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The Relationship Between Human Capital, Productivity and Market Value: Building Up from Micro Evidence

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Abstract

This paper investigates and evaluates the direct and indirect contribution of human capital to business productivity and shareholder value. The impact of human capital may occur in two ways: the specific knowledge of workers at businesses may directly increase business performance, or a skilled workforce may also indirectly act as a complement to improved technologies, business models or organizational practices. Our general approach is to use newly created firm level measures of workforce human capital and productivity, and to then examine links between those measures and market value. The new human capital measures come from an integrated employer-employee dataset being developed at the US Census Bureau. We link these data to financial information from Compustat at the firm level, which provides measures of market value and tangible assets. The combination of these two sources permits examination of the link between human capital, productivity, and market value.

Introduction

The measurement of intangibles and human capital – important for both goods producing and service producing industries –has always been a difficult challenge for the statistical system. The growth of the New Economy has made responding to the challenge even more urgent: understanding how such inputs affect the value chain of productivity, growth and firm value now surpasses the need to measure the impact of bricks, mortar and equipment. Yet the changes that have brought the New Economy into existence have, at the same time, highlighted the need for improvements to traditional measures of inputs and outputs (Haltiwanger and Jarmin, 2000). This is particularly true for human capital. Finding new measures of human capital, and quantifying them in such a manner that they can be introduced into a production function and produced on a scale that provides sufficient sample size for use in official economic statistics is a formidable challenge.

This paper uses micro level data on both employers and employees to demonstrate a new approach to addressing this challenge. We use new measures of human capital that directly capture the market valuation of the portable component of skill including the contribution of "observable" and "unobservable" dimensions of skill. In principle, the measures go beyond indirect proxies, such as measures of years of formal education, and quantify the value of individual specific skills, such as innate ability, visual or spatial skills, non-algorithmic reasoning, analytic or abstract decision-making, or "people skills" (Bresnahan *et al.*).

An additional challenge has been to document the sources of firm level heterogeneity in productivity, growth, and value. One of the key findings of the literature using micro level data is that there are large differences across many dimensions of firm inputs and outcomes. In particular, there is little uniformity among employers in either the ways they hire and terminate workers or the types of workers they hire. We therefore use measures of the dispersion of the firm level human capital distribution as well as firm specific tenure to capture relevant aspects of firm level differences in organizational capital and workplace practices.

We begin by describing the background, motivation and underlying specifications to this chapter, and follow it by describing newly created data sources and measures that underlie this study. The subsequent section provides an exposition of the measurement of human capital that is made possible by the new Census dataset. After this, we present exploratory empirical results that relate our new human capital measures to measures of firm performance including labor productivity and market value. The final section concludes the paper.

2. Background, Motivation, and Specifications

The literature on human capital and intangibles separately and together are quite broad ranging and impossible to summarize here. However, we provide a brief background to provide some perspective on our approach. We begin with a discussion of our methodology for measuring human capital and then consider the role of human capital at the firm level focusing on its potential relationships to productivity, market value, tangible and intangible assets.

a) Human Capital – Conceptual and Measurement Issues

The importance of human capital in accounting for observed differences in wages and productivity has a very long history in economics. Becker (1964) and many others helped the profession define the components of human capital and the contribution of human capital to productivity has been intensively and exhaustively studied (e.g., Jorgenson, Gollup, and Fraumeni (1987, hereafter JGF). While we clearly stand on their shoulders, our approach is different in key ways that depend critically on data availability. In particular, our conceptual and measurement approach depends not only on the availability of longitudinal matched employer-employee data but the availability of universe files of all workers and firms.

The starting point for our approach has been well documented and investigated in a series of papers by Abowd, Kramarz and Margolis (1999, hereafter AKM) and Abowd, Lengermann, and McKinney (2001, hereafter ALM). In this paper, we exploit newly developed measures of human capital that have emerged from this work and are part of a new program at Census called the Longitudinal Employer-Household Dynamics Program (LEHD). These and related papers emphasize a point that has long been known in the study of human capital – it is very difficult to measure human capital directly. The standard approach is to take advantage of the "usual suspects", for example, education and experience, and to build proxies for human capital using such measures. In the productivity literature referenced above, this approach has made extensive use of household data. JGF create detailed human capital measures from person level data in the U.S., using primarily the Current Population Survey (CPS), by exploiting wage differences across gender, experience and education groups. They aggregate these measures by industry and to the total economy level and have demonstrated that there is an enormous stock of human capital in the U.S. economy and that the stock and flows of this asset are vitally important for understanding labor productivity changes.

However, JGF (and subsequent related work including the Jorgenson, Ho, and Stiroh paper in this volume) recognize that this approach is constrained. Clearly, industry and economy-wide aggregates fail to capture the firm level variation that is a driving force in productivity growth. In addition, the existing data only provide a relatively small set of observable characteristics of workers, resulting in measurement problems, as well as the omission of measures of unobservable skill and confounding firm effects. The use of the possession of a college degree as a human capital measure, for example, fails to capture differences in school quality, and program of study (Aaronson and Sullivan, 2001). The increasingly important role of the unobserved component of skill has been highlighted by the large portion of wage variation that cannot be explained by these variables. This aspect is particularly evident in the recent literature on rising wage inequality in the U.S. (see, *e.g.*, Juhn, Murphy, and Pierce,1992). Finally, new empirical evidence (AKM) note that because earnings measures include the returns to working with particular types of firms – for example, large, highly unionized or profitable entities – and there is sorting between workers and firms, the estimates of returns to human capital may be biased.

While we will provide a more detailed description of the econometric and measurement approach in subsequent sections, it is useful to review the basic specification used by AKM and ALM so that we can discuss the conceptual nature of our human capital measures. The core model that is estimated is:

$$w_{ijt} = \theta_i + x_{it}\beta + \psi_{\mathrm{J}(i,t)} + \varepsilon_{ijt} \qquad (1)$$

The dependent variable is the log wage rate of 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 a 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. In what follows, we use the fixed worker effect θ plus the experience component of $x\beta$ as the core measure of human capital, called "*h*" (ie, $h_{it} = \theta_{it} + x_{it}\beta$).[1] We also exploit these components separately as they clearly represent different dimensions of human capital or skill.

For current purposes, this approach has three main conceptual and measurement advantages over earlier approaches. First, because we have data on the universe of workers and of firms, we can create both firm and industry based measures of human capital that include measures of dispersion as well as central tendencies. In particular, the new data permit the measurement of "*h*" and its underlying components for all workers. Further, because we can place all of these workers inside their employers, we can consider the full human capital distribution for each firm and industry. Second, the measure of "*h*" includes a broader measure of skill - the market valuation of a number of observable components – and as such, encompasses various measures of skill including education.[2] Because it includes the person effect, which can be thought of as the portable time invariant component of a person's wage, the measure of "*h*" also captures the influence of unobservable components of skill. Third, because the AKM approach controls for fixed firm effects in estimating the person effects, our measure of human capital does not reflect firm personnel policies that may impact the returns to observable and unobservable dimensions of skill.

We will explore all of these points in what follows. For example, in section 3, we report the characteristics of our human capital measures and, along the way, compare our results

[1] See ALM for details of the estimation procedure. Additional controls in *x* include year effects interacted with gender effects and full quarter employment adjustments (not all workers work full quarters).

[2] In most of the analysis that follows, we do not separate out the impact of observable characteristics such as education and unobservable components. For sub-samples of our universe files, we can measure education and some of the results (see, *e.g*,. in ALM) we refer to are based upon such analysis. There is a large ongoing effort at the LEHD Program to incorporate such observable characteristics on a more comprehensive basis including the development of robust imputation procedures for our universe files.

to more traditional estimates of human capital. For now, we proceed to thinking about how and why human capital may matter for productivity and market value.

b) Human Capital, Tangible Assets, Intangible Assets and Productivity

The relationship between output and inputs is summarized by the standard production function approach. Explicit recognition of human capital and intangibles augments this function in the following fashion:

$$y_{jt} = F_j(K_{jt}^T, K_{jt}^I, L_{jt}, H_{jt}) \tag{2}$$

where y_{jt} is output for firm j at time t, K_{jt}^T is tangible physical capital, K_{jt}^I is intangible capital, L_{jt} is labor input (number of workers/hours), and H_{jt} represents measures of the distribution of human capital of the workers at the firm.

The link between human capital, tangible assets and intangible assets may be complex conceptually and, in turn, pose difficult measurement, specification and econometric problems. For one, there may be complementarities between tangible assets and human capital (capital-skill complementarity) and likewise intangible assets and human capital. If some of the tangible and/or intangible assets are not observed or poorly measured, an estimated relationship between productivity and human capital may reflect such complementarities. Moreover, what we mean by intangible assets may be very closely connected to how human capital is organized. We turn to that set of issues now.

c) Defining and Measuring Intangibles

A major issue confronting the literature is the fundamental problem associated with describing something that is not readily measurable. Thus, while intangibles might be seen to be the “major drivers of corporate value and growth in most sectors” Gu and Lev (2001) there is little consensus as to what those intangibles are. In fact, they have been variously defined to be knowledge and intellectual assets (Gu and Lev, 2001), human capital, intellectual property, brainpower and heart (Gore, 1987), knowledge assets and innovation (Hall, 1998; and organizational structure (Brynjolfsson, Hitt and Yang, 2001). Measures of these variables have been equally diverse, ranging from a residual approach, to inference and, yet further, to direct measurement.

For example, while Gu and Lev conceptualize intangibles as knowledge assets (new discoveries, brands or organizational designs), they derive their measure of intangibles as a residual: the driver of economic performance after accounting for the contribution of physical and financial assets. In empirical terms, they identify the core drivers of intangibles as research and development, advertising, information technology, and a variety of human resource practices. In a series of papers, Hall uses direct expenditures on research and development as well as patent information to proxy for knowledge assets. Brynjolfsson, Hitt and Yang (2001), use survey data on the “allocation of various types of decision making authority, the use of self-managing teams, and the breadth of job responsibilities …" (p. 15) to construct a composite variable that acts as a proxy for organizational capital.

