AI and IT Intangible Capital

Prasanna Tambe
U. Penn, Wharton

Lorin M. Hitt
U. Penn, Wharton

Erik Brynjolfsson
MIT Sloan and NBER

Daniel Rock
MIT Sloan*

May 31, 2019

DRAFT COPY. Do not post, quote, or circulate.

Abstract

Investments in the skills and practices that accompany IT and, most recently, AI investment, may account for a significant fraction of value in technology-intensive firms. However, the stock of this "IT intangible capital" (ITIC) as well as how the accumulation of this capital has contributed to economic growth has remained elusive, even though it is generally a precursor to deriving productive benefits from technology investments such as investments in AI. To study this phenomenon, we a) use a new extended thirty-year firm-level panel on IT labor along with Hall's Quantity Revelation Theorem to trace the development of ITIC over the last thirty years, and then b) examine implications for the current wave of AI investment. Our estimates suggest that ITIC formed about 25% of firms' assets by 2016 and that most of this capital is owned by larger firms. For the recent wave of AI investment, a striking result is that high market values are associated with AI before they are associated with increased revenues, suggesting that investors anticipate significant future returns to AI related intangible assets that are otherwise unmeasured. While AI measures are strongly correlated with market value, we find little evidence that AI is already driving revenue or productivity.

1 Introduction

As the economy becomes increasingly digitized, IT-related intangible assets have continued to grow in importance. Yet, they remain poorly measured. Basic distinctions, such as price and quantity, remain elusive, which makes economic and business inference difficult. In particular, the management practices, information structures, and employee skills accompanying IT investment in general, and AI most recently, comprise a growing category of IT intangible capital (hereafter, referred to as "ITIC") (Hall, 2001; Brynjolfsson et al., 2002; Bresnahan et al., 2002).

*Correspondence: tambe@wharton.upenn.edu. Comments are appreciated. We are grateful to Guy Berger, Di Mo, and Jonathan Haskel, and to seminar participants at MIT, the NBER Conference on Research on Income and Wealth, the Workshop on Information Systems and Economics, and the International Conference on Information Systems for valuable feedback. We thank the LinkedIn Economic Graph Research team for providing access to firm-level skills and employment data.

AI is poised to begin a new wave of IT-related intangible capital accumulation. The twenty-first century will be the century of intelligent machines. Artificial intelligence (AI) has begun to transform the economy as it as enables machines to do more and more of the cognitive tasks that were once done only by humans. In the coming decade, many existing tasks will be replaced by machines, while new ones will emerge. Almost every job will be affected in some way and most will need to be redesigned. Businesses will rise and fall depending on how well they understand, foster and harness the changing skills that are needed to be productive. Economies will thrive if they can create and update the institutions needed to create these skills.

In particular, the branch of AI known as machine learning (ML) has advanced significantly in just the past decade, largely reflecting improvements in the area of deep learning, a technique that trains large neural networks on large datasets (Agrawal et al., 2016, 2018; Brynjolfsson and Mitchell, 2017). Three different types of advances, each of about two orders-of-magnitude, have combined to make this possible: 1) an increase in the quantity and quality of digital data, 2) improvements in computational power, reflecting not only the march of Moore's Law, but also new specialized architectures like GPUs and TPUs, and 3) improved algorithms (Brynjolfsson and McAfee, 2014). As a result, the performance of ML algorithms has improved significantly. In a highly cited example, the image recognition algorithms on the ImageNet Dataset improved from barely 70 percent in 2010 to over 97 percent today, and now surpass human level performance on the same data. Voice recognition and natural language processing, machine translation, recommendation systems, gaming and many other tasks have also seen striking improvements (Shoham et al., 2018). Because capabilities like vision, speech and decision-making are so fundamental for most occupations, these improvements to technology suggest that substantial changes in the nature of work can be expected.

This implies that firms have a large incentive to invest in creating and updating the skill sets needed to take advantage of emerging IT – most recently, machine learning (ML) – as these technologies become increasingly pervasive. Although many skills will be affected, the skills needed to implement ML are a notable special case: their value has grown markedly as new technologies like TensorFlow have boosted their economic impact (Rock, 2019). The magnitude and scope of the reskilling and business process redesign needed to put ML breakthroughs into practice means that it will require years if not decades before the full effects are felt, just as with earlier technological breakthroughs (Brynjolfsson et al., 2018).

This paper uses methods from the literature on intangible assets to document the changing prices and quantities of ITIC in US firms over the last thirty years, and then carries this through to the interaction between intangibles and AI investment in the current period. Our estimates suggest that the market value of ITIC rose and then fell sharply around the dot-com bust, but began to rise sharply from 2010 onwards, coinciding with a wave of investment in data, data science, and AI. Most of the fluctuations in value, however, can be attributed to changes in prices of ITIC. With some exceptions, quantities of ITIC steadily rose over our panel, which spans from 1987 to 2016. On average, ITIC levels appear, at the end of the panel, to comprise about 20% of the overall assets of firms in our sample. In terms of the current AI investment wave, our evidence suggests that AI-related intangible capital, while present in the valuations of public firms, has yet to make a meaningful impact on productivity. This is consistent with a literature on measuring intangible capital outputs that suggests a "learning" or "J-Curve" effect of new general-purpose technologies on productivity growth (Hornstein and Krusell, 1996; Greenwood and Yorukoglu, 1997; McGrattan and Prescott, 2010; McGrattan, 2017; Brynjolfsson et al., 2018).

2 Theoretical framework: Asset values and adjustment costs

This section walks through the theoretical underpinnings of the paper, which are drawn from Hall's Quantity Revelation Theorem. Hall argues that under assumptions of 1) competitive markets, 2) constant returns to scale production, and 3) full factor adjustment, prices and quantities of tangible and intangible capital can be recovered from the value of a firm's securities. The main departure in this paper from the method he describes is that, rather than using the total value of a firm's securities as our dependent variable, we use the component of its market value that is correlated with IT investment. The other difference in our approach is that we estimate (rather than calibrate) key parameters using firm-level data, which we can do, because we have access to a time-series of investment into a correlate of the intangible investment. After separating ITIC values into prices and quantities, we use the quantity data to estimate the contribution of ITIC stock to productivity and we estimate ITIC depreciation rates.

From Hall (2001), we have two equations that relate investment and market value in the presence of adjustment costs:

$$V_t/K_t = q_t \tag{1}$$

$$q_t = 1 + c'(i_t/K_{t-1}) \tag{2}$$

The ratio of the market value (**V**) per dollar of capital value (**K**) is Tobin's q. The marginal **q** value is 1 plus the marginal cost of adjustment at that level of investment growth (**i**/**K**). The 1 represents the numeraire price of capital purchase costs and the adjustment cost function is assumed to be convex in time.

Once capital is installed within a firm, its shareholder value is higher. This ratio is represented by **q**. Further, sunk adjustment costs can lead to an ex-post quasi-rent of installation equal to the difference between the competitive value of installed capital less the firm's specific adjustment cost. The sum of these values accrues to the shareholders such that we have the identity:

$$V(t) = \sum_{j=1}^{J} q_{j,t} K_{j,t} \tag{3}$$

The market value of the firm at time **t** is simply the sum of the values of its constituent assets, priced at their respective **q** values. Solving the system of equations above leads to a convenient way to recover **q** and **k** at some time t if we know the market valuation and previous period's capital stock of the firm.

$$c'(i_t/K_{t-1}) = c'(\frac{k_t - (1-\delta)k_{t-1}}{k_{t-1}}) = q_t - 1 \tag{4}$$

Now that we have that the marginal adjustment cost at a given level of net investment, per unit of capital stock in the previous period is equal to the **q** value of investment now minus the numeraire. From equation 1, we have that **q** is equal to the market value of a given asset divided by the asset replacement value. The point where the marginal adjustment cost function meets the **q** value hyperbola defines the equilibrium price and quantity of capital (Hall (2001) illustrates this as shown in Figure 1). With measures of **k** and net investment **i** (or gross investment and asset-specific depreciation rates), these equations can be solved to yield **q** and **k**.

Note that the **q** curve can be interpreted as the full market value of the firm or the **q** values

Notes: This chart is reproduced from (Hall, 2001). It graphs the solution to Hall's Quantity Revelation Theorem and solves for the equilibrium price and quantity of capital.

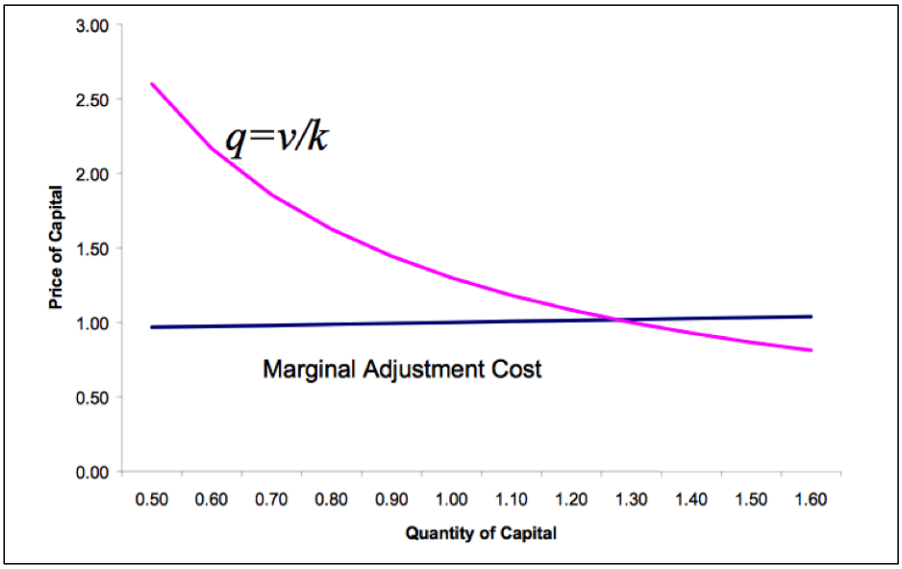


Figure 1: Price and quantity of capital

of specific assets. Cash, for example, has low adjustment costs, so the supply curve of cash is close to flat with a price of one dollar. Property, plant, and equipment has a higher installed price. The reason is that the asset replacement costs are set in competitive equilibrium. Differentiation in adjustment costs of highly liquid assets like cash is likely limited. The market does not permit "pure rents" in assets with little protection from competition. Sometimes capital quantities can be inferred from secondary market prices or from estimates of capital rents. However, in the case of intangible assets this is generally not possible.

Rather than solving directly for **q** we can estimate the following hedonic regression from observed capital stocks and observed market values to recover the **q** value as a vector of coefficients.

$$V_{i,t} = \mathbf{K}'_{i,t}\beta + \mathbf{X}'_{i,t}\xi + \gamma_i + \nu_t + \epsilon_{i,t} \tag{5}$$

The value of a firm is decomposed into its constituent assets **K** with controls **X** and fixed effects for firm **i** and time **t**. If all assets are measured perfectly then the coefficient vectors return the asset **q** values. Note that the controls and fixed effects are not necessarily required.

Now we introduce an issue where some element of the capital vector is omitted. Say we are

trying to measure the **q** value of some kind of human capital but we cannot properly measure the correlated intangible investments required to make human capital productive in firms. We estimate the following:

$$\hat{V}_{i,t} = \hat{\beta}_0 + \hat{\beta}_1 K_{i,t} + \hat{\beta}_2 (E^*_{i,t} + H_{i,t}) + \epsilon_{i,t}$$

Our human capital measure **E** includes the true **HK** value (with a star), but omits **H**, the total quantity of correlated intangible investments. The estimate is now incorrect for a couple of reasons. First, omitting **H** means that the estimate is too high because the capital stock as measured is too low. Our coefficient is then compensating for the lower capital value. Second, if the **q** value is different for the two asset types, a composite measure of the two types of correlated intangible investments (**E** and **H**) gives us the value-weighted **q** value for the total. The estimated coefficient is equal to the "true" value-weighted **q** plus an additional omitted variable bias from the correlation of the ("partialed-out") intangible correlate quantity with market value.

$$\hat{\beta}_2 = \beta_2 + \frac{Cov(\tilde{H}_{i,t}, V_{i,t})}{Var(V_{i,t})}$$

There are a number of options as to how to proceed. One is to simply accept the omitted variable bias and interpret the estimated market value as inclusive of intangible correlates and adjustment costs, all priced at a value-weighted **q** . This is an interesting and economically meaningful estimate even with bias. Given a set of balance sheet capital quantities and trying to measure the total value of intangible assets.

A second approach is to try to find a way to measure **H**. Assuming that we cannot do that (or that any measure of **H** would have too much measurement error to be helpful - a point to be discussed later), a third approach is to find an instrument which predicts **E** but not **H**. The use of instrumental variables will consistently estimate the correct coefficient on **E**. Identification of such an instrument is likely to be difficult, however, especially if **E** and **H** are strongly complementary. Further any effect on market value that the instrument might have acting through H would constitute a violation of the exclusion restriction.

