	-0.048	0.016

The pattern is a little less consistent when we turn to examining more detailed industries, such as primary metals, financial services, computer services and business services. While there is still quite a substantial amount of difference in up-skilling across industries – ranging from 12% in primary metals to 4% in financial services, the sources of these changes are quite different. In the financial services industry, for example, there was a huge increase in workforce human capital within each business, but this was offset by a remarkably large offset in both the cross term and in net entry. In financial services, new businesses are actually less skilled than exiting businesses. In stark contrast, the computer services industry saw a very large upskilling as a result of higher human capital levels of entering businesses relative to exiting.

Figure 5

Human Capital Decomposition: Detailed Industries



	Total	Within	Between	Cross	Net Entry
Primary Metals	0.123	0.115	0.003	-0.012	0.018
Financial Services	0.044	0.101	0.014	-0.063	-0.013
Computer Services	0.073	0.067	0.014	-0.056	0.043
Business Services	0.056	0.072	-0.003	-0.036	0.02077

c) A more detailed analysis of the adjustment of continuing firms

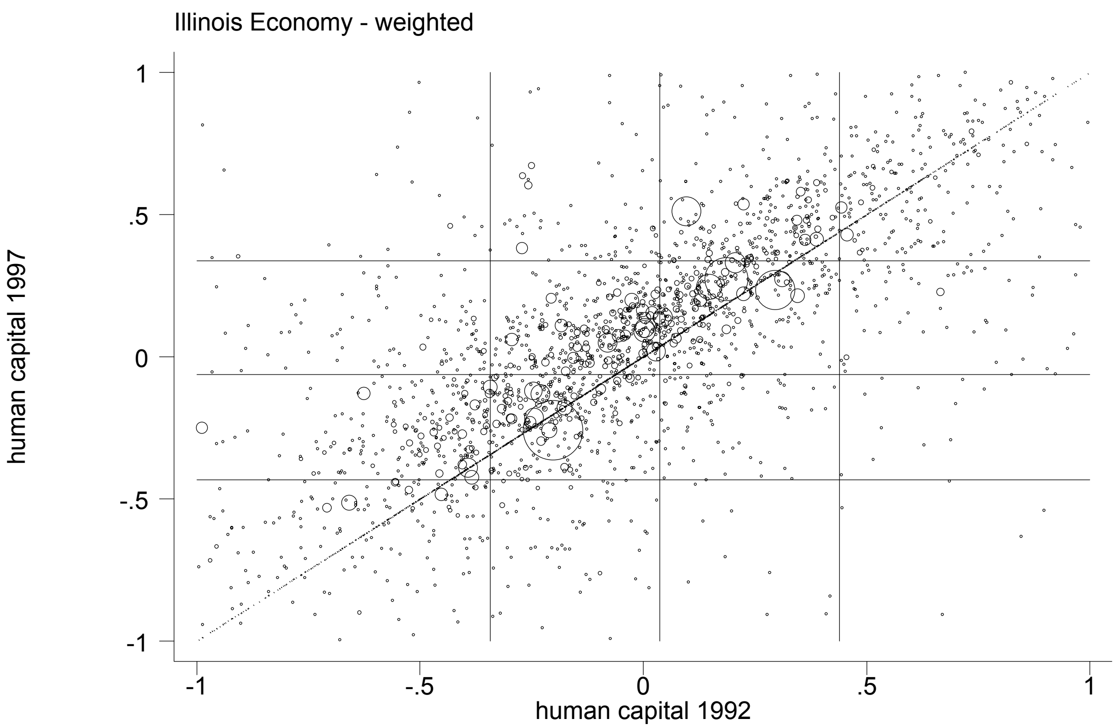
The workforce adjustment of continuing businesses is undeniably a prominent contributor to the overall adjustment of human capital in the Illinois workforce. We now turn to examining just how this adjustment occurred between the two periods of interest for continuing businesses by plotting the 1992 mean human capital of the workforce in each business against the same measure in 1997 using a 45^0 line as a reference point. Businesses that are on the 45^0 line have not changed their workforce competition in the five year period; businesses above it have up-skilled; businesses below it have down-skilled. In addition we plot the quartile thresholds of the aggregate Illinois economy for both years[9], so that we have the visual equivalent of a transition matrix. Finally, we employment-weight the businesses so that we

[9] We plot a .2% random sample

can determine whether large or small businesses are the primary contributors to the observed changes in skill.