The results from using these measures suggest that intangibles vary considerably across firms and sectors and that they are important in accounting for fluctuations in the market. Gu and Lev, using the broadest measure of intangibles, find that the level and growth rate of intangibles vary substantially across industries. In particular, they find the highest levels in insurance, drugs and telecommunications, the lowest in trucking, wholesale trade and consulting. However, the highest growth rates are in consulting, machinery and electronics industries; the lowest in retail trade, restaurants and primary metals. Gu and Lev also find that intangible driven earnings (by two different measures) are much more highly correlated with stock market returns than are other measures – notably operating cash flow growth and earnings growth. Brynjolffson *et al*. find that organizational structure has a large impact on market valuation – firms that score one standard deviation higher than the mean on this measure have approximately $500 million greater market value. Hall finds that research and development accounts for a "reasonable fraction" of the variance of market value, but that this relationship is not stable, and there is still a great deal of unexplained variation; patents matter, but less than research and development.

Empirical studies also suggests that failing to include intangibles is likely to cause considerable bias in estimates of the impact of tangibles on both market value and output. Gu and Lev find that expenditures on capital, R&D, and technology acquisitions are all highly correlated with intangible capital. Similarly, Brynjolffson *et al*. find evidence for a strong correlation between organizational structure and investment in information technology.

Even if it is difficult to conceptualize and measure, organizational capital is closely linked to the way workers are organized, and in turn, to the apparently different human capital mixes across firms in the same industry. This perspective motivates our approach to the measurement of intangibles and organizational capital. With the entire distribution of human capital within each firm, we can quantify the relationship between outcomes like productivity and market value and the organization of human capital. For example, we can examine whether the driving force behind firm performance is the employment of uniformly skilled workers (that is, a narrow distribution of relatively high human capital workers) or whether it is due to the presence of a significant number of very highly skilled workers (*i.e.,* an over-representation of high human capital workers but not necessarily a high mean).[3] Alternatively, since we are able to construct various measures

[3] The literature on firm organization is very much relevant here. There is abundant evidence of firm-level differences in productivity outcomes, even in narrowly defined sectors (Foster, Haltiwanger and Krizan, 2001). Firm level differences in workforce composition (Haltiwanger, Lane and Spletzer, 2001), workforce turnover (Burgess, Lane and Stevens, 2000) and the organization of firms (Black and Lynch, 2000) appear to vary in equally idiosyncratic ways. The links between these are not well understood, but anecdotal evidence suggests that they are likely to be related. For example, Wal-Mart deliberately organized its firm structure to be very flat and non-hierarchical (in contrast to, say, Sears) with a great deal of employee ownership. This, in turn, has led to industry reports of relatively low turnover and observably substantially greater market value. Similarly, case study evidence (Frei *et al.*, 1999), demonstrates that businesses

of the distribution, we can examine the impact of firms' choices in combining different types of workers in different ways – for example, combining low skill and high skill workers.

d) The market value of a firm – tangible assets, intangible assets and human capital

The general approach for describing the market value of a firm, V_{jt} in terms of its tangible and intangible assets is well summarized, derived and motivated in Brynjolfsson, Hitt and Yang (2001, hereafter BHY) and can be written as:

$$V_{jt} = V(K_{jt}^{T}, K_{jt}^{I}, ...) \tag{3}$$

The market value of a firm is assumed to be an increasing function of the assets.[4] Defining and measuring all of the terms in this relationship is difficult, however. If the market is characterized by strong efficiency then, as Bond and Cummins (2000) point out, the market value of a company will equal the replacement cost of its assets (absent adjustment costs and market power). From this perspective, one way of measuring intangibles is a residual approach (see, *e.g.*, Hall, 2001) as they will reflect the difference between the market value and observed assets. Alternatively, direct measures of intangibles (*e.g.*, organizational capital as in BHY) can be included in an econometric specification explaining market value. However, note that the specification here potentially permits the coefficients on the various assets to reflect direct and indirect effects. One interpretation (BHY) of the coefficients is that there are likely to be complementarities with unmeasured intangibles and thus the coefficient on any measured asset will reflect the complementarity (i.e., covariance) between the measured and unmeasured assets. Thus, as BHY have found, the coefficient on IT capital in a linear specification of (3) is larger than one. BHY provide evidence that this reflects the complementarity between market value and organizational capital.

With these remarks as a background, should human capital be included in the set of variables in an econometric specification of the market value equation? A simple model in the absence of complementarities and a basic view of the role of human capital is that human capital may not be relevant here. That is, if all human capital is general human capital and it is fully compensated by the market and there is no complementarity between human capital and unmeasured tangible or intangible assets, then human capital will not be reflected in market value. However, there may be several sources of departures from this assumption. For one, human capital may not be fully compensated in the market. Second, the chosen mix of human capital may indeed be a key aspect of what is meant by "organizational capital." Under this view, it may not be the average

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organize call centers in fundamentally different ways – workforce composition is fundamentally related to turnover, and in turn, to market value (see, *e.g*., Batt, Hunter and Wilk, 2003, and Lane *et al*., 2003).

[4]BHY specifiy a linear relationship and emphasize the departure of coefficients from one. Hall (1998) discusses the alternative log linear relationship that may be relevant . We use the log linear specification in our analysis in part because our human capital measures are not on the same inherent scale and metric as the measures of assets and market value.

level of human capital at the firm that matters for market value *per se*, but rather how that human capital is organized.[5] Finally, in a manner analogous to the arguments and findings of BHY, human capital (its average and other measures of the distribution) may be complementary to unmeasured tangible and intangible assets. As such, it may be positively related to market value.

e) Econometric and Interpretation Issues

The previous subsections provided an overview of our approach. We explore newly created measures of human capital from longitudinal employer-employee data. These measures, in principle, encompass traditional measures and improve on some of the econometric difficulties. In what follows, we explore the relationship of these measures to productivity and market value at various levels of aggregation. The discussion above suggests that a host of econometric issues arise that complicate the estimation of any productivity or market value equation. At the heart of these issues is the well-known problem that tangible assets and intangible assets, including those involving some measure of human capital, are endogenous. In a related manner, for any given econometric implementation of equations (2) and (3), the observed measures may be proxies for unobserved measures

In this paper, we focus on identifying economically and statistically significant relationships rather than attempting to establish causality or to pin down direct vs. indirect effects.[6] We include measures of tangible assets and intangible assets in relatively simple specifications of productivity and market value equations. We recognize that our coefficient estimates reflect both direct and indirect effects of the assets that we measure. In particular, the impact of human capital on productivity and market value may reflect both direct and indirect effects of human capital. However, by looking at the impact on both productivity and market value we hope to make some progress on understanding the role of human capital in this context. If the human capital measures are mostly capturing general human capital for which the worker is fully compensated and if such human capital measures are not highly correlated with unmeasured intangibles (or other unmeasured assets), then human capital is likely to have a positive impact on productivity and very little impact on market value (because firms are fully paying for the human capital and thus generate no additional value from having higher human capital). However, if human capital measures (or some components or indices of our human capital measures) are positively related with productivity and market value, then this outcome suggests that the human capital measures are either directly or indirectly capturing some form of intangible asset associated with human capital.

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[5] A related argument is that the value creation of some firms is related to the human capital of the people at the top of the firm – *e.g.*, Microsoft's Bill Gates, or Apple's Steve Wosniak and Steve Jobs. For our purposes, this implies that there may be a relationship between firm performance and measures of the human capital at the top of the enterprise.

[6] In that sense, our approach follows very much in the spirit of Brynjolfsson *et al*.

We clearly recognize that exploring and separating out the direct and indirect effects of human capital in this context is important. However, as noted, our objective is to explore the relationships between our new measures of human capital and productivity and market value in a largely descriptive manner. We anticipate that identifying and quantifying the respective direct and indirect roles of these new measures of human capital in this context will be the subject of much research in the years to come.[7]

Before proceeding, one other related interpretation issue warrants mention. We are exploring the relationship between productivity and human capital measures on the one hand, and market value and human capital measures on the other. It is important to emphasize that these two measures capture very different aspects of firm performance. For one, as noted, any productive input that is fully compensated in the market may be related to productivity but unrelated to market value. For another, productivity captures current activity while market value reflects future profits and associated anticipated value. Thus, the factors that impact current activity may be very different from those affecting future profit streams. Along these lines, it is easy to argue that there are factors that inherently lead to a negative correlation between market value and current productivity. For example, a business with a high market value “new idea” may be actively expanding and investing in physical and human capital. Adjustment costs may imply that such a firm exhibits low current productivity.

3. Data

The key measures for this project are human capital, physical capital, productivity, and market value. The integrated employer-employee data allow us to construct firm-specific measures of human capital. The data from the Economic Censuses provide measures of output, employment and other inputs to explore the relationship between (labor) productivity and human capital measures. The Compustat data on publicly traded firms provide us with measures of output, employment, physical capital, and market value at the firm level. In terms of matching, we first match our employer-employee data to the Economic Census and other business level data at Census. We then match the Compustat data to the combined data from the integrated employer-employee dataset and the Economic Censuses and related data.

Chart 1 provides a brief summary of the data resources used for this project. The chart vastly simplifies the number and complexity of the linkages involved to construct the matched employer-employee datasets. The details of the linkages can be found in the

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[7] Cummins (in this volume) takes one approach to separate out some of these effects (although not in the context of using measures of organizational or human capital). He uses instrumental variable techniques to isolate the contribution of measures of tangible assets by trying to find instruments that are correlated with the measured tangibles but uncorrelated with unmeasured intangibles. As such, he attempts to identify the direct impact of the measured assets. Moreover, his approach in principle avoids another related problem of endogeneity from correlations of the asset variables with unmeasured productivity or market value shocks. Note, however, the unmeasured productivity and market value idiosyncratic shocks likely reflect the idiosyncratic factors that we are seeking to understand. By pursuing an estimation strategy for instruments that are supposedly orthogonal to these shocks, the role of intangibles may be missed entirely.

Data Appendix.[8] However, we provide summary information about the data and matching in the next two subsections.