A fourth and final option is to impose additional structure and solve for the **q**-value without the need for the regression specification. With **q** calibrated, the regression coefficient instead will

reveal the hidden quantity of **H**, and at a price of **q**, both **E** and **H** will be recoverable. The price paid in additional assumptions is the risk of implausibility or incorrect estimates. Not knowing the adjustment cost function precisely, we have that:

$$c'(\frac{k_t - (1-\delta)k_{t-1}}{k_{t-1}}) = \frac{V_t}{k_t} - 1 \tag{6}$$

We can observe market values, and we have to pick a starting capital value to solve the recurrence relation above. With last period's capital stock and the current market value, we can infer **q** and **k** in the current period. This also requires knowing the adjustment cost function. If we assume a quadratic function for adjustment costs, we can solve for the convexity of the adjustment cost function with a similar recurrence relation.

$$c(\frac{i_t}{k_{t-1}}) = \frac{\alpha_t}{2}(\frac{k_t - k_{t-1}}{k_{t-1}})^2 \tag{7}$$

$$c'(\frac{i_t}{k_{t-1}}) = \alpha_t(\frac{i_t}{k_{t-1}}) = q_t - 1 \tag{8}$$

$$c''(\frac{i_t}{k_{t-1}}) = \alpha_t \tag{9}$$

The first two equations are taken directly from Hall (2001). Convexity need not be symmetric, and in that paper the downward adjustment alpha is set to a constant value that is ten times the upward adjustment alpha. Asymmetric adjustment might motivate regression specifications that include a dummy and interaction set for growing vs. shrinking firms. But importantly the recurrence relation can extend to difference quotients to get a time-varying estimate of alpha.

$$c''(\frac{i_t}{k_{t-\Delta t}}) = \alpha_t = \lim_{\Delta t \to 0} \frac{q_t - q_{t-\Delta t}}{\frac{i_t}{k_{t-\Delta t}} - \frac{i_{t-\Delta t}}{k_{t-2\Delta t}}} = \lim_{\Delta t \to 0} \frac{\frac{V_t}{k_t} - \frac{V_{t-\Delta t}}{k_{t-\Delta t}}}{\frac{i_t}{k_{t-\Delta t}} - \frac{i_{t-\Delta t}}{k_{t-2\Delta t}}}$$

Since we can observe market value, in the short-run, a change in **q** per unit of investment growth permits calibration of the slope of the marginal adjustment cost curve. This introduces a new assumption of stability in this slope over short periods. Or perhaps less optimistically, that managers make investment decisions based on **q** and recent past values of marginal adjustment.

$$\alpha_t \approx \frac{\frac{V_t}{k_t} - \frac{V_{t-1}}{k_{t-1}}}{\frac{i_t}{k_{t-1}} - \frac{i_{t-1}}{k_{t-2}}} = \frac{\frac{V_t}{k_t} - \frac{V_{t-1}}{k_{t-1}}}{\frac{k_t - (1-\delta)k_{t-1}}{k_{t-1}} - \frac{k_{t-1} - (1-\delta)k_{t-2}}{k_{t-2}}}$$

One problem is that we do not know alpha without **q** (nor do we know **q** without alpha). We make the assumption that in the short-run, all changes in the value of capital are driven by shifts in the **q** curve, and not by changes to adjustment costs. In that case, empirical estimates of the previous two periods of **q** for all assets and the net investment rate for the observable component growth of **E** in the previous two periods can be used to find an initial alpha value. From there, the recurrence relation of the marginal adjustment cost curve can be used to solve for **q** in each period. Note that growth must be positive (negative) for the starting two periods to estimate asymmetric alphas for the positive (negative) accumulation rates of assets.

With a time vector of **q**-values, the hedonic regression exercise reveals the unobserved quantities. Specifically, we have that:

$$\hat{\beta}_2(E_t) = q_t(E_t^* + H_t)$$

$$H_t = \frac{(\hat{\beta}_2 - q_t)}{q_t} E_t^*$$

A few caveats: we require here (for now) that quantities of **H** and **E** are everywhere and always purchased together in bundles of fixed efficiency units. Thus we can retrieve an estimate of the unobserved **H**. Of course, measurement error in **E** can attenuate the original market value estimate (in the univariate case, though effects may vary otherwise). With fixed **q** this will lead to under-estimates of the quantity of unobserved correlated intangible quantities. An additional robustness check would be to run the market value regression for the cross-section each year. This would yield a vector of coefficients to compare to calibrated **q**. Calibrated **q** values also rely on a locally quadratic form. Allowing the time dimension to change alpha helps reduce the risk of misspecification. Higher order terms in a Taylor series approximation to the adjustment cost function are assumed away here, but in reality, these curves may not be as mathematically friendly.

Were these assets to be purchased separately and in varying mixtures, the error in these estimates would be wrong insofar as the same **q** value no longer applied to all types of assets in the bundle.

Conveniently, this type of variation ameliorates some of the omitted variable bias introduced by co-investment in the observed and unobserved asset varieties. If coefficient estimates are lower than **q** we have the issue that the unobserved quantity is negative (perhaps a puzzle), though this may instead indicate that there are unobserved factors negatively correlated with **E**.

In practice, we substitute physical capital q^k_{t-1} for ITIC in the denominator to avoid division by zero in early periods, and take the adjustment technology to be quadratic with constant returns to scale. Therefore, given a time-series of ITIC market values and assuming a value of 3.0 for the ITIC adjustment parameter α (Hall 2002 presents a justification of this value for α and a sensitivity analysis. We also provide a sensitivity analysis later in the manuscript.), we have two equations in two unknowns, the quantity and shadow price of IT intangible capital. Recovering ITIC stocks in any period requires solving an equation that is quadratic in capital stocks.

By setting initial values for ITIC, recursion through this system produces prices and quantities for IT-related intangible capital in each firm-year. We set initial values of ITIC capital from 1985 to zero. Hall argues that the method is not sensitive to initial conditions, and later in the analysis we test the sensitivity of our results to using different values of the α parameter as well as to how the initial ITIC values are seeded.

3 Data, Descriptives, and Empirical Analysis

3.1 Data

The key empirical contributions of the paper are the use of IT employment as a proxy measure for IT investment and the use of skills data as a measure of AI investment. Similar approaches has been used in prior work, although these studies have used different data sources (Tambe and Hitt, 2012). For this analysis, IT skills and employment offers specific advantages when compared to other available proxies that one might use for IT investment such as the CII CITDB database (also known as the Harte-Hanks data), which has probably been the most commonly used database used to measure firm-level IT spending (e.g. see Bresnahan et al. (2002)).

These IT labor measures use data on the employment histories of US IT workers to infer the distribution of IT employment in US firms. The data were obtained in 2018 from LinkedIn, a leading online professional network web site upon which individuals post employment histories, including for

each job they have held, information on employer, job title, and years spent at the firm. Employer data generally include name, size, and industry. We use the employment histories of the workers on LinkedIn who have job titles that identify them as IT workers to measure IT employment in public firms over the duration of our panel. [1]

We also use the skills histories, available from 2014 on, to measure firm-level quantities of different types of skills. We rely on LinkedIn's internal taxonomies to build these aggregate measures. In our analysis of AI skills, we use a larger cross-section over a shorter time frame. The skills dataset is available from 2014 to 2017. We again construct a balanced panel that includes firms in the technology industry where most of the AI investment to date has occurred. We build indices for skills related to AI, Data Science, Cloud Computing, Data Storage Technologies, Digital Literacy (Microsoft Office, MacOS, etc.), Management, and Advertising. Predictably, the magnitude of these indices tends to track firm size. We also include an index for the general human capital of the firm, computed as the sum of the years of education for all workers in the LinkedIn database for that year in a given company. Interestingly, nearly two thirds of all companies have yet to invest in AI as of the end of 2016. Our data suggest that AI investment is still nascent in business applications. Summary statistics for the skills indices are reported in Table 4. Correlations between these indices are reported in Table 4.

3.2 IT Intangible Capital Over the Last Thirty Years

Value of IT Intangible Capital

Table 3 reports results from regressions that relate market value to IT and other inputs using the Tobin's q framework. We closely follow the methods used in Brynjolfsson et al. (2002) (BHY). These estimates a) benchmark how the IT employment data perform in market value regressions that have been used in prior work but that relied on a much shorter IT capital panel and b) test the relationship between IT investment and market value in years after that covered by existing research

[1] Of course, not all workers participate on LinkedIn, and some workers who do participate report inaccurate or incomplete employment history information, so there will be error in these measures. These measures will tend to bias OLS estimates downward by an amount that is related to the share of the total variance of the measure that is attributable to the variance of the sampling error. There are two caveats. The high participation of IT workers within the US suggests that any measurement error should be less than what we might observe in the CI IT capital data or other comparable data sources. Prior work argues that this error may be as high as 30-40% of the total measure variance (Brynjolfsson and Hitt, 2003) and that IT employment data, as a measure of IT investment, are subject to less error (Tambe and Hitt, 2012).

by more than two decades. We report estimates using OLS and fixed effects as well as Least Absolute Deviation (LAD) methods. All regressions in this table include year and industry fixed effects, where industry is included at the two digit level. In a market value context, LAD methods minimize the impact of outliers (i.e. very large market value firms) on our estimates. Our point estimates, however, do not substantially change when using LAD methods. To meaningfully interpret the coefficients, we convert IT employment to millions of dollars by multiplying employment by 0.1, which implies a mean wage of $100,000.

Column (1) of Table 3 replicates the specification in BHY, using computer equipment based measures of IT capital stock. Estimates on Property, Plant, and Equipment (PPE) and other assets are close to their expected theoretical values of one, plus an increment for adjustment costs for that type of capital. The coefficient estimate on IT capital suggests that a dollar of IT capital is associated with about 15 dollars of market value, and the estimate is significant (t=2.059). The estimates from BHY equate a dollar of computer investment with only 11 dollars in market value, but the sample we use, from 1987 to 1998, is limited to the roughly 1,400 observations in our panel for which the CITDB data are available and it covers more years in the late 1990's when the market placed a larger premium on IT investment. The BHY estimates only include the years through 1994.

In column (2), we report estimates from regressions that use the IT labor measures, instead of the IT capital measures, in the time period that overlaps with the one used in column (1). When using this set of years along with the IT employment measures, the point estimate on IT employment is significant and suggests that a dollar of IT labor is associated with about nine dollars of market value (t=5.980). This estimate is sensitive to our assumptions about IT labor costs. If IT workers earn more than this amount, on average, it will lower this estimate, and if they earn less, it will raise this estimate. Nevertheless, this estimate is consistent with the argument that IT investment is associated with significant amounts of "excess" market value. Unlike when IT capital, IT labor should not directly generate value for the firm's owners. Therefore, all of nine dollars of value implied by the coefficient estimate should be attributable to intangible correlates and their adjustment costs. Column (3) includes both IT measures in the same regression and the results suggest that the IT labor measure is a more precise indicator of this value, due perhaps to measurement error (Tambe and Hitt, 2012) or as may be the case if IT labor is a better indicator of ITIC construction than IT capital. This would be the case, for instance, if IT workers could build new IT intangible on old

servers. The model in Column (4) further extends the sample through 2016. In this longer panel, each IT employee is associated about twelve dollars of value (t=15.802). Rather than falling after the 1990's, the coefficient estimate on IT grows larger when including the post-2001 period into the panel.

In column (5), we introduce firm fixed-effects. This specification uses within-firm IT variation in market value and IT investment. Including firm fixed-effects removes the effects of unobserved, time-invariant firm heterogeneity that could be correlated with IT investment and drive up market value through other mechanisms. The magnitude of the fixed-effects estimate on IT changes slightly, rising from twelve to about seventeen dollars of market value per dollar spent on IT employees (t=16.673). Finally, column (5) reports results using the LAD technique, which removes the effects of outliers. This estimate falls to about nine dollars per IT employee, which suggests that some of the elevated coefficient estimate on IT assets in column (5) is driven by a outlying observations with high IT investment levels and high market values. Nevertheless, the coefficient estimate on IT from the LAD test, which minimizes the impact of outlying observations on these estimates, is still economically and statistically significant. The estimates in columns (4) through (6) suggest that IT investment continues to be associated with excess market value through the last decade.

The method described above requires a time-series of intangible asset values to recover prices and quantities. To estimate an annual value for IT-related intangible assets, we use the specification in equation (4), but limit the sample for each regression to observations for a window around that year rather than use the whole panel (see BHY Table 3 for a similar approach). The coefficient estimates generated by the year-to-year regressions from 1987 through 2016 are shown in Table 6. The estimates on the IT employment coefficient rise and fall in a pattern consistent with the rising levels of IT investment that occurred from 1995 through 2001, as well as in the years after 2010, which coincides with a recent wave of technological investment around social media, analytics, and mobile technologies.