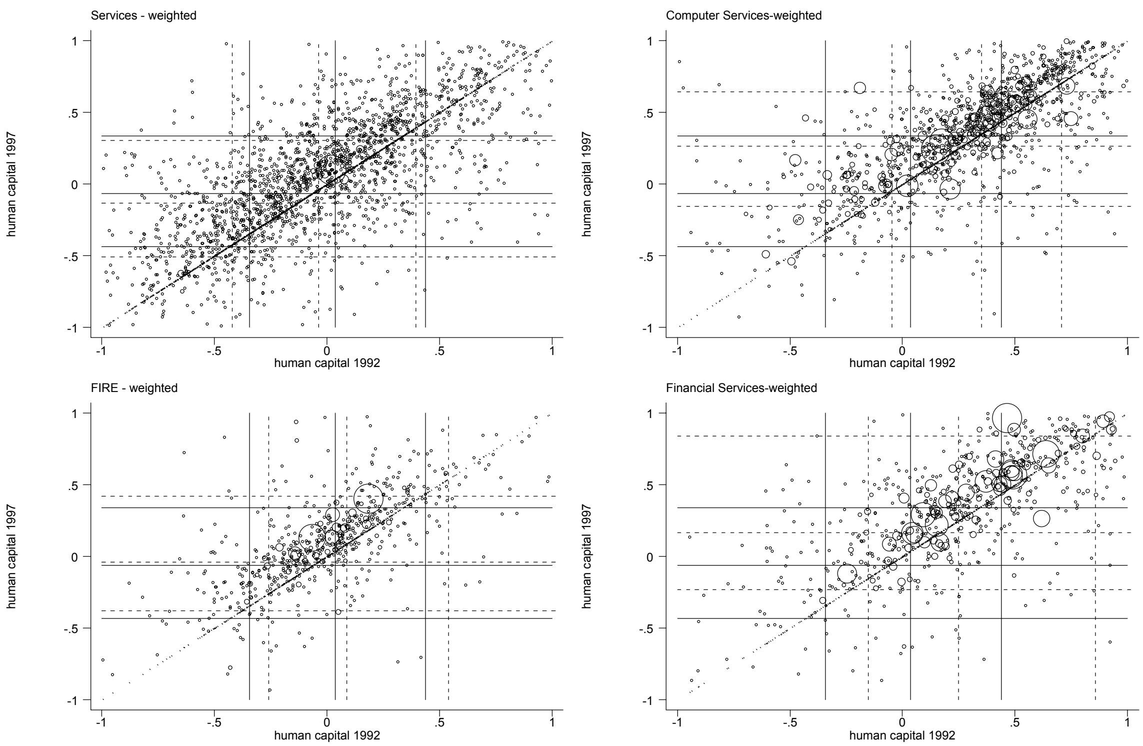
An examination of the graph uncovers several interesting results. First, businesses are quite heterogeneous – some have very high mean levels of human capital; others have quite low levels. Second, businesses are quite persistent in their choice of workforce composition: by and large, those that are in the top quartile in 1992 remain so in 1997, those that are in the bottom quartile stay in the bottom. Finally, while the up-skilling of the economy was, in fact, broadly based, some businesses actually reduced the skill level of their workforce during the period

Figure 6



The persistence, heterogeneity and differential adjustment patterns cannot be attributed to industry specific differences. When we examine the data in more detail, we see that the pattern exhibited for the entire Illinois economy is replicated in quite detailed industries.

Figure 7



However, that is not to say that there are no differences across industries – clearly the upskilling in FIRE is quite broadly based, while computer services saw some businesses down-skilling – particularly those that were at the upper end of the skill spectrum.

This leads to a series of related questions:

- How do businesses that fall in center of these distributions differ from those in tails. In particular, are there observable indicators of technology that can account for differences in the human capital across businesses?
- Does this vary systematically across continuing businesses, new businesses and exiting businesses?
- Can we identify observable characteristics of businesses that underlie the distribution of changes in human capital across continuing and entering/exiting businesses?

In order to address this and other issues, we turn to investigating the potential contribution of firm technology adoption to differences in demand for human capital across businesses.

5. Link between Human Capital and Technology

The analysis presented in this section empirically explores the influence a firm's use of technology has 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 explore different ways of characterizing both high and low human capital, (iii) we distinguish between more conventional measures of technology use (such as capital per worker) and indicators of newer, more computer-oriented technologies, and (iv) we conduct our analysis of differences across businesses both treating all businesses equally (unweighted) and weighting businesses by their employment (weighted). In what follows, we describe each of these features in more detail, provide descriptive statistics for the key variables used in this analysis, describe the specifications and estimation procedures used, and provide a discussion of our empirical findings.

a. Variable Measurement and Descriptive Statistics

A strength of our analysis is the ability to distinguish between businesses in more traditional manufacturing industries and those in the more service-oriented (human capital intensive) industries that are more prominent in the "new economy." Because the nature of the type of product produced varies substantially across these sectors, the role played by both human and physical capital may differ as well. For this reason, we analyze the link between technology use and skill demand in the manufacturing sector separately from service-oriented industries (services, retail, wholesale).

Human Capital

It is possible that technology investment affects demand for various skill groups differently. For this reason, we characterize high versus low human capital in several different ways. As our first measure of skill demand, we estimate the demand for workers with human capital levels above (versus below) the economy-wide median human capital. Specifically, we measure the proportion of workers at each business that have human capital levels above this median. In addition, we explore an alternative measure of the demand for high skilled workers – the proportion above the economy-wide 75^{th} percentile – and an alternative measure of the demand for workers with low levels of human capital – the proportion of workers below the 25^{th} percentile. Each of these three measures – the proportion above the median, the proportion in the top quartile, and the proportion in the bottom quartile – are used as outcome variables in our estimation of demand equations for worker human capital.

Statistics describing the distribution of human capital in manufacturing and in non-manufacturing are reported in table 2 and 3, respectively. In each table, we present both unweighted and employment-weighted quartile values for each of the three dependent variables. A comparison of these values across the two sectors reveals that weighting by employment has little effect on the human capital distribution in manufacturing. Weighting has a notable impact, however, among non-manufacturing businesses. For example, consider the first dependent variable – the proportion of workers above the median. For this variable, the range between the 25^{th} and 75^{th} percentiles falls from .4 to .25 when we weight by employment. Similarly, employment weighting lowers this range for the third variable – the proportion of workers below the 25th percentile – by .12 (from .41 to .29). These differing effects (across sectors) in employment weighting are not unreasonable. Manufacturing firms are often quite large, and it is common for businesses in non-manufacturing sectors (services and retail in particular) to employ very small numbers of workers.

While the distribution of the proportion of workers in the top quartile is very similar across sectors, the proportion of workers in the bottom quartile for non-manufacturers is higher at all points in the (weighted) distribution than for manufacturers. For example, the weighted median for this variable among non-manufacturers is .33 (versus .16 for manufacturers). Overall, non-manufacturers have a higher proportion of low-skilled workers (relative both to manufacturers and to the economy overall).