Chart 1

Data	**Demographic Data**	Links to	**Business Data**	Links to	**Financial Data**
Source:	UI files, CPS, SIPP		LBD, Economic Censuses, Annual Surveys, ACES, RD-1		Compustat
Statistical Unit(s):	Individual, EI		Establishment, EI, Firm		Firm
Key Variables	Earnings, Age, Education, Race, etc	via EI	Employment, Payroll, Sales, Productivity, R&D, Computer Investment, Entry, Exit, etc	via Firm Identifier	Financial Data: Market value, "Q," intangibles, R&D, advertising, Capital, Output, Employment
Availability	By State: Currently have IL, FL, MD for this paper for 1990s.		Nationwide - availability of some measures varies across sectors and years. Economic Census Data available in 1992-97.		Nationwide for 1980s and 1990s.

a) The integrated employer-employee data

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[8] The data appendix is in process and will be included in future drafts.

We exploit new Census Bureau data[9], (part of the Longitudinal Employer-Household Dynamics Program, LEHD) that integrates information from state unemployment insurance data and Census Bureau economic and demographic data in a manner that permits 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 elsewhere (see Burgess Lane and Stevens, 2000). Every state in the U.S., through its Employment Security Agency, collects quarterly employment and earnings information to manage its unemployment compensation program. This database enables us to construct quarterly longitudinal data on employers. The advantages of UI wage record data are numerous. The data are frequent, longitudinal, and potentially universal. The sample size is generous and reporting for many data items is more accurate than survey based data. The advantage of having a universe as opposed to a sample is that movements of individuals to different employers and their consequences for earnings can be tracked. It is also possible to construct longitudinal data using the employer as the unit of analysis. The LEHD Program houses data from a number of states comprising 60% of total US employment, but in this analysis, we use data from the states of Florida, Illinois and Maryland.

Perhaps the main drawback of the UI wage record data is the lack of even the most basic demographic information on workers (Burgess, Lane and Stevens 2000). Links to Census Bureau data overcome this for two reasons: First, the individual can be integrated with 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 data. Second, as discussed in the previous section, LEHD staff have exploited the longitudinal and universal nature of the dataset to estimate jointly fixed worker and firm effects using the methodology described in detail in Abowd, Lengermann and McKinney (2001) and in Abowd, Creecy and Kramarz (2002).

b) The Economic Censuses and related Business-Level Data

The Economic Censuses (conducted every five years) provide a comprehensive data on basic measures like output, employment and payroll for all of the establishments in the United States. In addition, in certain sectors (*e.g.,* manufacturing) more detailed questions on other inputs (*e.g.,* capital) are asked.

Our first goal is to create a matched dataset linking the human capital measures to the Economic Census data. For the current paper, we focus on the Economic Censuses in 1997. One issue that immediately arises is the level of aggregation. While the Economic

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[9] The development of these data has been generously supported by the Census Bureau, the National Science Foundation, the Sloan Foundation and the National Institute on Aging as part of a social science database infrastructure initiative.

Censuses are at the establishment level, the business level identifiers on our human capital measures are at the EIN, SIC (2-digit), and state level.[10] As such, we aggregate the Economic Census data to that level and match to the human capital files. While the unit of observation here is somewhere between the establishment and the firm, most of the observations are at the establishment level. For multiunits reporting under a single EIN in a state we aggregate the establishment data to the 2-digit SIC, state level. In what follows, we begin our analysis of the relationship between human capital and productivity using this "quasi-establishment" level data. For this analysis, we have roughly one half million business units that we can match to the Economic Censuses (out of a universe of roughly 700,000 business units at this level of aggregation from the UI files for the 3 states used in this analysis). Most of the UI businesses that we cannot match to the Economic Censuses are out-of-scope of the Economic Censuses (*e.g.,* agricultural businesses).

We are also able to accomplish essentially the same thing in non-Census years using the Census Business Register, previously known as the Standard Statistical Establishment List (SSEL). While the SSEL has limited information, it does identify the ownership structure of firms so that we can further aggregate to the enterprise/firm level. Doing the latter aggregation permits us to match enterprise level data on human capital to Compustat.

Since we are working with only 3 states, we are limited in our ability to examine evidence for large companies that operate in multiple states. We use a threshold rule (*e.g.,* 90 percent of employment in the company must be in these three states) to restrict attention to companies for which we can measure human capital and firm outcomes like market value and productivity in a comparable fashion. In what follows, we first aggregate our human capital estimates up to the firm level for all firms in our 3 states (using the 90 percent rule as noted). The resulting sample contains roughly 450,000 firms. We use this sample to investigate the relationship between human capital and productivity at the enterprise/firm level. We then restrict attention to Compustat firms that restricts the sample substantially as there are approximately 13,000 Compustat firms nationally. For this restricted sample, we again investigate the relationship between human capital and productivity and also investigate the relationship between human capital and market value.

4. Human Capital Estimates

The results of the human capital estimation are based upon data for the states of Florida, Illinois and Maryland for the years 1990-99 and use the specification in (1). While the methodology and estimates that we use are discussed in detail in ALM, we provide a brief summary of some of the features of the human capital estimates before relating these new estimates to productivity and market value.

[10] The identifiers in the LEHD Program's human capital data provide additional geographic and industry information but they are not coded down to the workplace (establishment) level. Ongoing research attempts to refine the most disaggregated economic entity available in these data.

Some of basic features of the estimates (for the state of Illinois) are shown in Table 1. Table 1 illustrates a number of interesting points. First, the contribution of worker and firm effects to worker earnings are roughly equal.[11] Second, the R^2 of this earnings regression (1- $.402^2$) is approximately .84 – a great deal higher than regressions based simply on worker characteristics. Third, in ALM they augment the analysis by decomposing the person effect into the part attributable to time-constant observable characteristics such as gender and education and the part attributable to unobservable characteristics. The fourth and fifth rows of the table illustrate the results of this decomposition. The unobserved component is much more important and more highly correlated with wages than the observed component of the person effect. Fourth, the different components of human capital (*i.e.*, the person effect and the experience component) exhibit different variation and covariation. Indeed, an interesting feature of the person effect and experience effect components is that they are negatively correlated. While this result is not surprising as, for example, younger generations of workers are more highly educated, it is important to note as it reminds us that there are different dimensions of skill that need to be taken into account. Finally, one surprising aspect of this comprehensive decomposition of the wages is that the correlation between the person effect and the firm effect is virtually zero at the individual level. While we do not pursue explanations of this somewhat surprising finding, we note that aggregations of the person and firm effects to various levels of aggregation yields a strong and positive relationship. For example, ALM show that at the industry level, person and firm effects are positively related. Interestingly, Abowd, Haltiwanger, Lane and Sandusky (2001) show that at the firm level, person and firm effects are positively related after controlling for output, local wage effects and broad industry. These results by industry and at the firm level are quite relevant here since they suggest systematic sorting of workers across different firms and industries.

In the next subsections, we first provide some summary information about how these new measures compare with the JGF-like measures of human capital. We also describe the differences in the two components of the AKM measure of human capital – experience and person effects – and how they vary across workers. Finally, we examine the degree to which the human capital measures vary across firms and industries

Table 1
Summary of Estimated Wage Equation [a]

Component	***Standard Deviation***	***Correlation with*** $\ln w$	$x\beta$	θ	α	$u\eta$	ψ	ε
Log real annual wage rate ($\ln w$)	0.915	1.000						
Time-varying personal characteristics ($x\beta$)	0.533	0.334	1.000					
Person effect (θ)	0.710	0.549	-0.405	1.000				
Unobserved part of person effect (α)	0.674	0.481	-0.427	0.949	1.000			
Non-time-varying personal characteristics ($u\eta$)	0.224	0.295	0.001	0.315	0.000	1.000		
Firm effect (ψ)	0.379	0.523	0.160	0.021	-0.017	0.119	1.000	
Residual (ε)	0.368	0.402	0.000	0.000	0.000	0.000	0.000	1.000

Notes: a. based on 46,562,383 annual observations from 1990 to 1998 for 9,831,217 persons and 450,006 firms in the State of Illinois. Sources: Authors' calculations using the LEHD Program Employment Dynamics Estimates data base.

[11] We do not exploit the firm effects in this draft of the paper but plan to incorporate in future drafts.

a) A Comparison of New and Traditional Measures of Human Capital

While in principle, the JGF methodology can be applied equally well to measuring both sectoral and aggregate labor quality, in practice, the LEHD approach permits more within and across industry heterogeneity. In separate work, Lengermann (2002) has developed sectoral aggregates of human capital following the Jorgenson, Gallop and Fraumeni (JGF) approach and compared them to LEHD estimates. Briefly, the JGF approach incorporates data from the Censuses of Population, the Current Population Survey (CPS), and the National Income and Product Accounts (NIPA) and based labor quality indices on cell based totals of labor inputs classified by sex, age, educational attainment, employment class, and industry. We summarize the results of two different types of comparison here.

The first “direct” approach compares the JGF indices to sectoral labor quality derived from industry averages of our human capital measure for the period 1995-1998. JGF formally define labor quality as the ratio of the total volume of labor to hours worked, where volume is measured by a constant quality index of labor quantity. The LEHD measure of industry average human capital follows essentially the same logic, where the measure of labor volume is also based on a constant quality human capital measure, and where total employment substitutes for total hours worked. Neither approach is completely satisfactory, because while LEHD data cannot measure hours worked, the JGF constant quality index of labor quality confounds firm heterogeneity with person heterogeneity.

We compare the growth rates in the human capital indices over the 1995-98 period using the LEHD-based and JGF approach. The within-industry growth rates are highly correlated – the employment-weighted average of the sectoral correlations is 0.79. However, there is much higher average growth for any given industry and more cross-industry variation in those growth rates in the LEHD measures compared to the JGF measures (the average growth rate for the LEHD measure over the 4 years is 0.04 with the cross industry standard deviation of 0.067 while the corresponding growth for the JGF is 0.014 with a cross industry standard deviation of 0.001).

In what follows, we exploit cross sectional variation (across firms) in their human capital while the JGF procedure focuses on generating growth rates of human capital by industry. As such, the JGF measures are not well-suited to examining within-year, cross-industry variation. Thus, as a second “indirect” approach we approximate the JGF labor quality indices by indices derived from predicted industry average wages obtained by regressing wages on age, education, and sex using the CPS. For this purpose, we use the same cells used by JGF. We show that the time series growth rates of these indirect measures are highly correlated with the actual JGF measures (the employment-weighted average correlation is 0.73). Thus, the CPS-based approach does a reasonable job of approximating the more sophisticated JGF measures.