Using this series of coefficient estimates, we can generate estimates of ITIC values in each firm-year as described in equation (5), producing an ITIC value time-series for firms in our panel. Figure 4 illustrates how the average ITIC value for firms in our panel changes over time. The chart suggests that for the average firm in our panel, the average ITIC value (i.e. the component of market value correlated with investment into IT labor) has fluctuated substantially, and that the dot-com bubble

and bust had a large effect on the value of ITIC computed using this method. For the average firm in our panel, ITIC values rose to about seven billion dollars during the height of the dot-com boom, before falling to about half that value in the years following the bust. These values then continued to fall through the early and mid 2000's, before rising once again shortly after the financial recession, which coincides with a wave of investment in data science and machine learning.

Prices, Quantities, and Depreciation

The fluctuations in ITIC value illustrated in Figure 4 reflect changes in the prices or quantities of IT-related intangible capital over these years. Figures 5 and 6 summarize these results and illustrate how the price and quantity of IT-related intangible capital have been changing over the last three decades. The prices and quantities that are shown are averaged over each of the firms in our sample. The dominant feature for ITIC prices in Figure 5 is its rise and subsequent fall, which corresponds to the late 1990's dot-com bubble. By contrast, ITIC prices in recent years have been relatively stable. The price—which is also Tobin's q for this asset—is close to its theoretical value of 1, but rises sharply around the peak of the dot-com bubble. Figure 6 indicates a steady accumulation of ITIC quantities, except for a slowdown in the growth rate after the dot-com bust and a decline in quantities for a few years after. A theoretical prediction is that as Tobin's q for this asset rises above 1, firms will invest greater amounts into the asset until Tobin's q value is driven back to 1. This theoretical relationship appears to be consistent with the two illustrations, as the rise in q corresponds to accelerated investment by firms during the late 1990's.

These figures suggest that the large market value changes around the dot-com boom and bust were driven by adjustments in ITIC price, rather than changes in the quantities of ITIC possessed by firms. Although the bust appears to have removed the effects of investor mispricing from ITIC values, the slowdown in the development of IT asset stocks continued through the Great Recession. The dominant feature in Figure 6 is the steady rise in ITIC quantities in the panel.

To place the growth of this asset in perspective, we can compare how ITIC growth compares to the growth in physical capital for these firms. Figure 7 makes this comparison explicit. By the end of our sample period, ITIC quantities had grown, on average, to approximately 25% of physical capital, and comprised about 20% of firms' assets.

To compute depreciation, we estimate the following perpetual inventory equation, where labor

investment is lagged under the assumption that it takes one period for the output of IT labor investment to be converted to useful ITIC:

$$q_{it} = \delta q_{i,t-1} + I_{i,t-1} + \epsilon_{it} \tag{10}$$

In Table 7, we report depreciation estimates using our computed ITIC quantity time series. All regressions include year and firm fixed-effects. Column (1) reports estimates of δ from the depreciation equation as specified in 10. The estimated depreciation rate is about 5%, which is very low. Column (2) uses current period investment rather than lagged investment, and the depreciation estimate rises slightly, to about 7% a year. Columns (3) through (5) alter the window of analysis. The key finding here is that as the window gets shorter, the depreciation estimate rises. In more recent years, the depreciation estimates range from 9 to 14%.

ITIC and productivity

Table 8 displays results from Cobb-Douglas regressions, similar to those used in prior work that estimate the contribution of IT to productivity (Brynjolfsson and Hitt, 1996, 2003), and that include measures of labor, non-IT capital, and IT capital stock along with ITIC stock in the same balanced panel of firms that used to compute ITIC quantities. The IT capital stock measures used in the regression are from the CITDB database, and are the same IT capital stock measures used in prior work on IT productivity. These IT capital stock figures have the notable limitation, however, that they are available only through 2000 (and the data quality arguably begins to suffer before that), so our productivity estimates are limited to a shorter panel of years focused around the early 1990's.

The Ordinary Least Squares (OLS) estimates in column (1) do not include ITIC, and show that the output elasticity of IT capital in our sample is similar to that shown in other work, about 4 to 5%. Including ITIC measures in column (2) suggests that the ITIC estimate is significant but smaller in magnitude to IT capital—in other words, firms' investments in workplace organization and skills make a similar contribution to productivity over and beyond investments in computing equipment. The ratio of the coefficient estimates on ITIC and IT capital stock, however, is lower than might be expected from survey evidence of the relative shares commanded by each of these inputs. One possible reason is that the years in the first half of the sample used in the productivity regression

preceded a large wave of IT investment for firms in much of the economy. We test this assertion in Column (3) by using observations in the latter part of the sample, from 1997 to 2000, which was associated with a large run-up in IT investment, and we find that the estimated output elasticity of ITIC rises significantly relative to IT capital. The coefficient estimates from this test suggest a factor share for ITIC that is close to double that of IT capital stock. It is worth noting that our prior estimates suggest that ITIC quantities have grown significantly after 2000. These productivity results probably provide a lower bound of the recent contributions of ITIC to productivity. Column (4) tightens up the industry controls–to the two digit level–but we obtain very similar results. Column (5) adds R&D investment as a regression input, which generates another type of intangible asset. This narrows the sample considerably because R&D investment is not available for all firms in our sample, but the ITIC estimate remains similar.

Another reason for the smaller than expected estimate on ITIC in the full productivity sample is measurement error. Errors in measurement of ITIC quantities using our methods are likely not only to exert a downward bias on the ITIC coefficient estimate, but also to transmit an upward bias to the measure of IT capital stock given the high correlations between these two inputs. Fixed-effects estimates should remove some of this measurement error, but will also remove much of the effect of ITIC if this input is slow varying, and prior work has argued that IT-related organizational assets change slowly relative to IT capital. Columns (6) and (7) report results after adding firm fixed-effects. The output elasticity of ITIC falls and the point estimate is less than IT capital.

Table 9 includes human capital as a factor of production. The first two columns estimate the production of ITIC stock, using IT and human capital as inputs. When using both OLS and fixed-effects models, the regression estimates suggest that it is the combination of technology and human capital, rather than either of these factors alone, that produces ITIC. In other words, these factors are complements in the production of human capital. Columns (3) through (6) are productivity regressions that include human capital as a production factor. Because human capital is included directly, we use employment rather than labor in the production equation. Column (3) shows that IT and human capital separately contribute to productivity. When an interaction term between these two factors is included in column (4), however, the main effects on these factors disappear, leaving only the interaction term as significant. This result is consistent with that from Column (2) which suggest that technology and human capital appear together in firms that have accumulated

ITIC. Finally, columns (5) and (6) show that the coefficient estimate on ITIC in the productivity equation is driven to zero when a technology and human capital interaction variable is also included.

3.3 Implications for AI investment

Perhaps the newest and most exciting vintage of IT-related intangible capital is currently associated with advances in AI. Which industries are the first adopters of new AI and ML technologies? Given the concentrated nature of ITIC across firms, it should be of little surprise that the accumulation of AI-related intangible capital is similarly concentrated. As in (Rock, 2019), we use a data set of self-reported skills records from LinkedIn to measure the AI intensity of U.S. publicly traded firms. Our sample runs from 2014 to 2017. This is too short a panel to safely disentangle price and quantity effects in AI-related intangible capital accumulation, but long enough to facilitate valuation and productivity analyses.

Additionally, similar caveats to the other uses of LinkedIn data apply for the purposes of this set of analyses. There is likely considerable measurement error and reporting bias by occupation, firm, and year. Some skills as well are more likely to show up on the LinkedIn platform, particularly skills associated with technical knowledge. Most members of the platform have relatively sparse skill reporting behaviors. To the extent that skills on the platform are underreported, the estimates can be considered upper bounds on likely correlations. On the other hand, over reported skills, as might be the case for those masquerading as having more skills than they actually do, would lead our estimates to understate correlational evidence. As the firm-level skills indices are skewed, we apply log transformations.

As reported in 14, the AI skills per employee tend to be highest in Information (NAICS 52) and Scientific and Professional Services (NAICS 54) industries. In contrast to AI, Software Engineering (16), Database Engineering (15), and Data Analyst (13) talent tends to be relatively more prevalent in Retail Trade (NAICS 44-45), Healthcare Services (NAICS 62), Manufacturing (NAICS 33), and other services in comparison to AI. Some of the most promising arenas for AI to make a difference, such as healthcare and education, currently reflect very little overall investment in comparison to other industries.

Our key result concerning AI-related intangible capital stems from the question of whether or not AI is already having an impact on productivity. Our results are mixed, but suggest that generally

AI-related capital is more likely in an accumulation and development phase than in a position to be harvested. We run the following regressions, similar to the analysis for ITIC:

$$Y_{it} = \alpha_i + \beta AI_{it} + \boldsymbol{\gamma'} \boldsymbol{X_{it}} + \boldsymbol{\delta'} \boldsymbol{Z_{it}} + \zeta_t + \epsilon_{it} \tag{11}$$

In 11, shown in 4, Y is excess market value (specifications (1) and (2)), Revenue ((3) and (4)), and Value Added ((5) and (6)). Excess market value refers to the market value of the firms beyond their book value of assets. It is the total q-value of the firm in levels. Value Added is computed as the difference between revenues and costs of goods sold. i and t refer to firm fixed effects and time fixed effects respectively. AI is operationalized as our AI skills index from LinkedIn data, whereas $\boldsymbol{X_{it}}$ is a vector of firm-year skills indices in data science, cloud computing, data storage technologies, digital literacy, business management, and advertising. $\boldsymbol{Z_{it}}$ corresponds to firm size features (book value of assets and total years of education accumulated across workers at the firm). In specifications (2), (4), and (6), the firm and year fixed effects are replaced with an industry-year fixed effect. Industries are defined by 4-Digit NAICS codes. The panel is balanced for the 2014 to 2017 period.

The coefficients on the AI index skills are then interpreted as the correlations with the outcomes, adjusting for other types of possible confounding skills, human capital, and firm size by assets. The first check on whether AI-related intangible capital is already having an impact on business value is to see if the q-value of public firms using AI is correlated with the AI skills investments their employees have already made. We find (column (1)) that indeed there is a statistically significant correlation between AI skills and intangible market value. Adjusting for the time-invariant features of firms and firm-invariant time effects, a one percent increase in the AI skills index is correlated with a \$9.3 million increase in q-value. Data Science skills and overall education quantities are positive and statistically significant at a 10% level. As this is a regression of firm size on firm size, the R^2 is high (94%) as well. Using only industry-time fixed effects, the coefficient on the AI skills index increases to almost \$64 million per one percent increase in AI skills conditional on the other input features. This indicates that AI skills are more predictive of market value in the cross-section of firms than they are within firms, an important component of understanding the relationship between the other outcomes and AI skills.

There is no convincing positive correlation between revenue and the AI skills index within firms.

Between firms there is a strikingly large correlation between revenue and AI skills of nearly $33.2 million per one percent change in the AI skills index. (column (4)). Firm fixed effects wipe out this correlation and the difference between the coefficients on AI skills in column (3) and column (4) of Table **??** is statistically significant. In other words, the differences in revenues between firms with and without AI skills is driven by higher revenue firms investing more in AI. The case is similar for value added. One could argue that the benefits of AI investment are more likely to show up in cost savings. Alas, the coefficients on AI in predicting value added provide evidence to the contrary. It is firms with more value added that have more AI skills, but firm fixed effects absorb this relationship. This is similar to running a productivity regression wherein revenue (or value added) is purged of its correlation with labor (or in our case, aggregated education years) and capital inputs. The residual is a combination of a noise term and firm productivity. The lack of a predictive relationship between firm-level residual and AI skills suggest that AI has yet to meaningfully change productivity.

These empirical patterns lead to a number of possible explanations for the impact of AI-related intangible capital. We see a correlation between market value and AI, but not between actual revenues or value added. AI-intensive firms are selected from more successful firms overall, it seems. The first explanation is that the market pricing of AI-related intangible capital is incorrect. It could be AI hype lifting the valuations of these firms. The second is that investment in AI has fixed cost properties. Companies might become "AI-enabled", at which point the marginal investment in employee AI skills is less valuable. There are likely large upfront investments to implement AI in organizations that previously depended on different business processes. But a different explanation that is consistent with years of analysis of other types of IT-related intangible capital is that the accumulation phase of AI capital is still ongoing. Before business process innovation, occupational redesign, brand value, research and development, and other types of complements are produced, it will appear as though expenses in service of AI technologies will be wasted. Market prices, however, recognize that an intangible asset is being created. The firms making these investments are not penalized in the same way; the market expects that the return value of AI-related intangible capital is in the future. (Brynjolfsson et al., 2018) refer to this phenomenon as the "Productivity J-Curve". The market value effects from ITIC preceding productivity or revenue improvements have been historically puzzling, but numerous studies reiterate that often the benefits were just on the horizon (Hall, 2000; McGrattan and Prescott, 2010). The revenue and value added benefits have yet to

arrive, but asset prices reflect that these valuable assets exist within firms.