We are particularly interested in the how human capital changes over time. Descriptive statistics for the difference between 1997 and 1992 human capital are reported in tables 2a and 3a, and the numbers reflect the growth in human capital documented in the first portion of this paper. Even for the 25th percentile business in both sectors, for example, the proportion of employees having human capital above the economy-wide median rises. The magnitude of increase for the ASM sample ranges from a four percent rise for the 25th percentile firm to a 17 percent increase for the 75th percentile business. Despite the rise in share of high skilled workers (those above the median) relative to lower skilled, the data reveal a different pattern for the share of workers in the top and bottom quartiles. The share of workers in the top quartile, for example, falls overall. Among non-manufacturers, the fall in share of most highly skilled ranges from a fall of about 13 percent for the 25th percentile business to 0 (no change) for the 75th percentile firm. In contrast, the proportion of workers in the bottom quartile increases in both sectors, and ranges from a 1 percent increase in proportion of lowest skilled for the 25th percentile firm to a 10 percent increase for the 75th percentile firm (ASM numbers). There are few differences in human capital changes between the two samples, but one small difference is worth noting. For the rise in proportion of lowest skilled workers, employment weighting augments the pattern in the ASM sample (suggesting that larger manufacturers are more likely to increase their share of very low skilled workers). Among non-manufacturers, however, weighting by employment reveals something quite different. For this sample, smaller businesses are more likely to have increased employment of lowest skilled workers. In general, however, weighting by employment has little impact on these statistics characterizing changes in human capital

Technology Use

A third feature of our analysis is the use of a rich set of technology measures. For both manufacturing and service sectors, for each of the three human capital measures described above, we estimate the effect of six different measures of technology on the demand for skilled workers. Among these measures are three variables reflecting use of “newer,” more computer oriented technologies: investment in computers as a proportion of overall machinery investment, spending on computer software and data processing services as a proportion of annual sales, and total inventories as a proportion of sales. Inventory holdings act as a proxy for integration of information technology, which we do not observer directly.[10] One advantage enjoyed by businesses with access to more sophisticated 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.

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[10] 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.

As noted above, it is possible that technology holdings may affect the demand for human capital differently in different sectors. It is also possible, however, that the types (and importance) of technology used may vary across businesses of different types. For this reason, we contrast the effect of these measures of newer technologies on skill demand with the impact on human capital demand of the following more traditional measures of technology use: capital stock per worker and machinery investment as a proportion of overall capital investment. Lastly, 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 firm fixed effect, $\varphi_{J(I,t)}$. For this reason, we include $\varphi_{J(I,t)}$ in our list of controls.

Descriptive statistics for these technology measures also are reported in tables 2 and 3. These numbers indicate that across-sector differences in technology investment are striking. First, computer investment (as a proportion of machinery investment) is much higher among non-manufacturing businesses. For example, the non-manufacturing weighted median is .09 (versus .03 for manufacturers), and the 75th percentile is .28 (as opposed to .11). Interestingly, this pattern is even more notable when comparing unweighted numbers. Weighting by employment lowers computer investment overall among non-manufacturers (suggesting that smaller firms invest more) and increases it among manufacturing businesses. For machinery investment (as a proportion of total capital investment), although the unweighted numbers show little difference across sectors, weighting by employment substantially lowers all numbers for non-manufacturers (manufacturers remain mostly unaffected by weighting). For example, the weighted median machinery investment for non-manufacturers is .76 (versus .93 for manufacturing). This, while non-manufacturers appear to invest more heavily in "new" technologies (computers), it is not surprising that the manufacturing sample appears to invest more heavily in machinery overall.

The sample of non-manufacturing firms is much more highly capital intensive than the sample of manufacturing businesses. For example, the weighted median value of capital intensity for manufacturers is 4.36; for non-manufacturers, the median is 10.23, over twice as large. Although one might be inclined to attribute this difference to differences across sectors in typical employer size (non-manufacturing firms are smaller on average and thus contribute a small number to the denominator of our capital intensity measure), weighting by employment should account for these differences. Interestingly, weighting by employment (and thus assigning more importance to large employers) increases all numbers. For inventory holdings (as a proportion of sales), the 75th percentile varies little across sectors – about 15 percent of sales. However, the median inventory holdings is much high for manufacturers than for non-manufacturers. In the case of businesses in service industries, this finding is not surprising. The distribution of spending on computer software and data processing services (as a proportion of sales) for manufacturers is very similar to that of non-manufacturers. The values of this variable are very small at all points in the distribution. For example, the range between the weighted 25th and 75th percentiles among manufacturers is .0006.

The last row of each table characterizes the distribution of $\varphi_{J(I,t)}$, the time-invariant firm fixed effect. These numbers show that the median firm effect in the non-manufacturing sample is much lower than among manufacturers (-.11 versus .25). Additionally, there is a dramatic difference across sectors in the inter-quartile range (.25 for manufacturers as opposed to .55 for non-manufacturers). Thus, there is much more variability in firm effects across businesses in the non-manufacturing sector.

Changes in technology use between 1992 and 1997 are characterized in tables 2a and 3a. Two measures of technology change are available for both sectors – the change in total inventories (as a proportion of sales) and the change in spending on computer software and data processing (also as a proportion of sales). Although there is virtually no change in the inventory holdings of businesses in the non-manufacturing sample (median change of zero), the ASM sample shows a range of changes that spans across both increases and decreases in the inventory to sales ratio between 1992 and 1997. For example, inventories as a fraction of sales falls by .03 for the 25th percentile firm yet rises by .02 for the 75th percentile business. Recalling that the median manufacturing firm has an inventory/sales ratio of .1 in 1992, these changes represent a rise of twenty percent and a fall of thirty percent for the 75th and 25th percentile firms, respectively. Thus, to the extent that changes in this inventory measure capture changes in integration of information technology into input and output delivery scheduling, expanded use of this practice does not appear common to all manufacturers; furthermore, it is virtually non-existent among non-manufacturers.