We compare the cross-industry variation in the CPS-based measures with the same variation using the LEHD measures for the year 1998. The two measures are, in principle, comparable because both rely on regression approaches that attempt to isolate the component of wages due to individual characteristics. However, because LEHD data permit the distinction of individual from firm contributions to wages, one might not expect them to yield identical results. Workers sort non-randomly into firms based on their own characteristics – both observable and unobservable – and the characteristics of firms. Furthermore, firm wage premia – the firm effects in the wage regression (1) – are not distributed uniformly across industries. These two facts mean that there exists a strong, positive correlation between person and firm heterogeneity at the industry level (AKM) – a correlation that the JGF cell-based analysis cannot disentangle.

We plot the industry level aggregates for the CPS-based approach against the industry level aggregates for the most inclusive measure of skill from the LEHD approach and report them in Figure 1. Although the levels are normalized differently, there is clearly a great deal of correlation between the two measures – indeed, the correlation is 0.76. However, there is somewhat more cross industry variation in the LEHD-based measure than in the CPS-based measure (the standard deviation of the former is 0.15 and the standard deviation of the latter is 0.13).

In summary, the LEHD-based measures by industry are closely related to those derived by JGF or a simpler but closely related CPS-based procedure. However, LEHD-based measures generate greater average growth and more cross-sectional variation in both growth rates across industries and in levels of human capital across industries within a year.

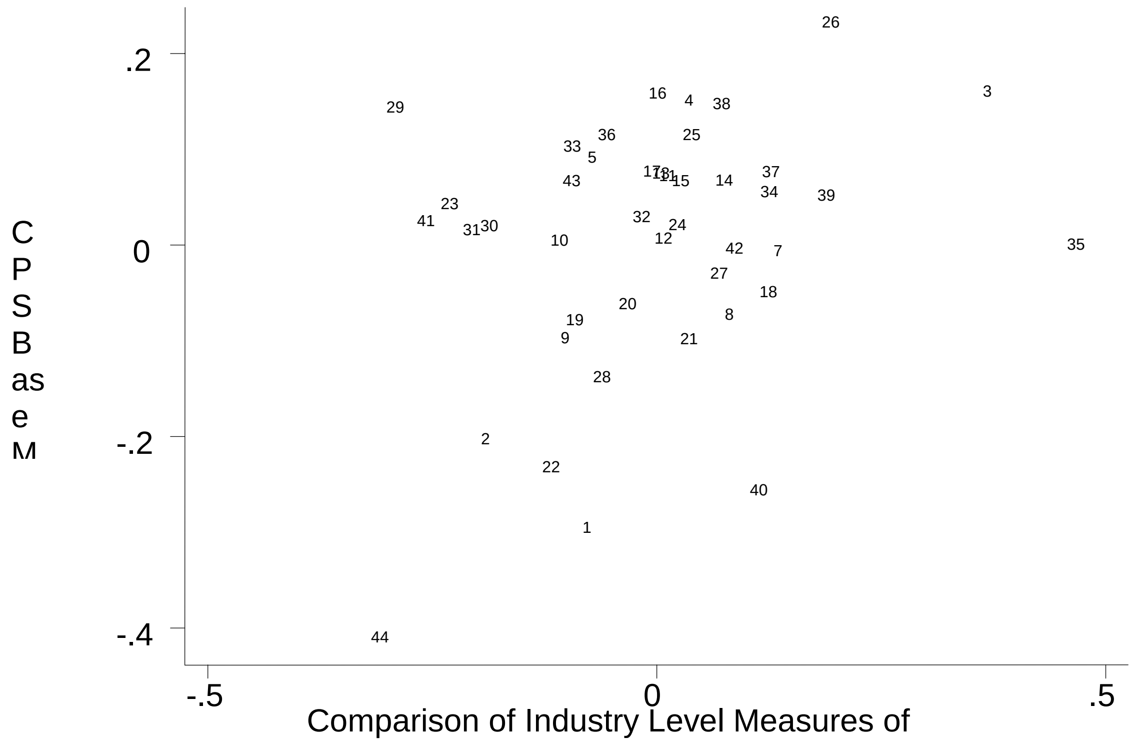


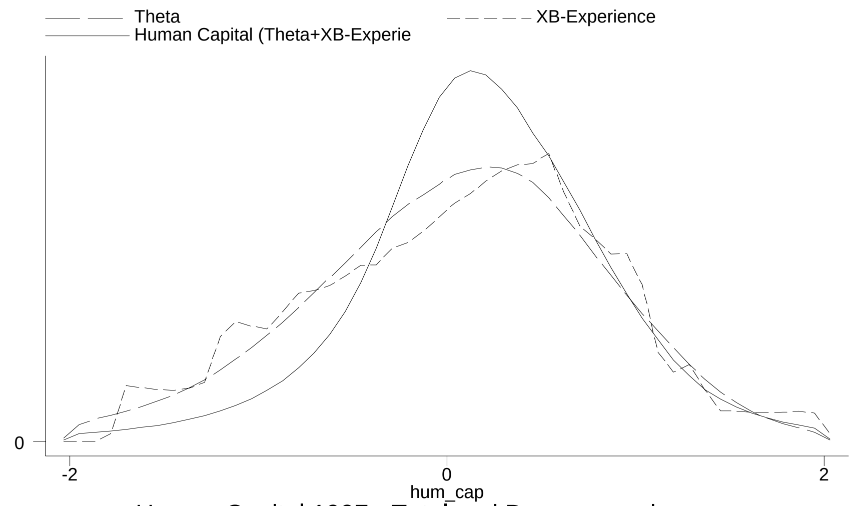
Figure 1

b) The construction of new human capital measures

A major contribution of this approach is the richness of the new measures of human capital, and these are fully discussed in ALM. Here, we explore some of the key features of the new measures, particularly aggregated to the firm level. For this purpose, we use four worker/firm traits to build measures of the human capital resources available to firms: the person effect (θ), overall labor market experience of each worker captured by the experience component of $x\beta$ (denoted $x\beta$ in this section), the sum of these two components (overall human capital, or "*h*"), and the amount of firm-specific tenure each worker has accumulated. The first three are traits of workers. The last, firm-specific tenure, captures some information about the worker and serves also as a way to measure a firm's ability to retain its workers.

We describe the distribution of the first three in Figure 2. The key point here is that the three measures differ substantially: while the distribution of the person effect is bell-shaped, has thick tails and high variance, the distribution of experience is less smooth, and the distribution of human capital, the sum of θ and $x\beta$, is roughly bell-shaped, centered about zero, and has much less mass at the tails than either experience or θ because the two measures are negatively correlated. This result is consistent with pairing in the population of workers of high person effect, low experience and low person effect, high experience. Indeed, the experience distributions for high θ and low θ workers are substantially different [12].

Figure 2



Human Capital 1997 - Total and Decomposed

The distribution of the fourth measure of human capital, firm-specific tenure, is bimodal: workers largely have either very short or very long spells of employment with specific firms. Just as with the experience measure, tenure is quite heterogeneous across skill groups: there are marked differences in tenure for high θ and low θ workers - suggesting that a worker's skill and length of attachment to specific firms are not independent. Not surprisingly, we find general labor market experience and firm-specific experience to be positively correlated. However, because this relationship is largely mechanical, we do not focus on it here.[13]

In sumary, our evidence suggests that the distribution of overall human capital among workers is influenced by the distribution of its two component parts as well as by the joint relationship between the person effect and labor market experience. The same patterns hold for firm-specific tenure.

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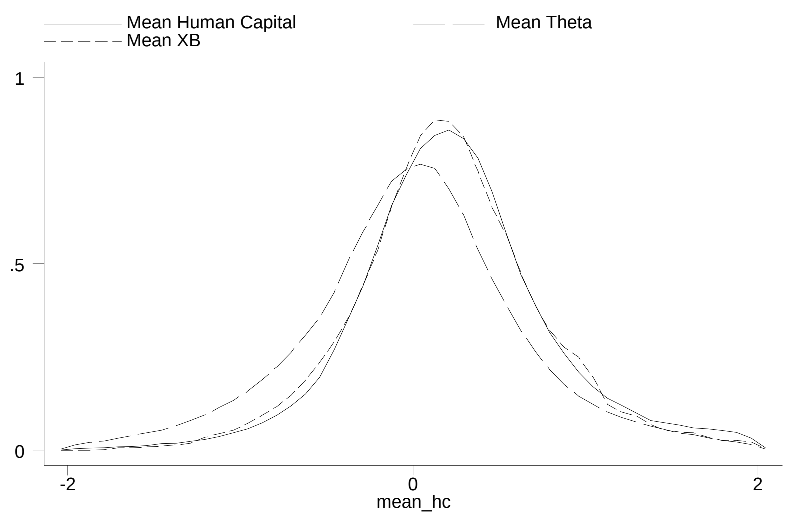
[12] When we examine the XB distribution for high theta workers it has very large mass at somewhat low experience and exhibits a continuous decline in mass as XB rises. The distribution for low theta workers, on the other hand, is bimodal: one peak occurs at extremely low experience, the other peak at very high XB. The close correspondence between worker age and XB may underlie this negative correlation between theta and XB. Younger workers have less general labor market experience but also may be more highly educated or are more likely to have an education that is well suited to the training needs of the current economy (all captured by a higher θ)

[13] The current draft uses a seniority measure that is left-censored. Future work will correct the seniority measure (as in AKM) for this problem.

c) The construction of firm level measures

While the different worker-level measures of human capital provide a useful context, the focus of this paper is on developing firm level measures of human capital and relating them to firm outcomes. Since we have constructed the entire distribution for each firm, any number of measures are available, but we begin with measures of central tendency for our three key measures: mean θ, mean $x\beta$ and mean "*h*," shown in Figure 3. Unlike the distributions for θ and $x\beta$ among workers, the distributions of mean θ and mean $x\beta$ across firms very closely resemble the bell-shaped distribution for composite human capital. All three distributions are roughly bell-shaped with low weight in the tails. It is evident that, as expected, the distribution of firm level mean human capital "*h*" is more compressed than that for all workers. However, it is also evident that the compression effect is even stronger for the experience and skill distributions – suggesting that some within-firm dispersion exists.