4 Conclusions

We use a new data source to illustrate that by 2016, the stock of IT intangible capital in our panel of firms had grown to about 25% of physical capital stock. Swings in the value of ITIC around the dot-com boom and bust appear to primarily be due to price fluctuations, but firms continued to steadily accumulate IT intangible capital after the bust and through the current period of investment in data and machine learning. Our depreciation estimates are fairly low, somewhere in between estimates of the depreciation of physical capital and R&D capital (Nadiri and Prucha, 1996). These findings have implications for AI returns which we show to be consistent with the available evidence on AI investment. The market likely recognizes that an intangible asset is being created, and we are still in the accumulation phase of this intangible asset.

The large increase in IT-related intangible capital in general, coupled with the surge in the value of skills needed for implementing ML in particular, suggest an important role for businesses reskilling the workforce. Our analysis shows that shareholders stand to benefit from when the employees of their firms have more of the right sets of skills. However, while the advances in technology have often been breathtaking, the reskilling of the workforce and the reinvention of business processes has lagged. This is reflected, for instance, in declining business dynamism according to work by (Decker et al., 2016). The key bottleneck for unlocking value often is not technology but people. Therefore, for adapting to ML enabled work, the grand challenge of the 21st century will be speeding the adoption of new skills and organizational practices that support these technologies.

References

Agrawal, A., Gans, J., and Goldfarb, A. (2018). *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press.

Agrawal, A., Goldfarb, A., and Teodoridis, F. (2016). Understanding the changing structure of scientific inquiry. *American Economic Journal: Applied Economics*, 8(1):100–128.

Bresnahan, T. F., Brynjolfsson, E., and Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Quarterly Journal of Economics*, 117(1).

Brynjolfsson, E. and Hitt, L. (1996). Paradox lost? firm-level evidence on the returns to information systems spending. *Management science*, 42(4):541–558.

Brynjolfsson, E. and Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *Review of Economics and Statistics*, 85(4):793–808.

Brynjolfsson, E., Hitt, L. M., and Yang, S. (2002). Intangible assets: Computers and organizational capital. *Brookings papers on economic activity*, 2002(1):137–181.

Brynjolfsson, E. and McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Brynjolfsson, E. and Mitchell, T. (2017). What can machine learning do? workforce implications. *Science*, 358(6370):1530–1534.

Brynjolfsson, E., Rock, D., and Syverson, C. (2018). The productivity j-curve: how intangibles complement general purpose technologies.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2016). Declining business dynamism: What we know and the way forward. *American Economic Review*, 106(5):203–07.

Greenwood, J. and Yorukoglu, M. (1997). 1974. In *Carnegie-Rochester conference series on public policy*, volume 46, pages 49–95. Elsevier.

Hall, R. E. (2000). E-capital: The link between the stock market and the labor market in the 1990s. *Brookings Papers on Economic Activity*, 2000(2):73–102.

Hall, R. E. (2001). The stock market and capital accumulation. *American Economic Review*, 91(5):1185–1202.

Hornstein, A. and Krusell, P. (1996). Can technology improvements cause productivity slowdowns? *NBER Macroeconomics annual*, 11:209–259.

McGrattan, E. R. (2017). Intangible capital and measured productivity. Technical report, National Bureau of Economic Research.

McGrattan, E. R. and Prescott, E. C. (2010). Unmeasured investment and the puzzling us boom in the 1990s. *American Economic Journal: Macroeconomics*, 2(4):88–123.

Nadiri, M. I. and Prucha, I. R. (1996). Estimation of the depreciation rate of physical and R&D capital in the us total manufacturing sector. *Economic Inquiry*, 34(1):43–56.

Rock, D. (2019). Engineering value: The returns to technological talent and investments in artificial intelligence. *Unpublished Working Paper*.

Shoham, Y., Perrault, R., Brynjolfsson, E., Clark, J., Manyika, J., Niebles, J. C., Lyons, T., Etchemendy, J., and Bauer, Z. (2018). The ai index 2018 annual report.

Tambe, P. and Hitt, L. M. (2012). The productivity of information technology investments: New evidence from IT labor data. *Information Systems Research*, 23(3-part-1):599–617.

Table notes: This table reports the 2005 summary values of key statistics for firms in the panel. IT employment is from the LinkedIn database. Employment is measured in thousands. IT employment is not scaled. All other variables are measured in millions.

Statistic	N	Mean	St. Dev.	Min	Max
Market value	224	35,499.73	61,464.69	216.71	471,424.40
PPE	224	6,361.24	12,366.93	5.76	107,010.00
Employment	199	59.92	146.14	0.60	1,800.00
Liabilities	224	13,062.15	33,535.22	28.06	460,442.00
Other assets	224	13,592.09	31,125.85	76.45	397,677.00
IT employment	224	1,196.77	4,586.27	1	65,002
Value added	199	4,815.30	8,110.44	38.79	58,131.00
Capital	199	10,829.17	22,250.51	18.59	223,252.00
Labor	199	2,507.76	4,496.25	23.99	39,186.00
Materials	199	13,066.65	29,786.43	46.67	244,953.70
Log wage bill	224	17.17	1.72	10.90	21.69

Table 1: Summary statistics for firm-level measures

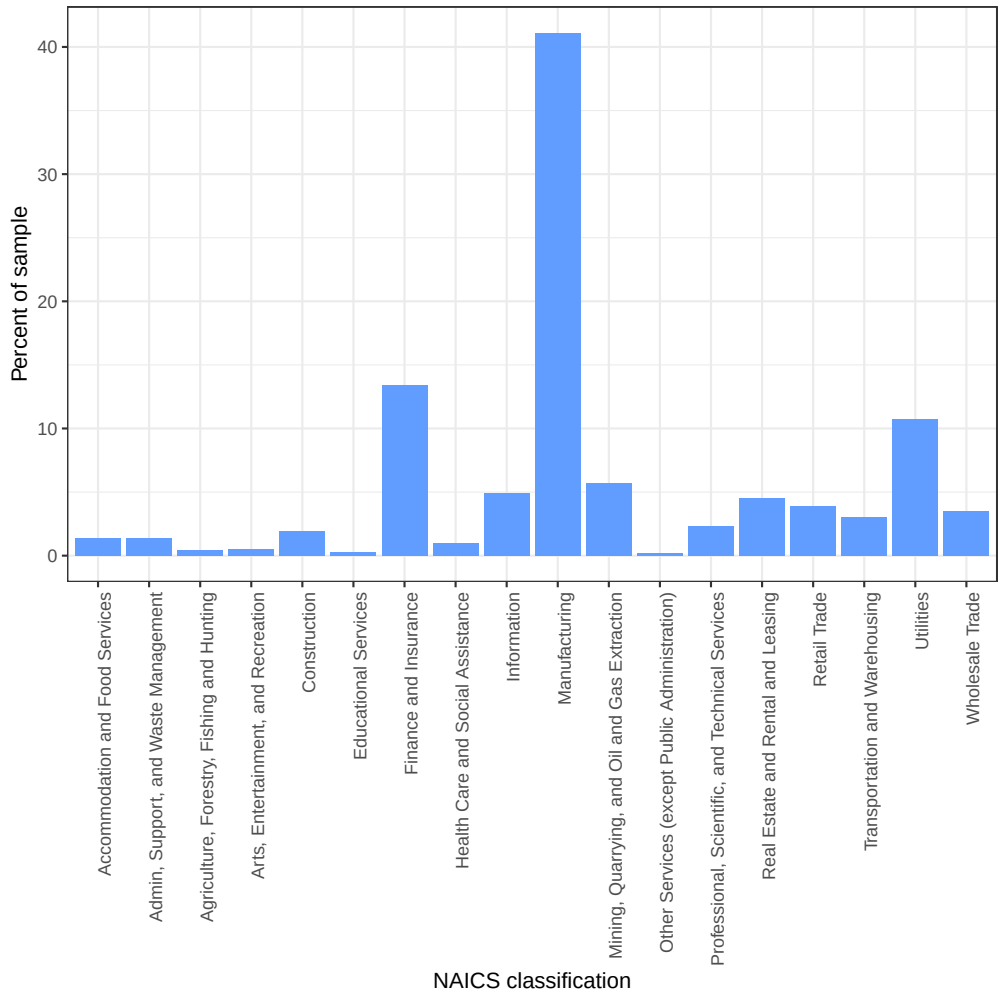


Figure 2: NAICS industry distribution of sample

Figure notes: This chart illustrates the distribution of firms in the 2005 cross-section of the sample over major NAICS industry codes (2 digit level). There are a total of 227 firms in the 2005 cross-section.

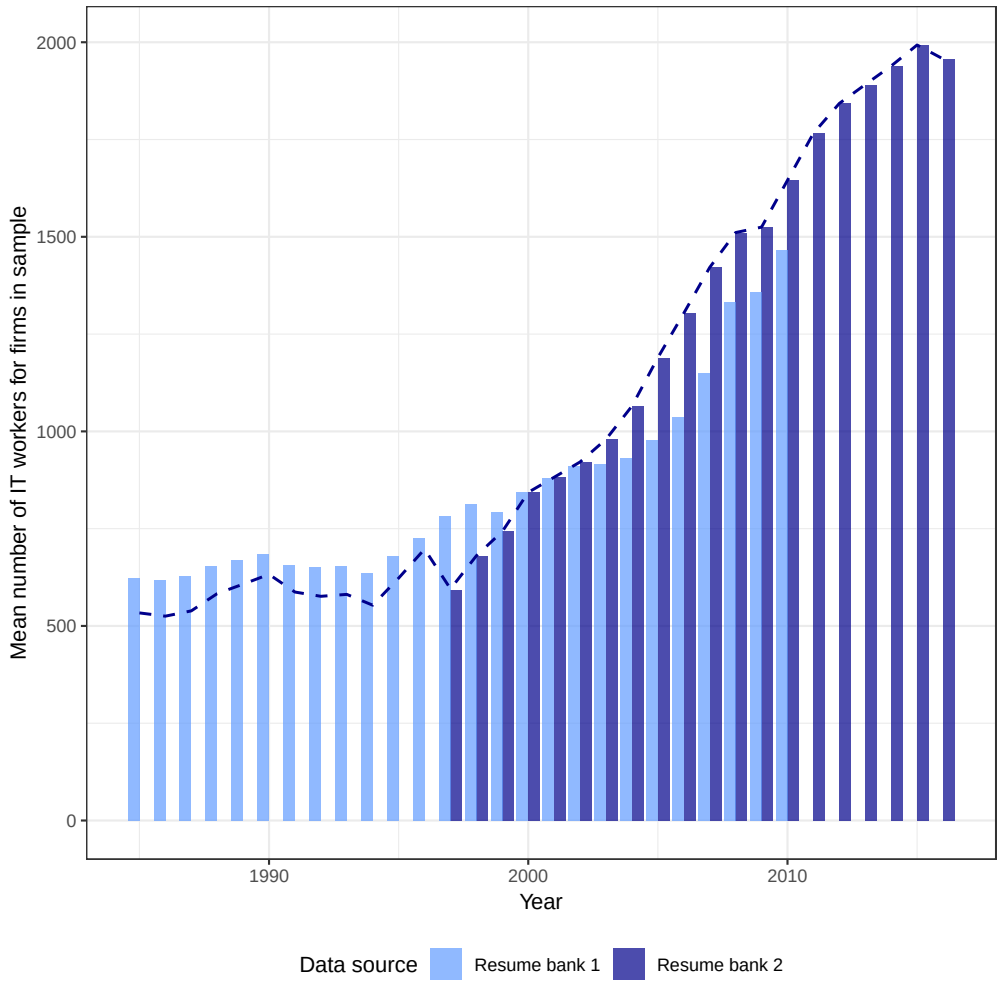


Figure 3: Year-on-year measures of firms' IT employment

Figure notes: This chart illustrates changes in measures of IT employment using data from the two different resume banks. The dashed line indicates the synthetic measure that combines the two different data sources into a unified measure of IT employment.

Table notes: This table reports pairwise correlations among the 2005 values of firms' assets that are included in the market value regression. MV is market value, PPE is Property, Plant, and Equipment, EMP is employment, LT is total liabilities, OA is other assets, and ITE is IT employment. N=227.