Spending on computer software shows quite a different pattern. In the ASM sample, the change in CST ranges from a decline of .04 percent of sales for the 25th percentile firm to a rise of .04 percent of sales for the 75th percentile business. Though small in magnitude, recall that the median ratio in 1992 is .02 percent of sales. Thus, the rise of .04 percent, for example, represents a doubling of spending on computer-related products and services between 1992 and 1997. This pattern of large relative change is even more notable among non-manufacturers. First, all changes are non-negative. The mean ratio for this group in 1992 is .0003 (.03 percent of sales). The change in this ratio between 1992 and 1997 ranges in value from zero for the 25th percentile firm to .0033 for the 75th percentile business – an increase of over 1000 percent relative to the median.

Table 2: Summary Statistics for 1992 Manufacturing Sample – unweighted (first row) and weighted (2nd row)

Variable	Median Business	25th Percentile Business	75th Percentile Business
Proportion of workers at Business above Median	0.46 0.51	0.31 0.33	0.63 0.63
Proportion of workers at Business above 75th Percentile	0.18 0.18	0.11 0.11	0.28 0.27
Proportion of workers at Business Below 25th Percentile:	0.19 0.16	0.1 0.10	0.33 0.29
Ratio of Computer Investment to Total Equipment Investment (NMC)	0.004 0.03	0 0	0.10 0.11
Ratio of Equipment Investment to Total Investment (MC)	0.98 0.93	0.83 0.84	1 1
Capital Intensity (ACS)	3.94 4.36	3.37 3.78	4.50 5.00
Inventory/Sales Ratio (ATI)	0.10 0.12	0.05 0.07	0.17 0.18
Ratio of Software and Data Processing Expenditures to Sales (CST)	0 0.0002	0 0	0.0009 0.001
Firm Effect ($\varphi_{J(I,t)}$)	0.14 0.25	-0.01 0.10	0.27 0.35

Table 2a: Summary Statistics for 1992 Manufacturing Sample – unweighted (first row) and weighted (2nd row)			
Variable	Median Business	25th Percentile Business	75th Percentile Business
Change in Proportion of workers at Business above Median	0.1025 0.1041	0.0430 0.0688	0.1728 0.1632
Change in Proportion of workers at Business above 75th Percentile	-0.0611 -0.0561	-0.1237 -0.1099	-0.0193 -0.0239
Change in Proportion of workers at Business Below 25th Percentile:	0.0568 0.0751	0.0171 0.0323	0.1026 0.1147
Change in Ratio of Equipment Investment to Total Investment (MC)	0 -0.0083	-0.0879 -0.0726	0.0735 0.0783
Change in Capital Intensity (ACS)	0.2495 0.1714	-0.0546 -0.0651	0.6000 0.4243
Change in Inventory/Sales Ratio (ATI)	-0.0051 -0.0058	-0.0343 -0.0468	0.0221 0.0228
Change in Ratio of Software and Data Processing Expenditures to Sales (CST)	0 0	-0.0004 -0.0009	0.0004 0.0002

Table 3: Summary Statistics for 1992 Non-Manufacturing Sample – unweighted (first row) and weighted (2nd row)			
Variable	Median Business	25th Percentile Business	75th Percentile Business
Proportion of workers at Business above Median:	0.45 0.45	0.26 0.29	0.66 0.55
Proportion of workers at Business above 75th Percentile	0.19 0.19	0.08 0.12	0.36 0.29
Proportion of workers at Business Below 25th Percentile:	0.25 0.33	0.09 0.17	0.5 0.46
Ratio of Computer Investment to Total Equipment Investment (NMC)	0.13 0.09	0 0.02	0.35 0.28
Ratio of Equipment Investment to Total Investment (MC)	0.91 0.76	0.71 0.50	1 0.98
Capital Intensity (ACS)	9.82 10.23	8.97 9.28	10.77 11.04
Inventory/Sales Ratio (ATI)	0.03 0.02	0 0	0.16 0.15
Ratio of Software and Data Processing Expenditures to Sales (CST)	0.0003 0.0004	0 0	0.001 0.001
Firm Effect ($\varphi_{J(I,t)}$)	-0.03 -0.11	-0.37 -0.37	0.22 0.18

Table 3a: Summary Statistics for 1992 Non-Manufacturing Sample – unweighted (first row) and weighted (2nd row)			
Variable	Median	25th Percentile	75th Percentile
Change in Proportion of workers above Median:	0.0694 .05556	0 0.0206	0.1488 0.1057
Change in Proportion of workers above 75th Percentile	-0.0523 -0.0398	-0.1297 -0.0891	0 -0.0057
Change in Proportion of workers Below 25th Percentile:	0.04144 0.0393	0 0.0183	0.1072 0.0781
Change in Inventory/Sales Ratio (ATI)	0 0	0 0	0.0262 0.0080
Change in Ratio of Software and Data Processing Expenditures to Sales (CST)	0.0013 0.0017	0.0000 0.0002	0.0033 0.0050

b. Specification and Estimation

Our empirical analysis of the relationship 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 and we estimate equation (3) using cross sectional data for a sample of manufacturing businesses using the technology measures from the ASM and a sample of service (retail, wholesale and service) businesses using the technology measures from the BES. As noted above, we use three different measures of the dependent variable in (3)– the share of workers at the business above the economywide median, the share of workers at the business above the economywide 75th percentile, and the share of workers below the 25th percentile.

