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A NEW APPROACH TO THE VALUATION OF INTANGIBLE CAPITAL

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ABSTRACT

In this paper, I argue that intangible capital is not a distinct input to production like physical capital or labor but rather it is the glue that creates value from other inputs. This perspective naturally leads to an empirical model in which intangible capital is defined in terms of adjustment costs. Estimates of these adjustment costs using firm-level panel data suggest that there are no appreciable intangibles associated with R&D and advertising whereas information technology creates intangibles with a 70% annual rate of return — a sizable figure that is nevertheless much smaller than reported in previous studies. As a bridge to previous research, I show that much larger estimates can be obtained by using ordinary least squares, which ignores the possibility that the value of the .rm and its investment policy are simultaneously determined. Larger estimates can also be obtained by ignoring the possibility that the stock market overstates the value of intangible-intensive companies.

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1 Introduction

Almost without exception, there are no direct measures of the returns to intangible capital. As a result, researchers have relied primarily on the equity market to infer the value of intangibles. The basic idea is straightforward. If the equity market reveals the intrinsic value of the firm, then subtracting the value of the firm's tangible assets from its market value reveals the value of the firm's intangible assets. Using this method, Hall (2001) argued that U.S. companies accumulated an enormous stock of intangible capital in the 1990s.[1]

Despite the appealing simplicity of the equity market measurement approach, considerable caution is warranted. According to this approach, Yahoo!'s intangibles were worth upwards of \$100 billion in 2000. However, they are now worth less than a tenth of that number. To be sure, this drop does not necessarily pose a problem for the equity market measurement approach. Yahoo!'s market capitalization could reflect changes in expected profits or expected returns or both. But this example illustrates a potential pitfall from relying on the equity market to reveal the value of intangible capital. The value of intangible capital will be mismeasured to the extent that asset prices depart from their intrinsic value.

The basic drawback of the equity market measurement approach is that it presents a catch-22: investors must have information about intangibles to value them; but investors do not have the information they need because intangibles, by their very nature, are extraordinarily difficult to value. This circularity calls into question the assumption of strongly efficient markets underlying the equity market measurement approach.

[1] The idea that the stock market reveals the quantity of capital in the absence of rents and adjustment costs was stated clearly by Baily (1981), who interpreted the stock-market data in the 1970s as showing that energy price shocks effectively destroyed a great deal of capital.

How can the value of the firm as revealed by equity markets be equal to the intrinsic value of the firm — defined as the present value of expected cash flows — when so little is known by market participants about the value of intangibles?

As an alternative proxy for the intrinsic value of the firm, I construct the discounted value of expected profits using analysts' forecasts. I/B/E/S has collected data on profit forecasts for a large sample of companies since 1982. The analysts provide forecasts of one-year-ahead and two-year-ahead profits as well as the growth rate of profits out to a five-year horizon. In formulating their forecasts, analysts assess whether a new supply chain management system, say, is expected to add to intangible capital and, as a result, generate additional profits. Thus, if intangibles are expected to contribute materially to a company's bottom line over the analysts' five year horizon, then their value should be reflected in analysts' forecasts.

Of course, analysts' forecasts are not a silver bullet. After all, the majority of analysts appear to have overestimated the growth rates of intangible-intensive companies in the late-1990s. And, there's little guidance about how to discount these forecasts. Just as the stock market may be a poor proxy for a firm's intrinsic value, so too may be the discounted value of expected profits. However, these two proxies deviate from a firm's intrinsic value for different reasons. The stock-market-based measure reflects any market inefficiency, whereas the analyst-based measure reflects any bias on the part of analysts' and mistakes in how the forecasts are discounted.

The econometric setup explicitly recognizes the fact that the two proxies measure the firm's intrinsic value with different kinds of error. Ultimately, identification of the model parameters depends on whether there are informative instrumental variables that are uncorrelated with the measurement errors inherent in the two proxies. Theory offers little guidance about the nature of the measurement errors and, consequently, identification is an empirical issue that must be investigated with diagnostic tests, such as the test of the model's overidentifying restrictions.

For my empirical work, I put together a dataset that distinguishes firms' expenditures on tangible capital, information technology (IT), and intellectual property (IP). Using these data, I estimate the return on each type of capital using both the stock-market- and analyst-based measures of the firm's intrinsic value. Perhaps the most interesting finding is that organizational capital created by IT generates a return of 70% at an annual rate. Despite the magnitude of this estimate, it is considerably smaller than comparable estimates in previous studies. As a bridge to the previous research, I show that much larger estimates can be obtained by using ordinary least squares, which ignores the possibility that the value of the firm and its investment policy are simultaneously determined. Larger estimates can also be obtained by using a stock-market-based measure of the firm's intrinsic value.