	MV	PPE	EMP	LT	OA	ITE
MV	1	0.789	0.474	0.745	0.823	0.421
PPE	0.789	1	0.524	0.673	0.634	0.188
EMP	0.474	0.524	1	0.334	0.323	0.400
LT	0.745	0.673	0.334	1	0.971	0.248
OA	0.823	0.634	0.323	0.971	1	0.347
ITE	0.421	0.188	0.400	0.248	0.347	1

Table 2: Pairwise correlations among firms' assets

Table notes: This table reports results from the regression $MV_{it} = PPE_{it} + OASSET_{it} + IT_{it} + \epsilon_{it}$. MV is market value, PPE is property, plant, and equipment, IT is IT capital, and OASSET is all other assets. Column (1) is an OLS regression using the IT capital measures with the sample restricted to the years 1987-1998. Column (2) is an OLS regression using the IT employment measures with the sample restricted to the years 1987-1998. Column (3) is an OLS regression using the IT employment measures with the full sample. Column (4) adds firm fixed effects to the specification used in column (3). Column (5) is a least absolute deviation (LAD) regression. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

	OLS	OLS	OLS	OLS	FE	LAD
	(1)	(2)	(3)	(4)	(5)	(6)
PPE	1.764***	1.603***	1.740***	1.305***	1.124***	1.168***
	(0.111)	(0.078)	(0.111)	(0.032)	(0.031)	(0.040)
Other assets	0.938***	1.014***	0.901***	1.738***	1.840***	1.663***
	(0.060)	(0.043)	(0.061)	(0.019)	(0.018)	(0.057)
IT capital	15.002**		5.164			
	(7.286)		(8.044)			
IT labor		9.199***	6.951***	11.899***	16.906***	8.860***
		(1.529)	(2.437)	(0.753)	(1.014)	(1.351)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed-effects	No	No	No	No	No	No
Constant	No	No	No	No	No	No
Industry fixed-effects	Yes	Yes	Yes	Yes	No	Yes
Observations	1,398	2,448	1,398	7,017	7,017	7,017
R^2	0.732	0.745	0.733	0.822	0.907	
Adjusted R^2	0.722	0.740	0.724	0.820	0.904	

Table 3: Regressions of assets on market value

	Residual Market Value	Revenue	Value Added	Total Assets	Log(Education Years)	Log(AI Skills Index)	Log(Data Science Skills Index)	Log(Cloud Computing Skills Index)	Log(Data Storage Skills Index)	Log(Digital Literacy Skills Index)	Log(Management Skills Index)	Log(Advertising Skills Index)
Residual Market Value	1.00											
Revenue	0.49	1.00										
Value Added	0.67	0.80	1.00									
Total Assets	0.20	0.38	0.66	1.00								
Log(Education Years)	0.34	0.43	0.42	0.20	1.00							
Log(AI Skills Index)	0.45	0.36	0.43	0.25	0.48	1.00						
Log(Data Science Skills Index)	0.38	0.36	0.40	0.23	0.68	0.74	1.00					
Log(Cloud Computing Skills Index)	0.37	0.31	0.38	0.21	0.51	0.80	0.81	1.00				
Log(Data Storage Skills Index)	0.07	0.05	0.09	0.10	0.11	0.37	0.33	0.50	1.00			
Log(Digital Literacy Skills Index)	0.35	0.35	0.38	0.21	0.68	0.67	0.94	0.75	0.28	1.00		
Log(Management Skills Index)	0.35	0.33	0.38	0.21	0.66	0.70	0.96	0.83	0.35	0.95	1.00	
Log(Advertising Skills Index)	0.39	0.34	0.39	0.19	0.64	0.69	0.89	0.80	0.25	0.88	0.88	1.00

Table 4: Correlations between key skills regression variables

Variable	Mean	Std. Dev.	Min.	Max.	N
Total Assets (millions USD)	14133.414	109319.504	0.001	3287968	7365
Employment (1000s)	19.709	66.579	0.002	2300	2269
Log(Education Years)	9.858	2.186	2.264	16.512	2249
Log(AI Skills Index)	1.484	2.101	0	10.486	1652
Log(Data Science Skills Index)	4.211	2.776	0	12.504	1652
Log(Cloud Computing Skills Index)	2.581	2.551	0	12.626	1652
Log(Data Storage Skills Index)	0.022	0.024	0	0.215	1652
Log(Digital Literacy Skills Index)	5.479	2.903	0	13.175	1652
Log(Management Skills Index)	5.63	2.885	0	14.298	1652
Log(Advertising Skills Index)	3.338	2.628	0	11.843	1652

Table 5: Skills Index Panel Summary Statistics

Table notes: This table reports results from the regression $MV_i = PPE_i + OASSET_i + IT_i + \epsilon_i$ where the regression for each year is run on a window spanning three years before to one year after the focal year in Column (1), and includes both 2 digit industry and year fixed effects. Column (1) is the estimated coefficient on PPE, column (2) is the estimated coefficient on Other Assets, and column (3) is the estimated coefficient on the IT measure. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

Year	PPE	OA	IT	Obs
1988	1.250	0.848	0.103	170
1989	1.296	0.833	0.330	170
1990	1.380	0.806	0.594	170
1991	1.483	0.810	0.819	170
1992	1.531	0.851	1.012	170
1993	1.537	0.882	1.147	171
1994	1.566	0.898	1.423	170
1995	1.554	0.938	1.790	171
1996	1.636	0.960	1.992	171
1997	1.883	0.907	2.601	175
1998	2.504	0.708	3.951	175
1999	2.906	0.559	7.033	178
2000	3.129	0.484	11.676	179
2001	3.121	0.525	10.770	183
2002	3.047	0.592	9.570	184
2003	2.996	0.627	8.527	184
2004	2.931	0.659	7.369	184
2005	2.796	0.733	7.207	184
2006	2.747	0.804	7.101	184
2007	2.587	0.916	6.236	184
2008	2.247	1.136	5.244	183
2009	1.791	1.588	3.272	183
2010	1.774	1.504	3.179	183
2011	1.727	1.424	3.191	178
2012	1.656	1.469	3.404	176
2013	1.554	1.577	3.536	176
2014	1.398	1.647	3.828	175
2015	1.283	1.715	4.333	173
2016	1.161	1.823	5.127	173

Table 6: Coefficients from year-on-year market value regressions

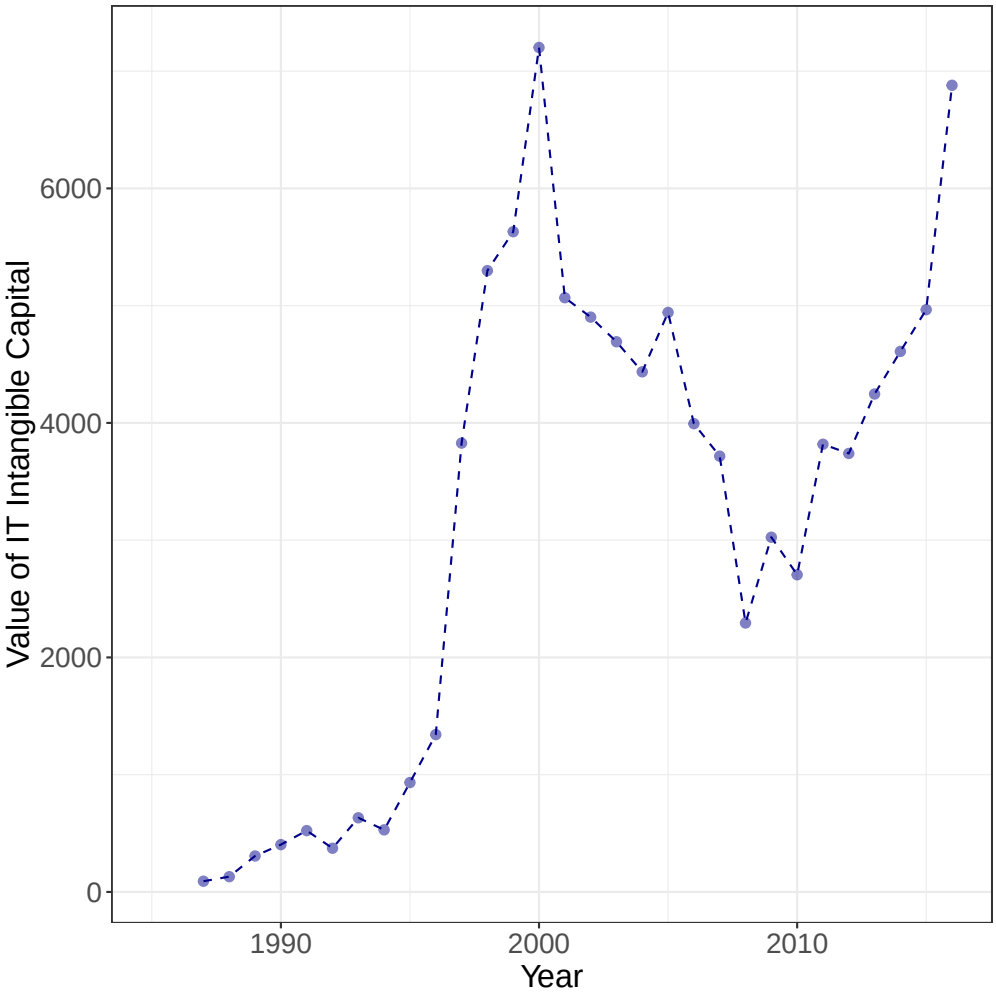


Figure notes: This chart illustrates averages value of IT intangible capital for the firms in our sample. The market value is computed in two steps. First, we estimate the regression $MV_{it} = \beta_{PPE} PPE_{it} + \beta_{OA} OA_{it} + \beta_{IT} IT_{it} + \epsilon_{it}$. Then, the coefficient β_{IT} for each firm is multiplied by the firm's IT employment to compute the component of market value correlated with the firm's IT assets.

Figure 4: Market value of IT intangible capital

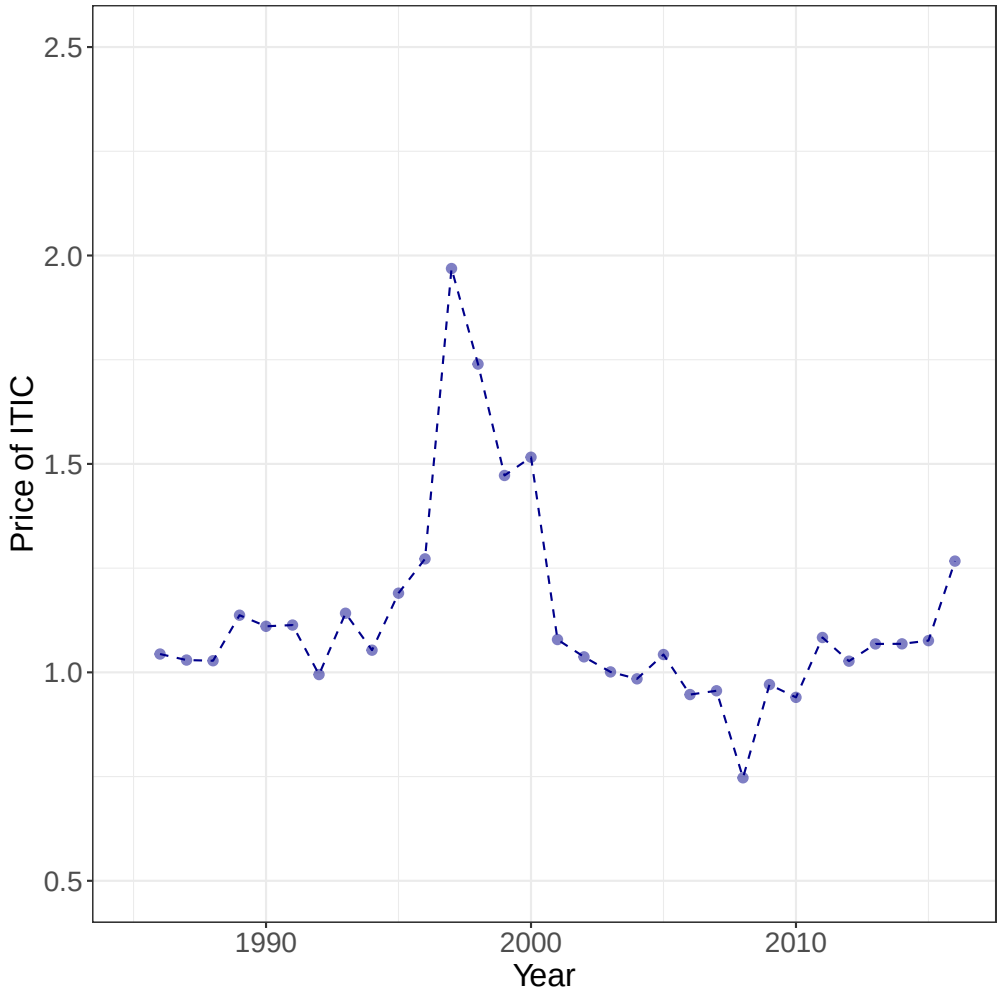


Figure notes: This chart illustrates average prices for IT intangible capital for firms in the sample. The average quantity of ITIC for each year is computed by solving equations 1 and 2 in the main text. The price is computed by dividing the value of ITIC by the quantity.