To implement equation (3), in addition to technology measures we require a measure of output and relative market wages. For output, we use the log of sales (in 1992 dollars). For relative wages, it would be inappropriate to use the wages observed at the firm level since we know via the Abowd and Kramarz decomposition that idiosyncratic firm effects play an important role in the determination of the distribution of wages. Thus, it is clearly not the case that firms take the wages they pay as given. In principle, we want to use the shadow market relative wages. One approach to capturing such relevant market effects is to include controls for local labor market effects – for example, we could just include local labor market (e.g., county) dummies for this purpose. However, for our matched employer-employee samples with technology measures, the number of businesses in a given county is not large so such an approach is not practically feasible. Instead, we construct a measure of relative wages in the local labor market (here defined as the county).

Specifically, we measure the ratio of the county level mean wage of the relevant skill group to the overall county mean wage for the county where each business is located. Thus, for example, if the dependent variable is the proportion of workers at the business above the economywide median then we use the county level mean wage of workers above the median relative to the overall county level mean wage. While it is reasonable to argue that (except for exceptionally large businesses) individual businesses do not exert much influence individually on the county level wage, caution must be used in interpreting these county level wages as being econometrically exogenous. For example, there may be common (demand/technology) shocks to businesses in the county (e.g. businesses of like technologies may choose to locate in close proximity) and as such caution needs to be used in interpreting the estimated coefficients. Nevertheless, controlling for such county effects provides a crude means of controlling for local labor market effects. Thus, by controlling for these local labor market effects, we can interpret our estimated technology effects as reflecting the differences in demand across businesses using different technologies controlling for the influence of local labor market effects.

We also estimate equation (4) for continuing businesses between 1992 and 1997. All variables are measured as before except that now we use first differences. We measure sales in 1997 in 1992 dollars using BLS price deflators. In addition, as noted above, we do not have all of our technology measures available in both years. The variables that we measure consistently in 1992 and 1997 are 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. 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), 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.

c. Findings from Cross Section Model

Results of the estimation of equation (3) are reported in tables 4 through 5. For each dependent variable, we report two sets of results. The row labeled SEP represents the specification with the technology measure in the column alone along with the output and local labor market controls (results not reported).[11] The row labeled COMB represents the pooled specification where all technology measures are included (as well as the firm effect $\varphi_{J(I,t)}$). We use these parameter estimates to make comparisons of the link between technology investment and human capital demand on several dimensions: across sectors, across different types of technology, across specifications (technology measures included separately and combined, employment weighted versus unweighted), and across different characterizations of demand for high and low skilled workers.

Old vs. New Technology

For firms in both the ASM (manufacturing) sample and the BES (non-manufacturing) samples, the estimated effect of the computer investment measure on human capital demand is positive and significant (negative for demand for workers in the lower quartile). For example, among manufacturers, businesses with ten percent higher investment in computers (relative to total machinery investment) have on average 1.5 percent more workers in the top quartile (relative to other quartiles). This positive relationship holds across all samples and specifications.

The impact on skill demand of the remaining two measures of new technologies - spending on computer software, etc, and inventory holdings - varies both by sample and by specification. The coefficient on computer software investment is not significant (though it is large and positive) in the unweighted estimates obtained from the ASM sample. However, weighting by employment yields a large, positive, and significant effect of software investment on skill demand. Note, however, that the parameter estimate falls substantially

[11] While the results vary across specification and sector, we find that the coefficients on output are statistically significant indicating non-homotheticity. In addition, we often find that the coefficient on the relative wage term is negative and significant which is what one would expect if the controls for local labor market effects primarily reflect differences in the relative supply of skilled workers across areas.

and loses significance when all technology measures (including the firm fixed effect) are included as explanatory variables. Thus, it is possible that this measure is correlated with use of other technologies or with some trait of the business that is captured by the firm fixed effect. Though unstable, these estimates typically have the expected sign (positive for computer software spending and negative for inventory holdings).

Capital intensity and machinery spending, the more conventional measures of technology, are also found to have a positive association with the proportion of high skilled workers (negative for proportion of workers with lower levels of human capital). Furthermore, with the exception of machinery investment in the manufacturing sample, these estimates are significant.

Employment Weighted vs. Unweighted

In general, weighting gives more importance in estimation to firms with higher employment. The effects of weighting in this case are quite simple to summarize: the estimated impact of investment in "newer" technologies on the demand for more highly skilled workers increases whereas the impact of spending on "older" technology measures does not change or diminishes (and often loses significance). One possible explanation for this finding is that larger employers differ from smaller employers in some way that we are not able to observe in the data. It is also possible, however, that both right and left hand side variables are measured with less error for large employers and that weighting by employment yields more precise parameter estimates.

Firm Fixed Effects

In nearly all cases, firms with higher fixed effects (those that pay their employees more on average than other businesses, holding constant the observable and unobservable traits of the workers) are found to have a higher proportion of workers in the top quartile, a higher proportion above the median, and a lower proportion in the bottom quartile. In addition, the coefficient estimates are quite large and significant. For example, among non-manufacturers, the weighted estimates suggest that firms that pay their workers ten percent more on average employ nearly 3 percent more workers above the median. These results are interesting in their own right – that is the finding that firms that pay systematically higher than average wages (controlling for worker characteristics) also employ systematically higher than average human capital workers is a striking finding. Interestingly, the unconditional correlation between these two variables (proportion of high human capital workers and firm effect) is typically not significant – it is after including the controls for output and local labor markets (and controlling for broad industry) that a significant relationship emerges.