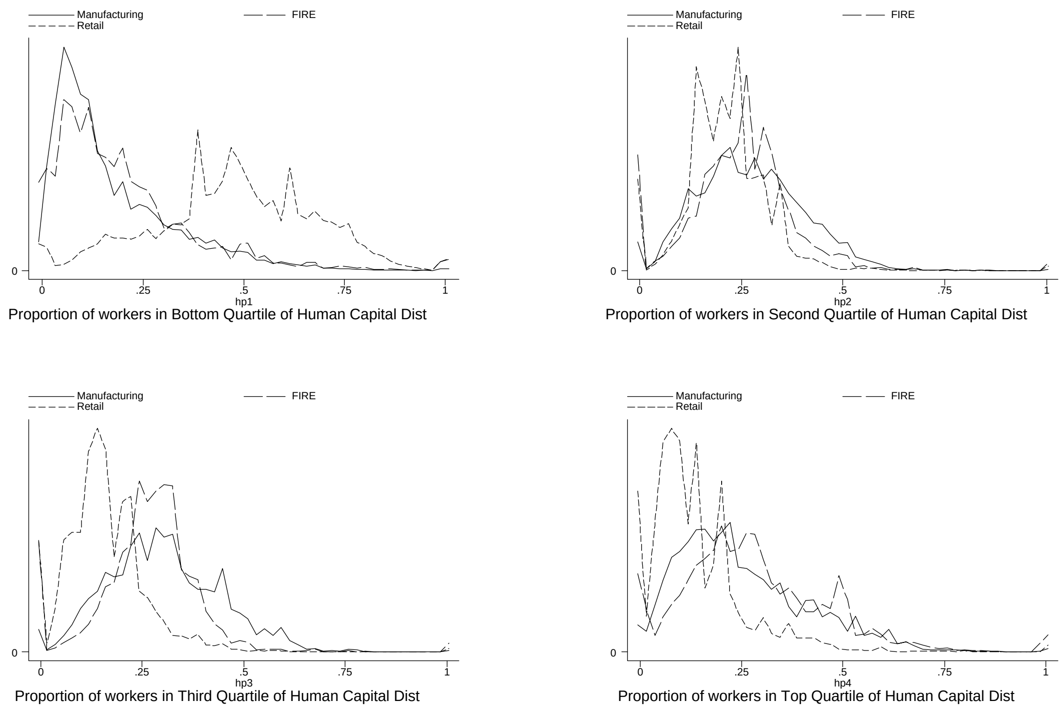
Figure 3



Distribution of EIN-SIC2 Mean Human Capital - Total and Decomposed

But we can do more than examine the distribution of firm-specific means. We can, for example, construct measures of the proportion of high skill and low skill workers in each firm. In this case, we choose as a measure of high skill the proportion of workers in a firm who are above the economy wide 75th percentile skill threshold, and as a measure of low skill the proportion of workers who are below the economy wide 25th percentile skill threshold. There are substantial differences both within and across industries, as illustrated in Figure 4. In particular, manufacturing and FIRE have very similar distributions for low-skill workers: very large numbers of firms have low shares. The distributions are quite different for higher skill groups: firms in FIRE appear to have an increasingly large share of high human capital workers relative to manufacturing firms. Specifically, while manufacturing firms have a larger share of workers in the second and third quartile of the overall human capital distribution, firms in FIRE have a larger share of highest human capital workers. Retail is an the exception. A large percentage of retailers have more than 50 percent of employment in the bottom quartile of workers (compared with less than 25 percent for the majority of businesses in Manufacturing and FIRE). Relative to firms in the other two sectors, most retailers have a smaller share of workers with intermediate (second and third quartile) levels of human capital. However, retailers in general have a larger share of top quartile workers than many manufacturers, though smaller than that of most firms in FIRE.

Figure 4



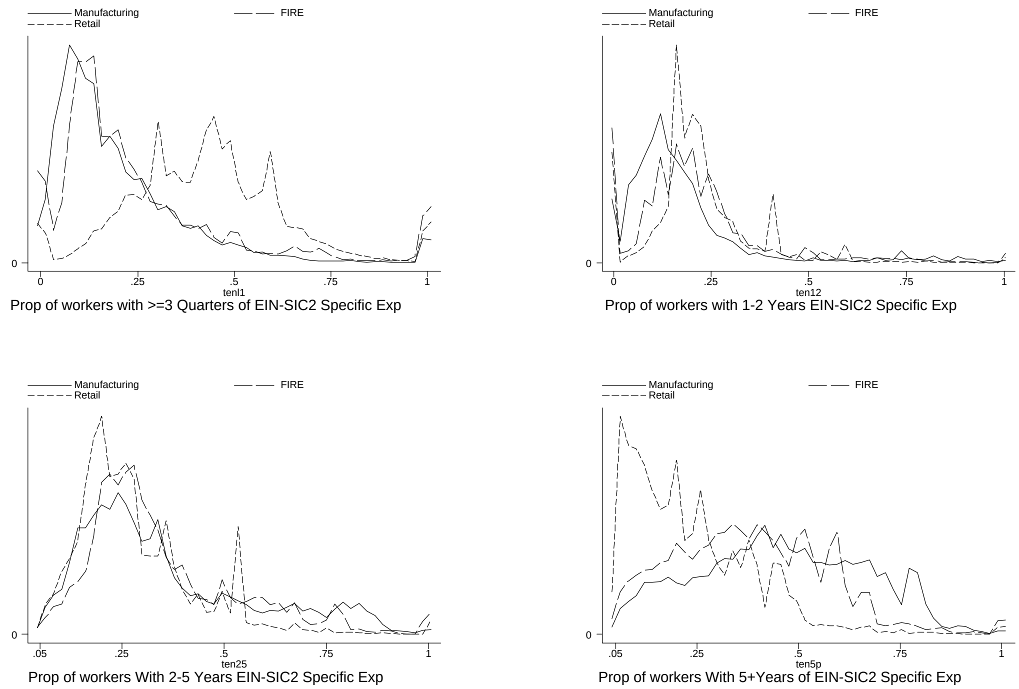
The richness of this picture is made even more evident when we examine the separate components of human capital. All three sectors, including manufacturing and FIRE, differ substantially in their share of high (low) θ and $x\beta$ workers. Though manufacturers and businesses in FIRE are very similar in share of low overall human capital workers (with retailers having notably more low human capital workers overall), this result is driven largely by $x\beta$. Businesses in the three sectors differ notably in share of low θ workers. However, there are some differences. Most FIRE establishments have a slightly higher proportion of low experienced and a much lower proportion of highly experienced workers than manufacturers. This pattern is reversed for the distribution of theta.

Thus, the negative correlation of the person effect and labor market experience observed among workers may be preserved both by manufacturers and service businesses in FIRE (though more evidence is needed to establish this conclusively). However, despite substantial within-sector staffing variation, the draws from the worker distribution made by each sector are not random – manufacturers systematically choose lower skilled and higher experience whereas the more service oriented FIRE establishments largely choose high-skill and low-experience workers. Retailers, on the other hand, choose a large number of low-skill workers as well as a large number of low experience workers. There is some evidence that employers in different sectors target workers in very specific segments of the joint skill/experience distribution.

We have also examined the dispersion of human capital within firms, particularly focusing on how this within-firm dispersion varies across observable characteristics like industry. We find, for example, that within-firm dispersion in both skill and experience is very similar for manufacturing firms and firms in FIRE, but very different for retail businesses. A large number of retailers evidence much wider ranges of "skill" levels within establishments than in other sectors. In addition, retailers are also more likely than businesses in the other sectors to be in one part of the distribution or another: either a workforce with very similar levels of overall labor market experience (low $x\beta$ dispersion) or workers with a wide range of experience (high dispersion). While this discussion only briefly touches on the interesting variation in the distribution of human capital across firms, for our purposes the main point is that there is considerable and systematic variation in the choice of the mix of workers across firms.

Our fourth measure of human capital - firm-specific worker tenure – also differs across sectors. Figure 5 illustrates the differences across sectors. Manufacturers and FIRE businesses have very similar shares of low tenure workers. In both sectors, most businesses have only a small fraction of workers who leave in less than one year. Among retail establishments, on the other hand, a large number of firms have fifty to seventy-five percent of workers who leave in less than a year. In all three sectors, the distributions are very similar for the share of workers who accumulate 1-2 years of firm-specific experience or 2-5 years of tenure.

Figure 5



Differences in firm personnel strategies are very evident as well. If we examine the subset of businesses who have at least one worker with high tenure (5 or more years), over 75 percent of workers at many manufacturing establishments have worked five or more years with the same employer. By contrast, among retailers having any high tenure workers, a very low fraction of all workers are in this tenure group.

To summarize, many workers traits are found in combination in the population of workers. High θ workers, for example, are more likely to have longer tenure spells with employers. When these human capital traits are grouped by businesses, we find that they are grouped in systematic ways by businesses in different sectors. Manufacturers, for example, tend to employ workers with high general labor market experience, select workers with lower "skill," and maintain longer duration relationships with their employees. Service businesses in FIRE, on the other hand, are more likely to employ high θ workers with little overall labor market experience but still have the ability to retain workers longer term. Finally, retailers primarily employ low θ, low labor market experience workers but exhibit far more within-firm diversity in these traits (experience in particular). Retailers also retain workers for far shorter periods of time than establishments in the other sectors. Because these differences in human assets across sectors are so pronounced and may be selected for productivity enhancing reasons, we take pains to capture these similarities and differences when building measures of a firm's human resources for use in later sections.