Figure 5: ITIC prices

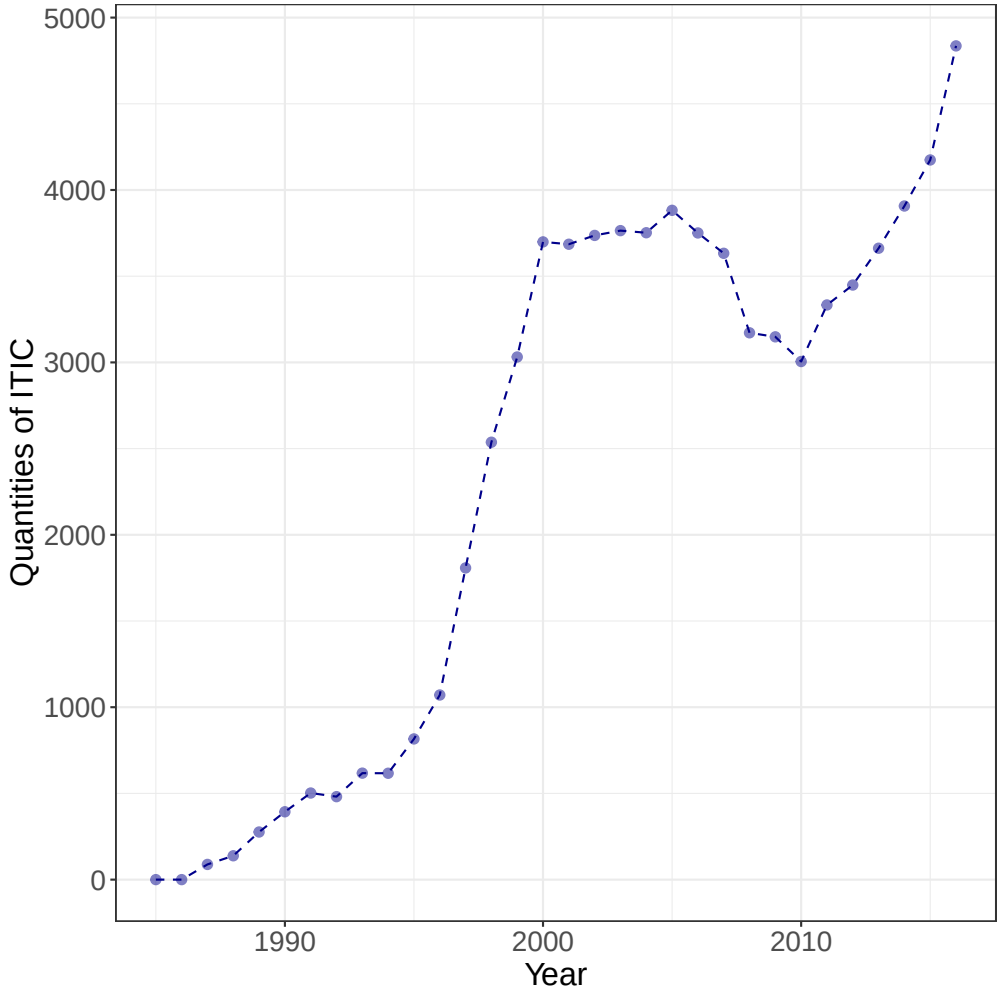


Figure notes: This chart illustrates quantities of IT-related intangible capital for the average firm in the sample. The average quantity of ITIC for each year is computed by solving equations 1 and 2 in the main text.

Figure 6: ITIC quantities

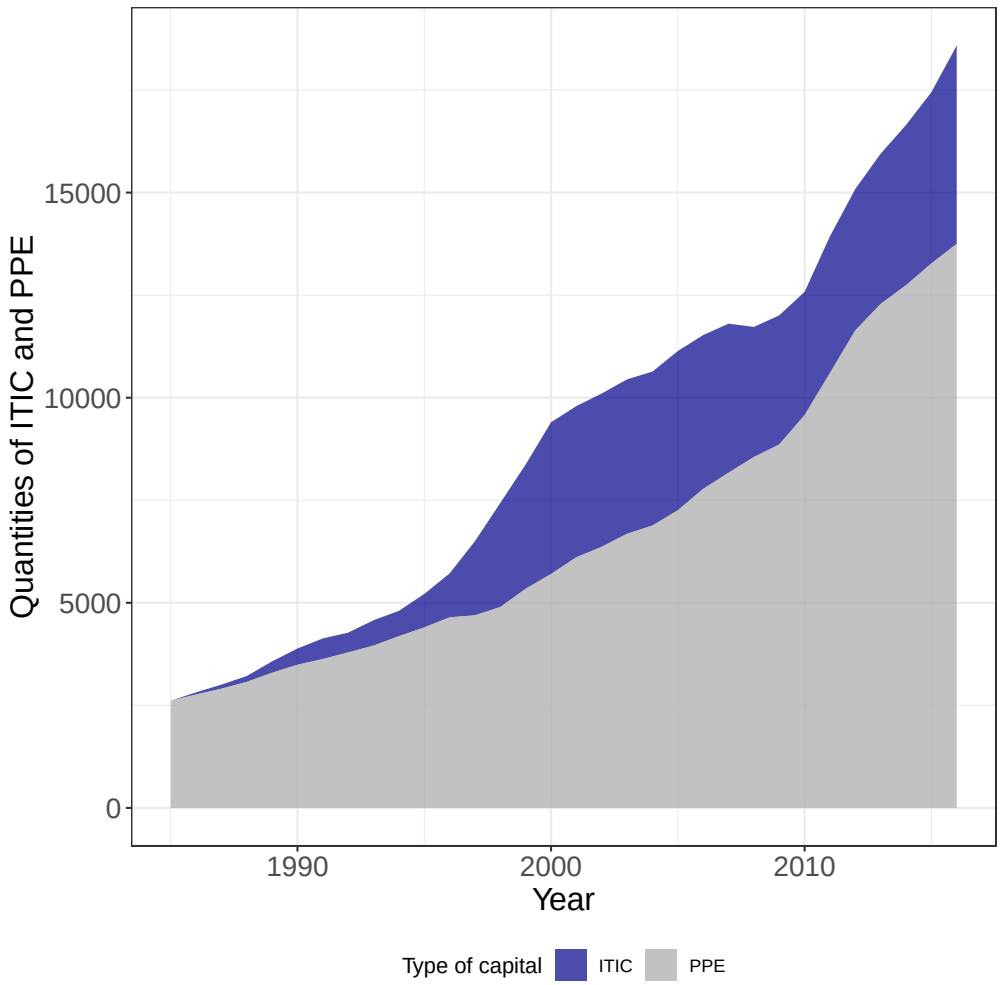


Figure notes: This chart compares year-on-year accumulation of quantities of IT intangible capital with that of Property, Plant, and Equipment (PPE). The average quantity of ITIC for each year is computed by solving equations 1 and 2 in the main text. PPE quantities are computed using data from Capital IQ.

Figure 7: Growth in PPE and ITIC

Table notes: This table estimates the perpetual inventory equation $ITIC_{it} = \delta ITIC_{i,t-1} + I_{it} + \epsilon_{it}$. The dependent variable is current period ITIC and the right-hand side includes last period ITIC and current investment. δ is (1-depreciation). All regressions have firm fixed-effects, industry, and years. Column (1) uses data from the years 1990 to 2016. Column (2) is an OLS regression with the full sample but we use current period investment instead of lagged investment. Columns (3), (4) and (5) restrict the sample to the years 1995 to 2016, 2000 to 2016, and 2005 to 2016, respectively. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

	1990-2016	1990-2016	1995-2016	2000-2016	2005-2016
	(1)	(2)	(3)	(4)	(5)
Past period ITIC	0.950***	0.929***	0.876***	0.874***	0.917***
	(0.004)	(0.004)	(0.005)	(0.009)	(0.012)
Lagged IT labor	0.131***		0.179***	0.178***	0.695***
	(0.014)		(0.019)	(0.027)	(0.039)
Current period IT labor		0.231***			
		(0.014)			
Observations	4,750	4,753	3,915	3,061	2,149
R^2	0.990	0.990	0.991	0.993	0.995
Adjusted R^2	0.989	0.990	0.991	0.993	0.994

Table 7: Estimates of ITIC depreciation rates

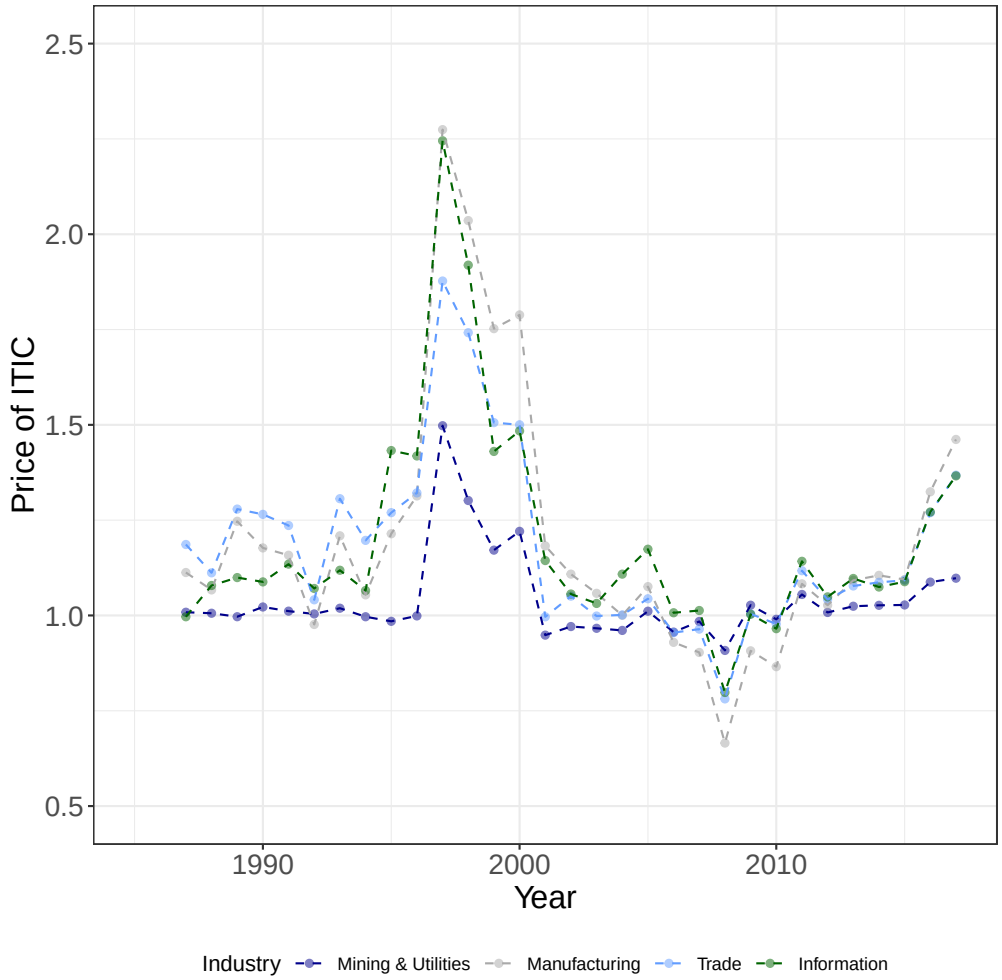


Figure notes: This chart illustrates prices of IT-related intangible capital where firms were assigned to one of four major industry affiliations: Mining and utilities, Manufacturing, Trade, and Information. Average ITIC quantities in each year were computed by solving equations 1 and 2 in the main text. Prices were computed by dividing ITIC value by ITIC quantity.

Figure 8: ITIC prices by industry

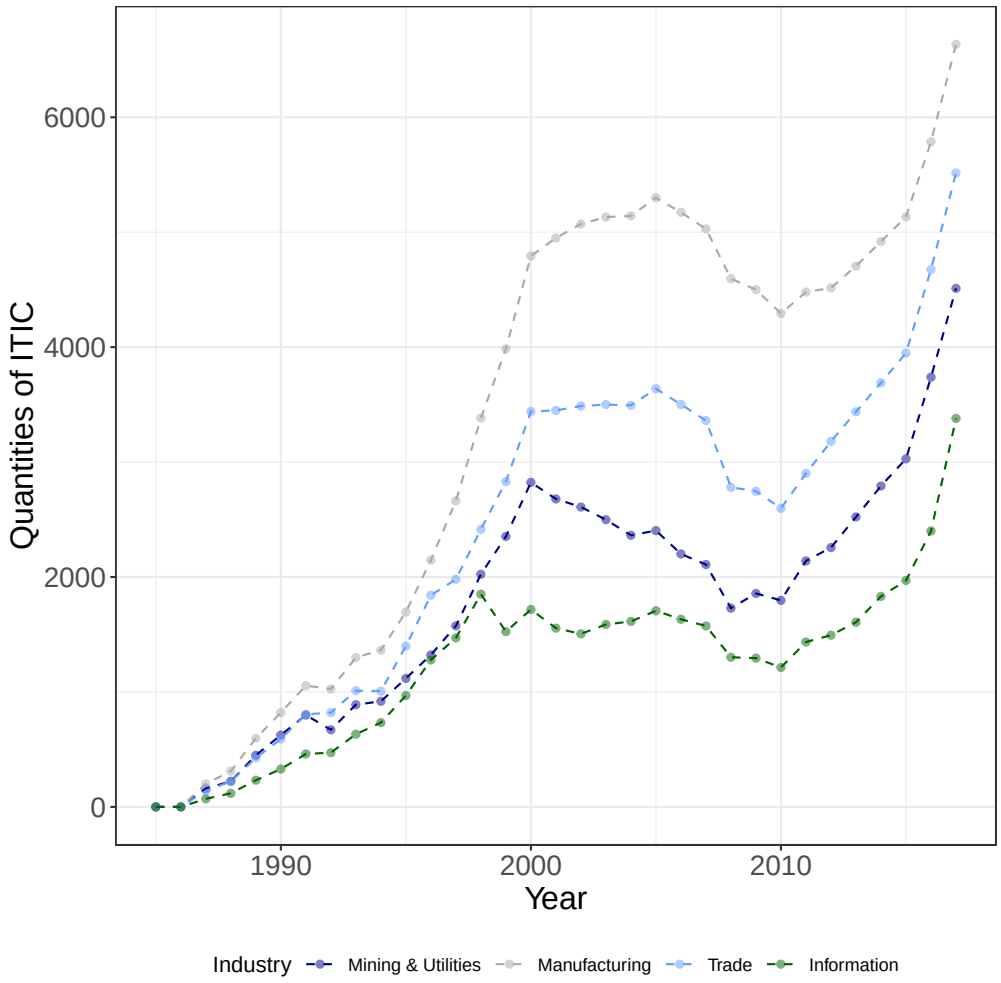


Figure notes: This chart illustrates quantities of IT-related intangible capital. Firms in our sample were assigned to one of the following four NAICS major industries: Mining, Manufacturing, Trade, or Information. Quantities of ITIC for each year are computed using the methods described in equations 1 and 2 in the main text.