Separated vs. Combined

There are two features of the combined models that could yield coefficient estimates that are markedly different from those obtained from estimating the effect of each technology measures separately. The first, simply, is that all technology measures are included in these equations. It is possible that certain technology measures proxy for use of other technologies. In addition, it is possible that the manner in which technologies are combined affects the demand for skilled labor in a way different from technology use overall. Lastly, we include the firm fixed effect, $\varphi_{J(I,t)}$, in these equations with the other technology measures. For the most part, the effect of each of the individual technology measures is of the same sign and magnitude even when all of the technology measures are included together. We find that effects tend to be somewhat smaller in the combined specification although a notable exception is the impact of computers in manufacturing where the magnitude is larger.

The one technology measure whose impact becomes erratic and insignificant when combined with the other measures is the computer software variable.

d. Findings from First Difference Model

The results of estimating equation 4 are reported in tables 6 (ASM sample) and 7 (BES sample). A few patterns emerge from these results that are worth noting prior to beginning an in-depth discussion of the estimates. First, the BES sample is quite small (104 observations) and the results are constrained by other data limitations. For example, we cannot measure capital intensity or equipment investment for the BES sample in 1997 and thus cannot include changes in either variable in the specification for the BES sample. In addition, we cannot measure computer investment intensity in either the ASM and BES sample in 1997 so we do not include a computer investment variable in these specifications. These data limitations serve as an important caution in comparing the results across sectors and in comparing the results between the level and the change specifications.

Also, as documented above, the share of high skilled workers (those above the median) at a business does rise between 1992 and 1997, yet the share or workers in the highest quartile at a business falls relative to other groups and the share of employment in the lowest quartile rises at a business. Thus, should we find that increased utilization of technology does indeed increase the share of workers in higher skill groups (tails of the human capital distribution included), this finding will to some extent go against the general direction of change observed in the data.

In general, estimation of equation 3 suggests that the top two skill quartiles (the proportion above the median) are more strongly related to technology use at a business, but that the relationship is weaker at the tails of the human capital distribution. In fact, in both the

ASM and BES samples, this pattern tends to continue to hold for the change specification given by equation 4 (though fewer technology measures are significant). Though these estimates are often insignificant and small, it appears that firms that expand their utilization of technology between 1992 and 1997 also increase their share of high skilled workers. Similarly, the effect of expanded technology use on the share of workers in the lowest quartile appears primarily negative, although increased technology is linked more frequently with a fall in the share of lowest skilled workers among manufacturers.

Capital Intensity: Changes in this variable are only available for the ASM sample. For all measures of skill change, an increase in capital intensity is associated with upskilling: businesses that become more highly capital intensive increase the proportion of workers above the median and in the top quartile and reduce their demand for bottom quartile workers. This finding is consistent with our findings from the estimation of equation 3, which suggest that more capital intensive firms have a higher proportion of high skilled workers. The magnitude of the effects are relatively small however. Using the interquartile range from Table 2a, the implied difference in changes of high skilled workers (measured as the share of workers above the median) due to changes in capital intensity across the 25th and 75th business is approximately 0.01.

Computer Investment/Equipment Investment: Because we have data on computer investment in 1992 only, we include the 1992 investment in computers (as a proportion of total equipment investment) as an explanatory variable in this specification. Although higher values of this variable are associated with positive changes in the demand for workers with human capital (in the top quartile only for ASM sample and for top two quartiles in BES sample), most estimates are small and insignificant. Somewhat surprisingly, for manufacturing businesses, 1992 computer investment has a positive effect on the change in the share of workers in the lowest quartile.

Equipment investment/Total Investment: For equipment investment, recall that we include the change in equipment investment for the ASM sample, but are limited to the 1992 spending on equipment (as a ratio of total investment) for the BES sample. Thus, it is difficult to make comparisons across sectors in the effect of changes in equipment spending on human capital demand. Interestingly, though, in both samples, employment weighting both increases the magnitude and improves the precision of these estimates, suggesting that the statistical relationship between this variable and changes in skill demand is more important among larger employers. Furthermore, estimates for both samples show that higher levels of equipment investment increase demand for both high skilled workers (those above the median) and very high skilled workers (those in the top quartile). For example, among non-manufacturers, recall that the equipment investment proportion ranged from 50 percent of total investment for the weighted 25th percentile firm to nearly 100 percent for the 75th percentile business. The (combined and employment weighted) parameter estimates reported in table 7 suggest that the 75th percentile (of equipment investment) firm in 1992 should increase its proportion of workers in the top quartile between 1992 and 1997 by .15*(.5), or by 0.075 more than the 25th percentile business. Note that the parameter estimates for the ASM sample (where a true change measure is used) are much smaller and imprecise.

Spending on Computer Software and Data Processing Relative to Sales: In both sectors, in all specifications, the effect of changes in CST on skill demand are very large relative to other parameter estimates. However, the sign and significance of these estimates varies both by skill measure and by sector. Among manufacturers, increases in CST between

1992 and 1997 reduce the relative demand for all skill groups. In addition, these estimates are not statistically significant. Among non-manufacturers, these same estimates are positive and statistically significant. For example, the 75th percentile firm (weighted) has an increase in CST of .0.005 while the 25th percentile firm has an increase of zero. The (employment weighted and pooled) estimates indicate that this difference implies that the 75th percentile firm will increase its share of high skilled workers by 0.02 (4.4*(.005)) relative to the 25th percentile firm.