5. The Relationship Between Productivity and Human Capital at the Micro Level

In this section, we explore the relationship between our various rich measures of establishment level human capital and establishment and firm level productivity[14] controlling, as possible, for other relevant factors (e.g., capital intensity). For this purpose, we focus on the 1997 Economic Census and our measure of labor productivity is revenue per worker. The latter measure is the standard measure used in official BLS productivity statistics for gross output per worker.[15]

An open question for this study is what measures of human capital are relevant. From a traditional viewpoint, we clearly want to control for some measure of the location of the distribution of human capital at a business. However, from the perspective of considering the organization of human capital at a business, we want to explore alternative measures that capture the interaction of different types of workers – the tails of the distribution and in a like manner the within-firm dispersion at the firm. Our approach is necessarily exploratory since there is little practical guidance from either theory or prior empirical research. Accordingly, we explore the role of the following measures: (i) the fraction of workers at the business above the state-wide median human capital threshold; (ii) the fraction of workers at the business above the state-wide 75th percentile human capital threshold; (iii) the fraction of workers at the business below the state-wide 25th percentile human capital threshold; (iv) the interaction of the latter two measures – literally the product of these two fractions; and (v) the fraction of workers at various levels of firm-specific tenure. For these measures, we consider them using the overall human capital measure "*h*" and also consider these measures based upon the separate components of human capital (the person effect, θ, and the experience component).[16] Moreover, we consider a range of specifications – parsimonious specifications with only a small number of summary human capital measures and richer specifications with a number of measures of the distribution included.

Table 5.1 presents the means and standard deviations of these measures along with labor productivity for our overall sample and the manufacturing only businesses. For the latter we can also measure capital intensity. The statistics reported in the table are based upon the employment-weighted distribution. In section 4, we have already discussed many of the features of the human capital distribution across businesses. However, a few points are worth making here. First, there is tremendous heterogeneity across businesses in their

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[14] Recall that the level of aggregation that we use to approximate the establishment is that of an EIN/SIC2/STATE cell. As noted above, while this is somewhere between the establishment and the firm, however, most of the units are single-units

[15]The official estimates include adjustments for changes in inventories in inventory holding sectors. However, studies by Foster, Haltiwanger and Krizan (2001) show that in manufacturing the correlation between labor productivity measured as shipments per worker and labor productivity measured as shipments adjusted for inventory changes is extremely high (almost 1).

[16]Note that the state-wide thresholds are based on the universe of all workers in the 3 states (not just workers employed at the businesses we match to the Economic Censuses). Note as well that we also generated versions of these measures based upon state by industry thresholds (so the interpretation would then be having a high fraction of highly skilled workers relative to, say, the median of the industry in the state). We found that the results are virtually identical to those reported here.

mix of human capital as evidenced by the very large standard deviations in the human capital measures. Second, it is apparent that manufacturing has higher labor productivity and workers with higher human capital (on both the person effect and experience dimension).

Table 5.2 presents our exploratory analysis of the relationship between our measures of the distribution of human capital using the measure "*h*" and Table 5.3 presents the analogous results using the components of "*h*" separately. Before discussing results for alternative specifications, it is important to note some features that hold for all results. In all cases, the results are based upon employment-weighted regressions. All analyses included 2-digit fixed industry effects, which are highly significant. Finally, in all cases, we control for fraction of workers with different amounts of firm-specific tenure. We find uniformly that businesses with workers with more tenure have higher productivity. This latter result is interesting in its own right because it suggests that the retention policies of businesses are important and obviously job tenure is an alternative relevant measure of firm specific human capital. Even more interesting, the explanatory power of each set of regressions is uniformly high, suggesting that measures of human capital are - either directly or indirectly – important drivers of cross-sectional differences in productivity. The fact that the explanatory power for the manufacturing sector regressions is uniformly substantially less than the regressions for all sectors is consistent with the notion that human capital is more important for the service sector than manufacturing – and more important for the "new" economy than the "old" economy.

Starting with the first columns in Tables 5.2 and 5.3, it is apparent that businesses with a greater fraction of workers above the median human capital level for their state are much more productive. For the overall human capital measure, a one standard deviation change in this fraction is associated with a 34 log point change in labor productivity (Table 5.2). For the person effect measure (Table 5.3), a one standard deviation change in the fraction of high human capital workers is associated with a 28 log point change in labor productivity. For the experience component, a one standard deviation change in the fraction of high human capital workers is associated with a 16 log point change in labor productivity (Table 5.3). While these effects are very large, observe that they reflect only a fraction of the standard deviation in measured labor productivity across businesses (which is 110 log points).

The second column of Tables 5.2 and 5.3 consider alternative measures of the distribution of human capital – focusing on the fraction of high human capital and low human capital workers. Businesses with more workers in the top quartile and fewer workers in the bottom quartile are substantially more productive. This latter result holds for both the overall "*h*" measure and the components of the human capital measures. Part of the motivation for this specification is to examine whether there is an asymmetric effect of changes in the upper tail and lower tail of the distribution of human capital in the firm. The results in Tables 5.2 and 5.3 indicate some interesting asymmetries. For the overall human capital measure, an increase in the lowest quartile has a larger absolute (negative) effect than the corresponding absolute (positive) effect from an increase in the upper quartile. Table 5.3 shows that this result is being driven by the person effect.

The third column presents an even richer specification in that it represents our attempt to capture the interaction between high skill and low skill workers. As before, we find that businesses with more workers in the top quartiles of the human capital distribution and fewer workers in the lowest quartiles of the human capital distribution are more productive. However, we also find that businesses that mix both high-skill and low-skill workers in high proportions (the interaction of the two tails in the overall human capital distribution) are more productive. But, as shown in Table 5.3, interestingly this finding is reversed for the components of "*h*". That is, the interaction of the two tails of the person effect component is associated with lower productivity and the interaction of the two tails in the experience effect is associated with lower productivity. We interpret these interaction effects as capturing a measure of dispersion in the human capital distribution within the firm.[17] In a like but more precise manner, these interaction effects are literally telling us whether an increase, say, in the upper tail of the distribution has a larger effect depending upon the share of workers in the lower tail.

We find it striking that the overall interaction effect goes one way while the components work in the opposite direction. Our interpretation is that it is good for productivity to have more uniformity of workers in terms of the person effect and experience separately but it is good for productivity to have a mix of workers across these different dimensions of skill.[18]

The magnitude of the effects in these richer specifications is also very large although it is somewhat more difficult to summarize the overall contribution of variation in the human capital distribution at the firm since a number of measures are taken into account. However, even a term-by-term analysis shows that the effects are large. For example, in the richest specification in column three, increasing the fraction of workers above the 75th percentile for the person effect measure of human capital by one standard deviation is associated with almost a 10 log point change in labor productivity.[19]

The last four columns of Tables 5.2 and 5.3 show results for the manufacturing sector. The fourth column replicates the first column but for manufacturing only. The fifth column adds capital intensity as an additional measure. For the most parsimonious specification, the results for manufacturing are quite similar to those for the overall economy when we do not control for capital intensity. Controlling for capital intensity does not change the qualitative nature of the results but does reduce the magnitudes of the effects substantially (although they remain very large). This aspect of the findings is important because it, not surprisingly, suggests that human capital is complementary with physical capital. Thus, as we discussed in section 2, we need to recognize that our

[17] The correlation between this interaction term and a direct measure of dispersion in the firm (e.g,. the within firm standard deviation of human capital) is around 0.5.
[18] We could test for this "covariance" effect across skill dimensions more directly and plan to do so in future drafts.
[19] Note that in making this calculation we have taken into account the interaction effect evaluated with a one standard deviation change in the 75th percentile for the person effect and at the mean for the 25th percentile of the person effect.

measures of human capital are capturing both direct and indirect effects (where the latter stem in part from unobserved factors such as tangible and intangible assets).

The last two columns of Tables 5.2 and 5.3 present results for manufacturing using the richer specification used in column 3 for all sectors – with and without controlling for capital intensity. Again, the results are quite similar to those for all sectors without capital intensity and again adding capital intensity reduces the magnitudes of most of the effects from the human capital measures. Interestingly, the interaction effects of the two tails become more important after controlling for capital intensity.

Putting the results for manufacturing together, there is clear evidence of capital-skill complementarity. Interestingly, it appears that there is capital-skill complementarity for all of the dimensions of skill we are investigating. That is, including capital intensity reduces the magnitude of the impact of the person effect, the experience component and the firm-specific tenure effects. There is some evidence that capital is more complementary with the most skilled workers as the last column of Table 5.2 shows that controlling for capital intensity reduces the effect of having a greater share of workers above the 75^{th} percentile much more than reducing the absolute impact of having a large share of workers below the 25^{th} percentile.

How sensitive are these results to the level of aggregation? We address this issue by aggregating establishment level data from the 1997 Economic Censuses to the firm level and estimating a set of similar regressions. The results are reported in Tables 5.4 and 5.5. While the qualitative results are very similar - the relationship between human capital and productivity is strong and positive – the magnitudes of the estimated coefficients on the human capital measures at the firm level are generally smaller than those in the "establishment" level regressions. This particularly holds true for the manufacturing sector, and particularly when using the overall "*h*" measure of human capital. This may be due to increased measurement error in the human capital measures at the firm level. This arises since the Census-based firm-level unit differs more from the UI-based data upon which the human capital measures are based that the EIN/SIC/State units used above. We also find that some of the interaction effects work somewhat differently or are less significant. Such interaction measures are potentially less meaningful at the firm level as the dispersion within the firm might reflect dispersion across separate establishments at the firm.

Overall, the results overwhelmingly make the case that understanding differences in labor productivity across businesses – particularly outside of manufacturing – involves understanding the differences in the human capital across businesses. Regardless of whether these are direct or indirect effects and regardless of endogeneity issues, it is clear that the differences in labor productivity across businesses are closely related to the differences in the human capital mix across businesses, as evidenced by the very large R^2 in the regressions. The results also clearly suggest that it is not simply a measure of central tendency of the human capital distribution that matters. The fraction of workers at the tails of the distribution and, in a related matter, the dispersion of human capital matters. Perhaps the most intriguing aspect of the results are the findings that the different components of human capital matter in different ways. Our results show that the most productive firms are those that have low dispersion in the person effect and low dispersion in the experience component but a mix of workers across person effect and experience components. These findings clearly suggest that the organization and mix of the workforce matters substantially.

6. Investigating the Relationship Between Market Value and Human Capital

While we have several alternative samples and levels of aggregation at which to investigate the relationship between productivity and human capital, market value is measured only at the firm level, and only for publicly traded firms. Therefore we are constrained to using the relatively small matched Compustat sample. We report the means and standard deviations of this subset of observations in Table 6.1 for 1997[20]. Clearly these firms are more human capital intensive than the full sample – the proportion of the workforce above the median economy-wide threshold of skill (all measures) is greater, as is the proportion above the 75th percentile. The proportion below the 25th percentile, by contrast, is smaller. However, there is still substantial heterogeneity in all measures: although the mean of each variable is different in the two samples, the standard deviations are very similar.