Figure 9: ITIC quantities by industry

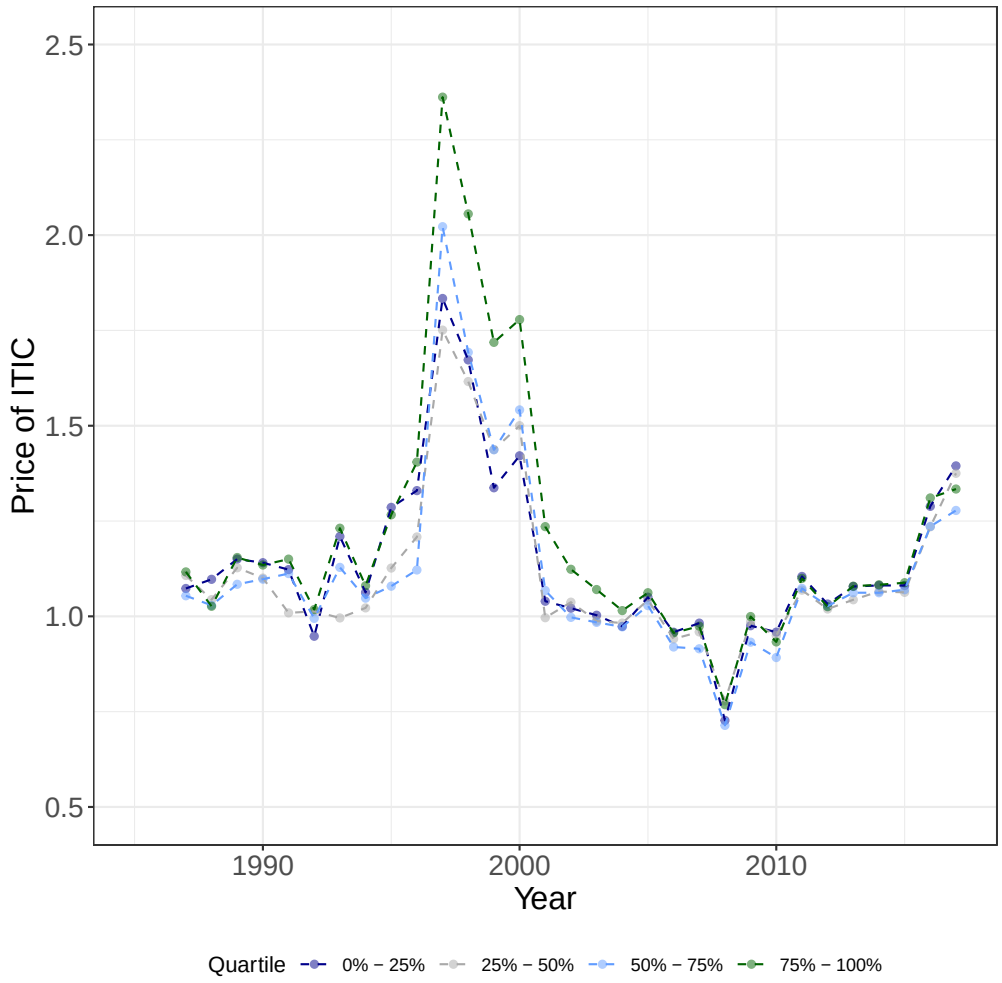


Figure notes: This chart illustrates prices of IT intangible capital for firms in the sample where firms are split into one of four quartiles according to the firm's market value in 2016. The price of ITIC in each year is computed by solving equations 1 and 2 in the main text.

Figure 10: ITIC prices by market value

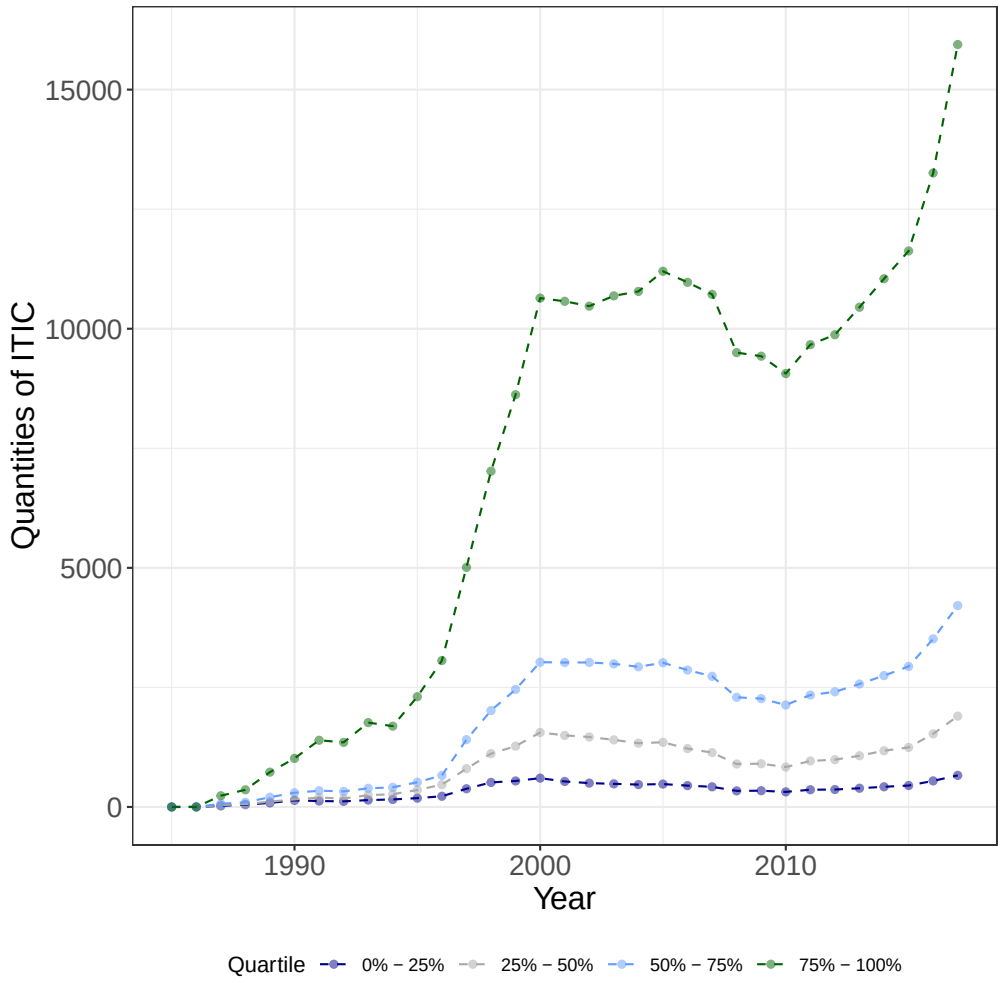


Figure notes: This chart illustrates quantities of IT intangible capital where firms are separated into one of four quartiles according to their 2016 market values. ITIC quantities for each year are computed by solving equations 1 and 2.

Figure 11: ITIC quantities by market value

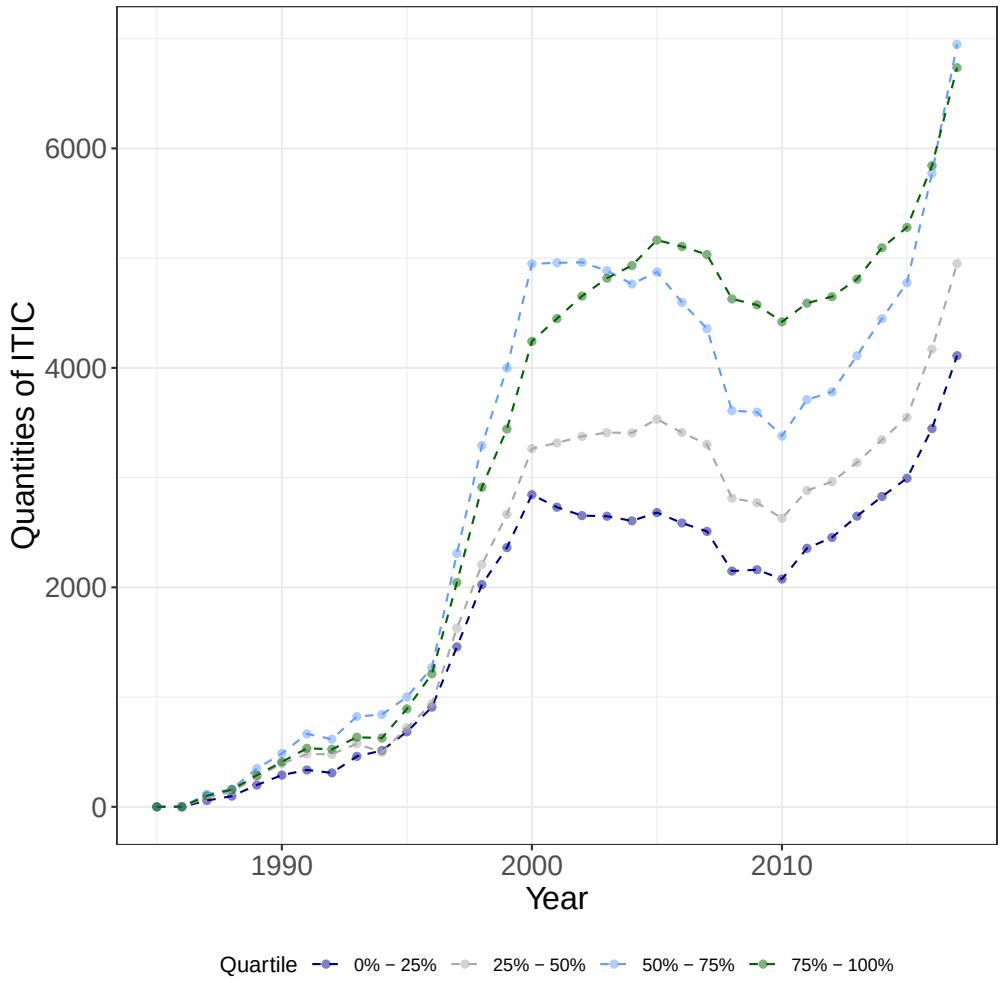


Figure notes: This chart illustrates quantities of IT intangible capital where firms are separated into quartiles according to the average level of human capital for workers employed at the firm. Human capital measures are computed at the firm level using the LinkedIn data. For firms in each quartile, quantities of ITIC in each year are computed using the methods described in equations 1 and 2 in the main text and then averaged across firms in the group.