Inventory/Sales: For both manufacturers and non-manufacturers, all coefficient estimates on the ratio of inventory holdings to sales are small, insignificant, and vary from positive to negative depending on the specification. Recalling that there is very little variation in this variable (in the BES sample in particular), this finding is not surprising

Table 4 Manufacturing for 1992
ASM Sample

Unweighted Dep Var		Comp. Inv. (NMC)	Equip. Inv. (MC)	Capital Intensity (ACS)	Inv. To Sales (ATI)	Comp. Soft. to Sales (CST)	$\varphi_{J(I,t)}$
		Technology Measure					
Proportion of workers above Median	Sep	0.0591	0.0436	0.0753	-0.0057	1.7504	0.2557
		0.0207	0.0249	0.0046	0.0035	1.2766	0.0206
	Comb	0.0993	0.0517	0.0670	-0.0055	0.4721	0.1830
		0.0195	0.0229	0.0047	0.0032	1.1885	0.0204
Proportion of workers above 75th Percentile	Sep	0.0512	0.0334	0.0361	-0.0041	1.6292	0.0440
		0.0150	0.0181	0.0035	0.0025	0.9255	0.0154
	Comb	0.0689	0.0349	0.0380	-0.0035	0.8946	0.0034
		0.0149	0.0175	0.0036	0.0025	0.9106	0.0155
Proportion of workers Below 25th Percentile	Sep	-0.0271	-0.0287	-0.0617	0.0054	-2.1692	-0.2997
		0.0164	0.0197	0.0036	0.0028	1.0093	0.0157
	Comb	-0.0581	-0.0368	-0.0485	0.0056	-1.2984	-0.2469
		0.0148	0.0174	0.0036	0.0024	0.9022	0.0155

Weighted Dep Var		Comp. Inv. (NMC)	Equip. Inv. (MC)	Capital Intensity (ACS)	Inv. To Sales (ATI)	Comp. Soft. to Sales (CST)	$\varphi_{J(I,t)}$
		Technology Measure					
Proportion of workers above Median	Sep	0.1314	0.0220	0.0850	-0.0028	3.5736	0.3017
		0.0220	0.0244	0.0043	0.0023	1.0505	0.0199
	Comb	0.1959	0.0521	0.0750	-0.0034	0.6858	0.2020
		0.0199	0.0214	0.0044	0.0020	0.9427	0.0199
Proportion of workers above 75th Percentile	Sep	0.1588	0.0005	0.0365	-0.0017	2.0299	-0.0007
		0.0151	0.0171	0.0032	0.0016	0.7357	0.0147
	Comb	0.1810	0.0116	0.0464	-0.0009	0.8806	-0.0612
		0.0148	0.0159	0.0033	0.0015	0.7012	0.0148
Proportion of workers Below 25th Percentile	Sep	-0.0470	-0.0017	-0.0615	0.0054	-2.6506	-0.3446
		0.0163	0.0179	0.0032	0.0017	0.7722	0.0136
	Comb	-0.1033	-0.0226	-0.0426	0.0067	-0.1735	-0.2933
		0.0138	0.0148	0.0031	0.0014	0.6511	0.0138

Note: Results based upon estimation of equation (3). Coefficients on output and relative wages not reported. Explanations for abbreviations for technology measures are in Tables 2 and 3. SEP refers to specification with controls and technology measure; COMB refers to specification with controls and all technology measures. Standard errors in smaller font below coefficients.

Table 5 -- Non – Manufacturing (Retail, Wholesale and Services) for 1992 BES Sample

Unweighted Dep Var		Comp. Inv. (NMC)	Equip. Inv. (MC)	Capital Intensity (ACS)	Inv. To Sales (ATI)	Comp. Soft. to Sales (CST)	$\varphi_{J(I,t)}$
		Technology Measure					
Proportion of workers above Median	Sep	0.1241 0.0269	0.1540 0.0406	0.0257 0.0056	0.0001 0.0003	0.0018 0.0045	0.1578 0.0232
	Comb	0.0981 0.0264	0.1426 0.0393	0.0257 0.0055	0.0012 0.0304	-0.0207 0.5125	0.1318 0.0231
Proportion of workers above 75^{th} Percentile	Sep	0.1184 0.0238	0.1331 0.0362	0.0151 0.0050	0.0002 0.0002	0.0029 0.0040	0.1013 0.0210
	Comb	0.1013 0.0238	0.1205 0.0356	0.0157 0.0050	0.0058 0.0276	-0.0955 0.4645	0.0791 0.0210
Proportion of workers Below 25^{th} Percentile	Sep	-0.1150 0.0239	-0.1273 0.0362	-0.0255 0.0050	-0.0006 0.0002	-0.0100 0.0040	-0.1607 0.0207
	Comb	-0.0909 0.0231	-0.1159 0.0345	-0.0237 0.0048	-0.0050 0.0267	0.0778 0.4502	-0.1353 0.0204
Weighted		Technology Measure					
Dep Var		Comp. Inv. (NMC)	Equip. Inv. (MC)	Capital Intensity(ACS)	Inv. To Sales (ATI)	Comp. Soft. to Sales (CST)	$\varphi_{J(I,t)}$
Proportion of workers above Median	Sep	0.1371 0.0203	0.1113 0.0252	0.0206 0.0043	0.0006 0.0010	0.0105 0.0166	0.2966 0.0188
	Comb	0.0589 0.0194	0.1072 0.0225	0.0171 0.0038	0.0228 0.0348	-0.3769 0.5865	0.2639 0.0195
Proportion of workers above 75^{th} Percentile	Sep	0.1267 0.0154	0.0841 0.0194	0.0197 0.0033	0.0006 0.0008	0.0097 0.0128	0.1662 0.0156
	Comb	0.0960 0.0156	0.0798 0.0180	0.0204 0.0031	0.0326 0.0281	-0.5415 0.4724	0.1205 0.0158
Proportion of workers Below 25^{th} Percentile	Sep	-0.0923 0.0185	-0.0728 0.0225	-0.0196 0.0038	-0.0010 0.0009	-0.0172 0.0148	-0.3421 0.0151
	Comb	-0.0015 0.0157	-0.0719 0.0180	-0.0105 0.0031	-0.0187 0.0281	0.3002 0.4735	-0.3305 0.0158

Note: Results based upon estimation of equation (3). Coefficients on output and relative wages not reported. Explanations for abbreviations for technology measures are in Tables 2 and 3. SEP refers to specification with controls and technology means; COMB refers to specification with controls and all technology measures. Standard errors in smaller font below coefficients.