Tables 6.2 and 6.3 present results of estimating equation (3) (the (log) market value regressions) using our two sets of human capital measures. [21] In all specifications, we find a strong and positive relationship between (log) market value and physical and other assets consistent with the theory and the empirical literature. [22] Our value-added is that we can also measure human capital at the firm level. In our simplest specification (the first columns of Table 6.2), a larger fraction of employees in the upper half of the human capital distribution is associated with significantly greater market value. This, in itself, is an interesting result, since, if highly skilled workers are compensated proportionately to their skill, *and* there is no complementarity between unmeasured assets and human capital, there should be no effect on market value once these other variables have been controlled. Yet the estimated effect of human capital effect is quite large: a one standard deviation increase in the proportion of the workforce that is above average is associated with an approximately 18 log point change in market value (set against a quite large standard deviation of market value of 1.86).

The decomposition of this result into its component parts (the first column of Table 6.3) is even more striking, however. In particular, all the effect on market value is due to workers who have higher θ – while both high-θ and highly experienced workers are more productive (Table 5.3), it is only the person effect that is related to market value. Equally

[20] Because we use a log specification, we eliminate firms with missing or zero values. This results in an even smaller sample than the Compustat matched sample used in the previous section. The excluded firms tend to have more skilled workers, with greater representation in the upper tail of both the person effect and experience components. They also have on average workers with greater than average levels of tenure.
[21] The reported results are based upon pooled data for 1995-98.
[22] For this log linear specification, the coefficients on a particular asset (e.g., log of physical capital) should reflect the share of that asset in the total.

interesting results are evident on the additional measure of human capital: firm specific tenure. By and large, longer tenured workers are more productive (Tables 5.2 and 5.3) – but the regressions presented in Tables 6.2 and 6.3 suggest that this translates into a substantial negative effect on market value. More research is necessary to determine whether this tenure effect is due to unionization, pension liabilities, rent sharing, recent firm growth, high turnover, firm age or a host of other possibilities.

When we examine the effects of human capital on market value using other measures of human capital (high-skill and low-skill workers, and the interaction between the two), we find very similar results (columns 2 and 3 of Tables 6.2 and 6.3). Firms with a workforce consisting of high-skill workers have higher market value – and this is entirely attributable to the θ component. Indeed, an examination of the second and third columns of Table 6.3 reveals that this is primarily due to a discount for having a very unskilled workforce. We find it striking that it is the person effect that is important here. Recall the person effect is the component that includes "unobservable" components of skill. Thus, one interpretation of these results is that value creation is highest for firms that do a better job of attracting and retaining workers with difficult to observe dimensions of skill.

Again, more research is necessary to determine whether these findings are due to the complementarities between high skill workers and unmeasured assets. We find little evidence that the interaction between high skill and low skill workers is instrumental in affecting firm market value. Although we found the dispersion within firms to be important for productivity, we find little evidence that such dispersion effects are reflected in market value. However, as noted above in discussing aggregation issues, these dispersion measures may be much less meaningful for large, complex multiunit firms which are over-represented in our market value regressions.[23]

Overall, there is evidence that a more skilled workforce is associated with greater market value, with skill as captured by the person-effect component driving this relationship. A workforce with more job-specific experience has a negative association with market value. We are not successful in teasing out what part of these distributions matter most, nor whether interactions between different parts of the distributions are important. Given the limitations of our sample, it is not clear whether the more detailed relationships we would like to examine are not there, or if our sample is simply too small to provide the needed precision.

7. Summary and Concluding Remarks

[23] In future drafts we plan to investigate the role of aggregation across establishments in the same firm in impacting the nature and impact of these dispersion measures.

We began by noting that measurement of intangibles and human capital is an important challenge for the federal statistical system, particularly given the advent of the New Economy. We argued that it was important to find and quantify new measures of human capital that could be introduced into a firm-level production function and used in official economic statistics. This paper uses universe micro level data on both employers and employees to create new measures that begin to address this challenge.

The paper provides an overview of these new measures, and documents substantial consistency with earlier measures pioneered by Jorgenson, Gollop and Fraumeni (1987) (and subsequent closely related work). But it extends their work in ways that permit these human capital measures to vary within and between firms in the same way that other inputs and outcomes can vary. In addition, we examine different aspects of human capital: pure skill, experience, tenure and a summary measure, and find marked differences in their distributions. We also use the richness of the data to describe the interrelationship of the firm level human capital distribution to capture relevant aspects of firm level differences in organizational capital and workplace practices.

Our preliminary results, which examine the relationship between human capital and market value and productivity, are intriguing. Not surprisingly, we find strong positive relationships between human capital and productivity in the micro data, with interesting interactions between high skill and low skill workers, which differ depending on the component of human capital used. We find that human capital is also related to market value even after controlling for total physical assets. Interestingly, it is the component of skill that includes “unobservable” (at least to the econometrician) factors that is most closely related to market value. At this stage of our analysis, we are unable to separate out the observable and unobservable components of skill. In future work, it will be quite interesting to explore this aspect of the analysis and results.

We close by emphasizing that this work is exploratory. It is exploratory on many dimensions including the new, micro-based measures of human capital that incorporate unobservable dimensions of worker’s skill and the role of such human capital in accounting for variation across firms in the U.S. economy. As we have emphasized, the strong empirical relationships that we have uncovered may reflect a variety of direct and indirect effects of human capital.

Table 5.1: Mean Values of Variables in Log Productivity Regressions				
Variable:	All sectors		Manufacturing Only	
	Mean	Std Dev	Mean	Std Dev
Log Labor Productivity	4.539	1.101	5.068	0.841
Fraction of Workers Above 50^{th} Percentile for Overall *"h"*	0.458	0.238	0.554	0.215
Fraction of Workers Above 75^{th} Percentile for Overall *"h"*	0.228	0.181	0.252	0.161
Fraction of Workers Below 25^{th} Percentile for Overall *"h"*	0.312	0.223	0.175	0.152
Interaction of Fraction Above 75^{th} Percentile and Fraction Below 25^{th} Percentile for Overall *"h"*	0.045	0.035	0.031	0.024
Fraction of Workers Above 50^{th} Percentile for θ	0.461	0.182	0.431	0.153
Fraction of Workers Above 75^{th} Percentile for θ	0.235	0.143	0.194	0.111
Fraction of Workers Below 25^{th} Percentile for θ	0.315	0.182	0.284	0.141
Interaction of Fraction Above 75^{th} Percentile and Fraction Below 25^{th} Percentile for θ	0.059	0.035	0.045	0.022
Fraction of Workers Above 50^{th} Percentile for Experience Component	0.492	0.205	0.622	0.151
Fraction of Workers Above 75^{th} Percentile for Experience Component	0.245	0.159	0.333	0.145
Fraction of Workers Below 25^{th} Percentile for Experience Component	0.259	0.193	0.144	0.102
Interaction of Fraction Above 75^{th} Percentile and Fraction Below 25^{th} Percentile for Experience Component	0.044	0.029	0.039	0.021
Fraction of Workers with 1-2 Years of tenure	0.207	0.156	0.180	0.168
Fraction of Workers with 3-4 Years of tenure	0.272	0.203	0.323	0.227
Fraction of Workers with 5+ Years of tenure	0.195	0.237	0.295	0.274
(Log) Capital Intensity	4.160	1.155	4.176	1.129

Table 5.2: The Relationship Between Labor Productivity and Human Capital – Dependent Variable is Log Labor Productivity

Explanatory Variable:	All Sectors			Manufacturing Only			
Fraction of Workers Above 50th Percentile for Overall *"h"*	1.422 0.006			1.462 0.021	0.867 0.021		
Fraction of Workers Above 75th Percentile for Overall *"h"*		0.868 0.008	0.849 0.009			0.587 0.035	0.015 0.034
Fraction of Workers Below 25th Percentile for Overall *"h"*		-1.087 0.008	-1.102 0.008			-1.647 0.044	-1.297 0.043
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for Overall *"h"*			0.194 0.039			0.279 0.220	0.359 0.216
Fraction of Workers with 1-2 Years of tenure	0.356 0.008	0.234 0.008	0.234 0.008	0.295 0.035	0.213 0.033	0.186 0.035	0.109 0.034
Fraction of Workers with 3-4 Years of tenure	0.331 0.007	0.237 0.007	0.237 0.007	0.314 0.027	0.114 0.026	0.217 0.028	0.009 0.027
Fraction of Workers with 5+ Years of tenure	0.502 0.007	0.428 0.007	0.427 0.007	0.458 0.024	0.219 0.024	0.380 0.026	0.110 0.025
Capital Intensity					0.281 0.004		0.293 0.004
R-squared	0.589	0.590	0.590	0.334	0.477	0.324	0.478
No. Obs.	478051			31117			

Notes: Sample is from 1997 Illinois, Florida, and Maryland UI-Based Firms (defined at EIN/2-digit SIC level) matched to Economic Census and Annual Survey of Manufactures data. All regressions include fixed 2-digit SIC effects. Top number in cell is coefficient, lower number is standard error. Results based upon employment weighted regressions.