Figure 12: ITIC quantities by workers' human capital

Table notes: This table reports results from the regression $Log(VA)_{it} = Log(K)_{it} + Log(L)_{it} + Log(IT)_{it} + \epsilon_{it}$. VA is value added (output - materials), K is capital, L is labor, IT is IT capital. Column (1) is the baseline regression on the full sample for which IT capital data are available. Column (2) includes ITIC. Column (3) restricts the sample to the years 1997 to 2000, and column (4) uses finer industry controls. Column (5) includes R&D. Columns (6) and (7) include firm fixed-effects. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

	OLS	OLS	OLS	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Non-IT Capital)	0.286***	0.267***	0.266***	0.354***	0.251***	0.429***	0.424***
	(0.008)	(0.009)	(0.020)	(0.027)	(0.014)	(0.017)	(0.017)
Log(Labor)	0.630***	0.608***	0.541***	0.484***	0.538***	0.382***	0.382***
	(0.010)	(0.010)	(0.021)	(0.025)	(0.018)	(0.014)	(0.014)
Log(IT Capital)	0.045***	0.042***	0.045***	0.041**	−0.004	0.022***	0.027***
	(0.008)	(0.008)	(0.016)	(0.018)	(0.014)	(0.006)	(0.006)
Log(ITIC)		0.022***	0.093***	0.089***	0.018***		0.004
		(0.004)	(0.018)	(0.020)	(0.006)		(0.003)
Log(R&D)					0.121***		
					(0.011)		
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes	No	No
Constant	No	No	No	No	No	No	No
Observations	1,465	1,329	457	457	638	1,465	1,329
R^2	0.950	0.956	0.930	0.942	0.965	0.986	0.988
Adjusted R^2	0.949	0.955	0.928	0.936	0.964	0.984	0.986

Table 8: Productivity regressions

Table notes: This table reports results from the regression $Log(VA)_{it} = Log(K)_{it} + Log(E)_{it} + Log(HK)_{it} + Log(IT)_{it} + \epsilon_{it}$. VA is value added (output - materials), K is capital, E is employment, HK is human capital, and IT is IT employment. Columns (1) and (2) test associations between investment in HK and IT on quantities of ITIC in firms, without and with firm-fixed effects. Columns (3) through (6) estimate production functions with combinations of HK, IT, and ITIC. Standard errors are shown in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

	Log(ITIC)		Log(VA)			
	OLS	FE	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Capital)	0.245***	0.085	0.322***	0.323***	0.339***	0.351***
	(0.031)	(0.072)	(0.014)	(0.014)	(0.016)	(0.014)
Log(Employment)	0.199***	0.285***	0.511***	0.513***	0.573***	0.536***
	(0.035)	(0.081)	(0.016)	(0.016)	(0.018)	(0.016)
Log(IT emp)	−0.036	−2.780***	0.126***	−0.339*		−0.344**
	(0.382)	(0.537)	(0.010)	(0.178)		(0.172)
Log(HK)	−0.729***	−1.139***	0.288***	−0.004		−0.087
	(0.258)	(0.296)	(0.045)	(0.120)		(0.117)
Log(ITIC)					0.032***	−0.114***
					(0.010)	(0.013)
Log(IT emp x HK)	0.103**	0.316***		0.062***		0.073***
	(0.050)	(0.071)		(0.023)		(0.023)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	No	No	No	No	No	No
Observations	1,242	1,242	1,242	1,242	1,242	1,242
R^2	0.855	0.962	0.939	0.939	0.927	0.943
Adjusted R^2	0.853	0.956	0.938	0.938	0.926	0.942

Table 9: Productivity regressions with human capital

	(1) Excess Market Value	(2) Excess Market Value	(3) Revenues	(4) Revenues	(5) Value Added	(6) Value Added
Total Assets			0.08***	0.04***	0.04***	0.03***
			(0.02)	(0.01)	(0.01)	(0.00)
Log(Education Years)	1362.14*	3455.83***	950.34***	3320.86***	463.66***	952.39***
	(801.55)	(662.64)	(305.39)	(662.14)	(126.65)	(181.67)
Log(AI Skills Index)	928.79***	6384.37***	-71.35	3332.38***	63.43	1143.62***
	(248.47)	(1259.79)	(151.80)	(673.20)	(39.13)	(220.62)
Log(Data Science Skills Index)	767.04*	-1460.77*	90.72	-1220.20*	5.86	-590.91***
	(392.41)	(795.77)	(80.55)	(623.73)	(36.80)	(220.66)
Log(Cloud Computing Skills Index)	189.70	1075.45	31.52	437.49	-26.48	342.57**
	(235.99)	(730.69)	(179.59)	(546.33)	(37.25)	(163.67)
Log(Data Storage Skills Index)	-5650.68	-103177.93***	-2939.62	-44438.77*	3478.53	-17440.26**
	(14101.90)	(36148.04)	(9126.53)	(22590.43)	(2523.62)	(7331.85)
Log(Digital Literacy Skills Index)	126.96	454.46	125.64	205.09	10.75	69.92
	(360.17)	(1624.07)	(157.47)	(651.77)	(46.22)	(292.15)
Log(Management Skills Index)	186.93	-2112.36	143.56	-595.43	191.75**	-202.06
	(631.81)	(1507.33)	(411.27)	(702.91)	(91.97)	(264.65)
Log(Advertising Skills Index)	293.85	2966.00**	111.14	571.97	6.48	471.31**
	(223.61)	(1293.71)	(183.94)	(638.34)	(34.44)	(205.74)
Firm and Year FE	X		X		X	
Industry-Year FE		X		X		X
R^2	.9392377	.3404959	.985477	.5394115	.9880268	.6634429
N	5,288	5,076	5,288	5,076	5,288	5,076
Clusters	1,322	149	1,322	149	1,322	149

Table 10: Regressions by AI and other technologies

Table Notes: Standard errors are clustered at the firm level for (1), (3) and (5), industry level (4-Digit NAICS Code) for (2), (4), and (6). Data skills indices are computed as the logged cumulative total skills from the LinkedIn resume records within each skills group, aggregated by firm and year. Excess market value is the publicly traded value of firm less the book value of assets from Compustat. Value Added is the difference between REVT and COGS from Compustat. The panel is balanced from 2014-2017.

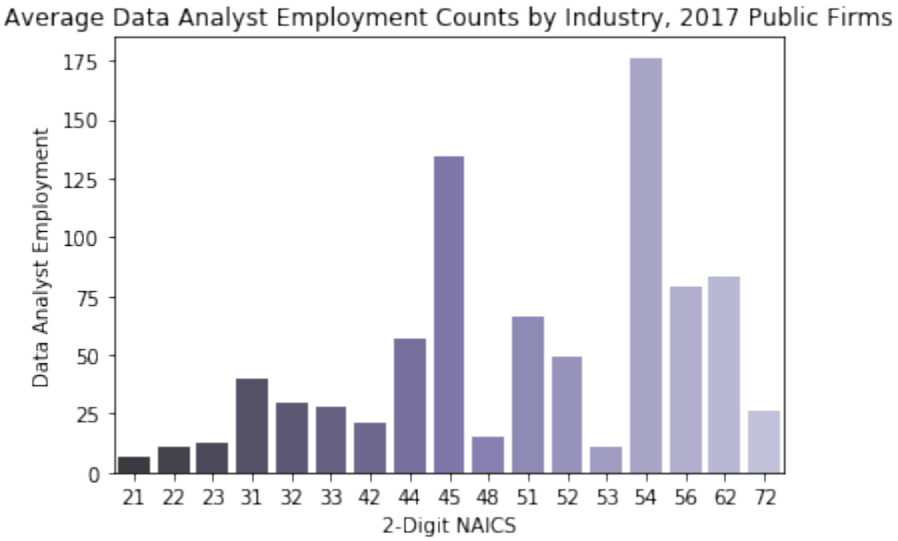


Figure notes: This chart illustrates average quantities of Data Analyst employment per firm within industry for a balanced panel of publicly traded US firms in 2017. Industries are categorized as 2-Digit NAICS codes. Industries with fewer than 10 firms are omitted.

Figure 13: Data Analyst Industry Distribution, 2017

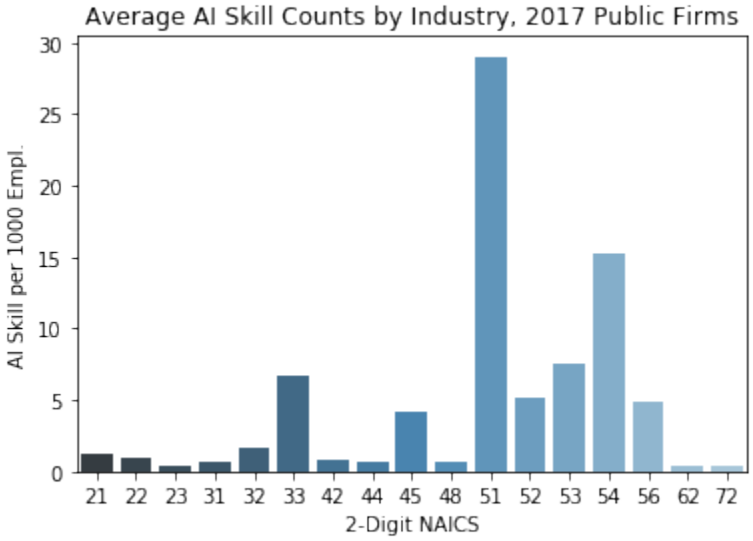


Figure notes: This chart illustrates average AI skills per 1000 employees for a balanced panel of publicly traded US firms in 2017. Industries are categorized as 2-Digit NAICS codes. The Information (NAICS 51) and Professional, Scientific, and Technical Services (NAICS 54) industries have the highest concentration of AI skills. Industries with fewer than 10 firms are omitted.

Figure 14: AI Skills Industry Distribution, 2017

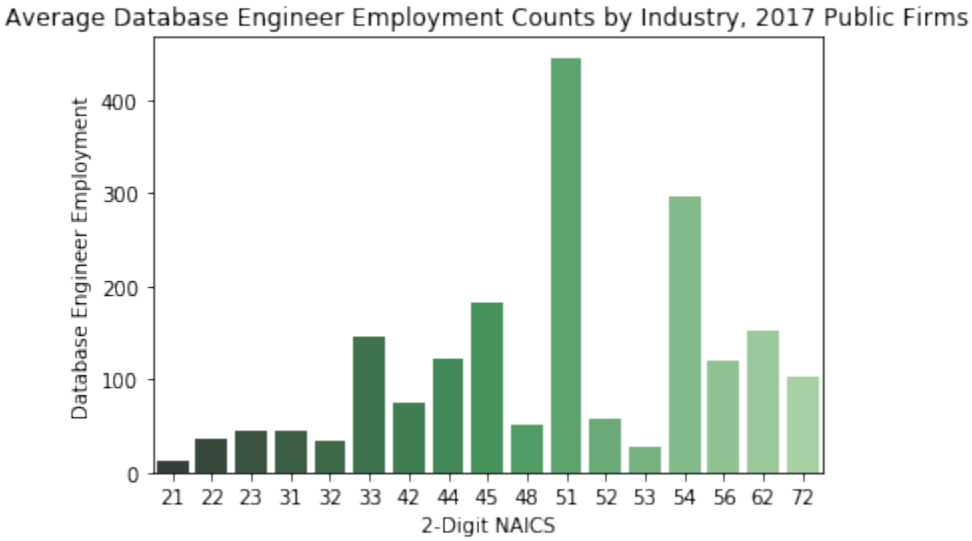


Figure notes: This chart illustrates average quantities of Database Engineer employment per firm within industry for a balanced panel of publicly traded US firms in 2017. Industries are categorized as 2-Digit NAICS codes. Industries with fewer than 10 firms are omitted.

Figure 15: Database Engineer Industry Distribution, 2017

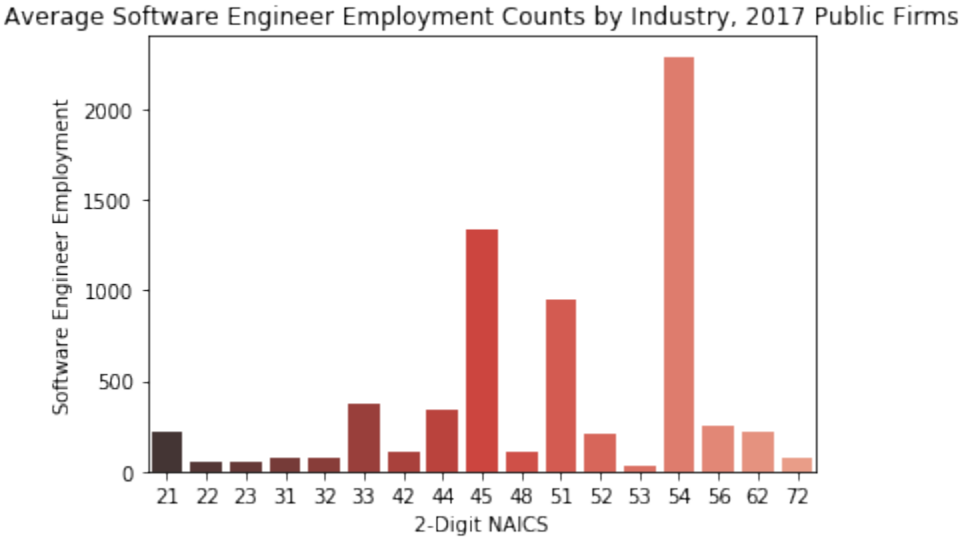


Figure notes: This chart illustrates average quantities of Software Engineer employment per firm within industry for a balanced panel of publicly traded US firms in 2017. Industries are categorized as 2-Digit NAICS codes. Industries with fewer than 10 firms are omitted.

Figure 16: Software Engineer Industry Distribution, 2017