Table 6 -- Manufacturing for 1992
ASM Sample

Unweighted Dep Var		Technology Measure: Change Equip. Inv. (CMC)	Change Capital Intensity (CACS)	Change Inv. To Sales (CATI)	Change Comp. Soft. to Sales (CCST)
Change Proportion of workers above Median	Sep	-0.0047	0.0174	-0.0097	-1.1694
		0.0183	0.0048	0.0117	1.1337
	Comb	-0.0102	0.0177	-0.0062	-1.2192
		0.0182	0.0048	0.0116	1.1234
Change Proportion of workers above 75th Percentile	Sep	0.0119	0.0102	0.0015	0.0057
		0.0139	0.0036	0.0089	0.8627
	Comb	0.0092	0.0101	0.0041	0.0072
		0.0139	0.0037	0.0089	0.8600
Change Proportion of workers Below 25th Percentile	Sep	-0.0288	-0.0142	-0.0040	-0.6002
		0.0159	0.0042	0.0102	0.9900
	Comb	-0.0248	-0.0143	-0.0074	-0.5482
		0.0159	0.0042	0.0101	0.9797

Weighted Dep Var		Technology Measure: Change Equip. Inv. (CMC)	Change Capital Intensity (CACS)	Change Inv. To Sales (CATI)	Change Comp. Soft. to Sales (CCST)
Change Proportion of workers above Median	Sep	0.0412	0.0213	-0.0127	-0.8913
		0.0167	0.0047	0.0091	0.7780
	Comb	0.0350	0.0206	-0.0031	-0.9659
		0.0166	0.0048	0.0093	0.7655
Change Proportion of workers above 75th Percentile	Sep	0.0277	0.0033	0.0025	-0.9948
		0.0139	0.0039	0.0076	0.6452
	Comb	0.0257	0.0031	0.0043	-0.9505
		0.0140	0.0041	0.0078	0.6470
Change Proportion of workers Below 25th Percentile	Sep	-0.0153	-0.0161	-0.0001	-0.7864
		0.0158	0.0044	0.0087	0.7355
	Comb	-0.0128	-0.0176	-0.0083	-0.7052
		0.0158	0.0046	0.0088	0.7280

Note: Results based upon estimation of equation (4). Coefficients on output and relative wages not reported. Explanations for abbreviations for technology measures are in Tables 2 and 3. SEP refers to specification with controls and technology means; COMB refers to specification with controls and all technology measures. Standard errors in smaller font below coefficients.

Table 7 -- Non – Manufacturing (Retail, Wholesale and Services) for 1992 BES Sample

Unweighted Dep Var		Technology Measure: Change Inv. To Sales (CATI)	Change Comp. Soft. to Sales (CCST)
Change Proportion of workers above Median	Sep	0.0052	2.4395
		0.0688	1.6127
	Comb	-0.0515	2.9894
		0.0764	1.8106
Change Proportion of workers above 75th Percentile	Sep	0.0155	0.9419
		0.0543	1.2846
	Comb	-0.0030	0.9736
		0.0610	1.4455
Change Proportion of workers Below 25th Percentile	Sep	-0.0138	-1.7509
		0.0635	1.4937
	Comb	0.0244	-2.0104
		0.0710	1.6794
Weighted Dep Var		Technology Measure: Change Inv. To Sales (CATI)	Change Comp. Soft. to Sales (CCST)
Change Proportion of workers above Median	Sep	0.0758	3.3430
		0.0466	1.0866
	Comb	-0.0328	3.8753
		0.0614	1.4762
Change Proportion of workers above 75th Percentile	Sep	0.0302	0.9645
		0.0410	0.9840
	Comb	0.0059	0.8694
		0.0557	1.3390
Change Proportion of workers Below 25th Percentile	Sep	-0.0594	-2.7898
		0.0413	0.9682
	Comb	0.0344	-3.3492
		0.0546	1.3157

Note: Results based upon estimation of equation (4). Coefficients on output and relative wages not reported. Explanations for abbreviations for technology measures are in Tables 2 and 3. SEP refers to specification with controls and technology measure; COMB refers to specification with controls and all technology measures. Standard errors in smaller font below coefficients.

Concluding Remarks

Our main results are summarized as follows:

- There are large and persistent differences in the level of human capital across businesses in the Illinois economy even after having controlled for detailed industry. Using our measures of human capital, the business at the 75^{th} percentile of the distribution had average human capital that was more than 40 percent larger than the business at the 25^{th} percentile.
- There have been substantial changes in the distribution of human capital within and between businesses in the Illinois economy over the 1990s. The median business increased its average human capital level by almost 10 percent between 1992 to 1997. For continuing businesses, the median change was also positive but a large fraction of continuing businesses exhibited de-skilling (that is decreases in the mean human capital at the business). Several factors contributed to the overall change. Holding employment shares constant, the average business exhibited substantial increases in human capital. Another important contributing factor accounting for the overall upskilling over this period of time is that entering businesses had substantially greater skill levels than the exiting businesses they were displacing. Interestingly, an offsetting factor is that businesses that downsized tended to increase human capital while those that upsized tended to decrease human capital – the reallocation of employment across continuing businesses thus acted as a net drag on the overall change in human capital.

- 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 find that the level of human capital at a business is positively related to the firm effect from an Abowd-Kramarz type wage decomposition. That is, firms that pay workers above average wages controlling for worker characteristics employ a greater share of high skilled workers. 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. 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.

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