Table 5.3 The Relationship Between Labor Productivity and Human Capital – Dependent Variable is Log Labor Productivity

Explanatory Variable:	All Sectors			Manufacturing Only			
Fraction of Workers Above 50th Percentile for θ	1.515 0.007			1.693 0.032	1.016 0.031		
Fraction of Workers Above 75th Percentile for θ		0.757 0.010	0.821 0.012			0.662 0.063	0.5443 0.062
Fraction of Workers Below 25th Percentile for θ		-1.142 0.009	-1.084 0.010			-1.92 0.049	-1.19 0.049
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for θ			-0.467 0.043			-0.203 0.253	-0.488 0.254
Fraction of Workers Above 50th Percentile for Experience Component	0.763 0.007			1.301 0.035	0.525 0.034		
Fraction of Workers Above 75th Percentile for Experience Component		0.462 0.010	0.590 0.011			1.479 0.046	0.871 0.046
Fraction of Workers Below 25th Percentile for Experience Component		-0.399 0.009	-0.254 0.010			0.009 0.074	0.302 0.077
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for Experience Component			-1.507 0.045			-1.609 0.271	-1.696 0.274
Fraction of Workers with 1-2 Years of tenure	0.364 0.009	0.303 0.008	0.296 0.008	0.362 0.036	0.284 0.034	0.254 0.035	0.212 0.033
Fraction of Workers with 3-4 Years of tenure	0.473 0.007	0.418 0.007	0.405 0.007	0.444 0.028	0.224 0.027	0.323 0.028	0.152 0.027
Fraction of Workers with 5+ Years of tenure	0.650 0.007	0.599 0.007	0.581 0.007	0.588 0.027	0.342 0.025	0.396 0.027	0.221 0.025
Capital Intensity					0.310 0.004		0.285 0.003
R-squared	0.579	0.584	0.585	0.299	0.464	0.342	0.486
No. Obs.	478051			31117			

Notes: Sample is from 1997 Illinois, Florida, and Maryland UI-Based Firms (defined at EIN/2-digit SIC level) matched to Economic Census and Annual Survey of Manufactures data. All regressions include fixed 2-digit SIC effects. All regressions are employment-weighted.

Table 5.4: The Relationship Between Labor Productivity and Human Capital at the Firm Level– Dependent Variable is Log Labor Productivity

Explanatory Variable:	All Sectors			Manufacturing Only			
Fraction of Workers Above 50th Percentile for Overall *"h"*	1.235 0.005			0.867 0.017	0.596 0.016		
Fraction of Workers Above 75th Percentile for Overall *"h"*		0.681 0.007	0.596 0.008			0.142 0.027	0.050 0.025
Fraction of Workers Below 25th Percentile for Overall *"h"*		-1.046 0.007	-1.118 0.007			-1.186 0.030	-0.895 0.028
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for Overall *"h"*			0.945 0.033			1.564 0.143	1.201 0.133
Fraction of Workers with 1-2 Years of tenure	0.415 0.008	0.317 0.008	0.321 0.008	0.206 0.027	0.189 0.025	0.122 0.028	0.120 0.026
Fraction of Workers with 3-4 Years of tenure	0.468 0.006	0.371 0.006	0.375 0.006	0.113 0.022	0.129 0.020	0.023 0.022	0.053 0.020
Fraction of Workers with 5+ Years of tenure	0.555 0.006	0.469 0.006	0.468 0.006	0.342 0.019	0.228 0.018	0.256 0.019	0.156 0.018
Capital Intensity					0.241 0.003		0.240 0.003
R-squared	0.540	0.549	0.549	0.282	0.392	0.290	0.398
No. Obs.	455,783			30,314	29,850	30,314	29,850

Notes: Sample is from 1997 Illinois, Florida, and Maryland Firms (defined as having at least 90% of employment in those states) matched to Economic Census and Annual Survey of Manufactures data. All regressions include fixed 2-digit SIC effects for the main industry, and indicators for whether the firm had establishments in 1, 2, or 3+ 2-digit SIC categories. Top number in cell is coefficient, lower number is standard error. Results based upon employment-weighted regressions.

Table 5.5 The Relationship Between Labor Productivity and Human Capital Components at the Firm Level– Dependent Variable is Log Labor Productivity

Explanatory Variable:	All Sectors			Manufacturing Only			
Fraction of Workers Above 50^{th} Percentile for θ	1.352 0.006			1.085 0.022	0.812 0.021		
Fraction of Workers Above 75^{th} Percentile for θ		0.580 0.008	0.590 0.009			0.027 0.037	0.026 0.034
Fraction of Workers Below 25^{th} Percentile for θ		-1.069 0.008	-1.063 0.008			-1.233 0.032	-0.923 0.030
Interaction of Fraction Above 75^{th} Percentile and Fraction Below 25^{th} Percentile for θ			-0.082 0.035			1.714 0.151	1.415 0.140
Fraction of Workers Above 50^{th} Percentile for Experience Component	0.640 0.006			0.392 0.025	0.221 0.023		
Fraction of Workers Above 75^{th} Percentile for Experience Component		0.249 0.008	0.239 0.008			0.032 0.032	-0.042 0.030
Fraction of Workers Below 25^{th} Percentile for Experience Component		-0.510 0.008	-0.520 0.009			-0.612 0.049	-0.464 0.045
Interaction of Fraction Above 75^{th} Percentile and Fraction Below 25^{th} Percentile for Experience Component			0.134 0.039			0.553 0.179	0.588 0.165
Fraction of Workers with 1-2 Years of tenure	0.430 0.008	0.356 0.008	0.356 0.008	0.255 0.028	0.224 0.025	0.195 0.027	0.179 0.025
Fraction of Workers with 3-4 Years of tenure	0.587 0.006	0.512 0.006	0.511 0.006	0.246 0.022	0.233 0.020	0.180 0.022	0.182 0.020
Fraction of Workers with 5+ Years of tenure	0.673 0.006	0.615 0.006	0.615 0.007	0.491 0.020	0.343 0.019	0.413 0.020	0.289 0.019
Capital Intensity					0.247 0.003		0.240 0.003
R-squared	0.537	0.544	0.544	0.278	0.395	0.296	0.406
No. Obs.	455,783			30,314	29,850	30,314	29,850

Notes: : Sample is from 1997 Illinois, Florida, and Maryland firms (defined as firms having at least 90% of employment in those states) matched to Economic Census and Annual Survey of Manufactures data. All regressions include 2-digit SIC fixed effects for the main industry, and indicators for whether the firm had establishments in 1, 2, or 3+ 2-digit SIC categories. Top number in cell is coefficient, lower number is standard error. Results based upon employment weighted regressions.

Table 6.1 Sample Means for Market Value Regressions		
	Mean	Std Dev
Log Market Value	4.524	1.865
Log Capital	2.635	2.041
Log Other Assets	3.473	1.869
Fraction of Workers Above 50th Percentile for Overall *"h"*	0.639	0.199
Fraction of Workers Above 75th Percentile for Overall *"h"*	0.382	0.219
Fraction of Workers Below 25th Percentile for Overall *"h"*	0.149	0.135
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for Overall *"h"*	0.039	0.030
Fraction of Workers Above 50th Percentile for θ	0.592	0.195
Fraction of Workers Above 75th Percentile for θ	0.324	0.179
Fraction of Workers Below 25th Percentile for θ	0.190	0.139
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for θ	0.045	0.029
Fraction of Workers Above 50th Percentile for Experience Component	0.549	0.176
Fraction of Workers Above 75th Percentile for Experience Component	0.273	0.170
Fraction of Workers Below 25th Percentile for Experience Component	0.168	0.127
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for Experience Component	0.034	0.022
Fraction of Workers with < 1 Year of tenure	0.276	0.217
Fraction with 1-2 Years of tenure	0.256	0.183
Fraction with 3-4 Years of tenure	0.333	0.218
Fraction with 5+ Years of tenure	0.134	0.199

Table 6.2 Market Value and Human Capital–1995-1998 Pooled Sample			
Explanatory Variable:			
Fraction of Workers Above 50th Percentile for Overall *"h"*	0.896 0.207		
Fraction of Workers Above 75th Percentile for Overall *"h"*		0.648 0.252	0.629 0.263
Fraction of Workers Below 25th Percentile for Overall *"h"*		-0.348 0.345	-0.418 0.429
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for Overall *"h"*			0.390 1.562
Fraction of Workers with 1-2 Years of tenure	-0.235 0.171	-0.209 0.171	-0.211 0.170
Fraction of Workers with 3-4 Years of tenure	-0.796 0.174	-0.755 0.180	-0.757 0.181
Fraction of Workers with 5+ Years of tenure	-0.781 0.213	-0.713 0.221	-0.714 0.221
Log Capital	0.352 0.031	0.353 0.031	0.353 0.031
Log Other Assets	0.575 0.030	0.577 0.0329	0.577 0.030
R-squared	0.822	0.821	0.821
No. Obs.	1,350		

Notes: Sample is from 1995-1998 Illinois, Florida, and Maryland Firms (defined as having at least 50% of employment in those states) matched to SSEL and Compustat data. All regressions include fixed year effects, fixed 2-digit SIC effects for the main industry, and indicators for whether the firm had establishments in 1, 2, or 3+ 2-digit SIC categories. Top numbers in cells are coefficient estimates, lower numbers are robust standard errors.

Table 6.3 Market Value and the Components of Human Capital–1995-1998 Pooled Sample			
Explanatory Variable:			
Fraction of Workers Above 50th Percentile for θ	0.945 0.257		
Fraction of Workers Above 75th Percentile for θ		0.299 0.306	0.376 0.325
Fraction of Workers Below 25th Percentile for θ		-1.221 0.436	-1.076 0.517
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for θ			-1.427 1.747
Fraction of Workers Above 50th Percentile for Experience Component	0.099 0.256		
Fraction of Workers Above 75th Percentile for Experience Component		-0.027 0.312	-0.101 0.329
Fraction of Workers Below 25th Percentile for Experience Component		0.077 0.409	-0.035 0.478
Interaction of Fraction Above 75th Percentile and Fraction Below 25th Percentile for Experience Component			1.33 1.862
Fraction of Workers with 1-2 Years of tenure	-0.183 0.173	-0.237 0.180	-0.264 0.180
Fraction of Workers with 3-4 Years of tenure	-0.695 0.183	-0.714 0.182	-0.745 0.178
Fraction of Workers with 5+ Years of tenure	-0.584 0.224	-0.592 0.217	-0.617 0.219
Log Capital	0.352 0.031	0.349 0.031	0.350 0.031
Log Other Assets	0.566 0.031	0.566 0.030	0.566 0.030
R-squared	0.822	0.824	0.825
No. Obs.		1,250	

Notes: Sample is from 1995-1998 Illinois, Florida, and Maryland Firms (defined as having at least 50% of employment in those states) matched to SSEL and Compustat data. All regressions include f ixed year dummies, fixed 2-digit SIC effects for the main industry, and indicators for whether the firm had establishments in 1, 2, or 3+ 2-digit SIC categories. Top numbers in cells are coefficient estimates, lower numbers are robust standard errors.

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