2 The Valuation of Intangible Capital

2.1 Intangible Capital: An Instrumental Definition

I distinguish between two types of intangibles, intellectual property and organizational capital. Broadly defined, IP includes patents, trademarks, copyrights, brand names, secret formulas and so on. For my purposes, I define organizational capital as business models, designs, and routines that create value from information technology. Without a doubt, organizational capital is a broader concept than suggested by this very narrow definition. For example, innovative compensation policies and effective training programs are surely part of organizational capital. Indeed, the systematic focus on creating organizational capital can be traced to industrial pioneer Fredrick Winslow Taylor and his intellectual forbearers. I adopt a definition based on IT not because IT is qualitatively different from any other method or technology that aids organizational efficiency, but because sizable, measurable outlays are devoted to it.

This dichotomous taxonomy suits my empirical model and the data. In terms of the data, companies report expenditures on R&D and advertising, which create what I have defined as intellectual property. These expenditures can be capitalized to create the IP capital stock. It may seem like such a stock is essentially arbitrary — there is little guidance, for example, about how R&D and advertising depreciate — but it should be recognized that the stock of property, plant, and equipment is a similarly unpalatable concept, even though researchers have become sufficiently inured of it.[2]

As a practical matter, it is also important to distinguish between intellectual property and organizational capital because outlays on R&D, advertising, and IT have behaved differently over time. In particular, R&D and advertising appear to be declining in relative importance. Outlays on IT have soared while advertising as a proportion of nonfinancial corporate gross domestic profit grew modestly from 3.9% in 1980-89 to 4.1% in 1990-97; The comparable figures for R&D are 2.3% and 2.9% (Nakamura 1999). Hence, if intangibles create extraordinary gains in firm value, arguably the most plausible driver is organizational capital, not intellectual property.

[2]Indeed, the accounting for physical assets in financial statements may be about as deficient as the accounting for IP. Physical assets are capitalized at historical costs and are depreciated in ways that may be poor approximations to their service flow. Perpetual inventory capital stocks constructed from such data may also be only loose approximations to the service flow of capital.

So what exactly is organizational capital? As a purely mechanical matter, I define organizational capital as an adjustment cost from IT investment, defined as the difference between the value of installed and uninstalled IT.[3] Suppose a company purchases database software. By itself, database software does not generate any value. At a minimum, the software has to be combined with a database and, perhaps, a sales force. Organizational capital defines how the database is used and, consequently, how software investment creates value.

A specific example helps illustrate the definition. Dell's value depends on a unique organizational design that sells build-to-order computers direct to customers. There's little difference between Dell's and HP's tangible capital stock since both companies assemble computers. The reason any given piece of tangible capital is more valuable when it is installed at Dell has to do with Dell's unique business model and routines, organizational capital that combines the usual factors of production in a special way. HP cannot simply replicate Dell's tangible capital stock and become as profitable as Dell. Hence, it doesn't make sense to think about organizational capital, or intangibles more generally, as separate factors of production that can be purchased in a market. In most cases, intangibles are so closely connected with traditional factor inputs — like a computer or a college graduate — that their valuation on a standalone basis is nearly impossible (see, e.g., Lev 2001).

This definition contrasts sharply with the tendency in the literature to think about intangible capital as pretty much like any other quasi-fixed factor of production. In that mold, firms buy intangibles like they buy machinery. But intangibles, by and large, are different from other factors because companies cannot order or hire intangibles.

[3] This rather narrow definition based on IT adjustment costs is motivated by a broader interpretation of organizational capital in terms of adjustment costs, as in, for example, Prescott and Visscher (1980).

That's because intangible capital usually has to do with the distinctive way companies combine the usual factors of production. Treating intangibles as an input itself misses this point all together.

The model in the next section formalizes this observation by defining intangibles as whatever makes installed inputs more valuable than uninstalled inputs — that is, whatever makes a Dell out of the same computers and college graduates that HP can buy. Realistically, this definition isn't exhaustive since there are intangibles that aren't associated with specific expenditures. For example, a good idea — selling computers using the Internet in Dell's case — can be thought of as a type of intangible capital. Nevertheless, most intangibles are closely associated with some sort of outlay; after all, it usually takes at least some investment to make a good idea profitable.

My definition of organizational capital might seem similar to the more familiar concept of multifactor productivity or IT-biased technical change. Indeed, organizational capital is like IT-biased technical change in that both boost the marginal product of IT capital. However, there is a critical difference: organizational capital is costly to create; by contrast, MFP and IT-biased technical change require no specific outlays, which is why they are called 'manna from heaven.' Organizational capital should be distinguished from embodied technical change as well. Embodied technical change characterizes the capabilities of a particular asset — disk drives are more efficient and reliable than they used to be — but organizational capital depends on how the firm utilizes an asset. Returning to the example above, both Dell and HP can buy the same technology embodied in a new disk drive but the drive is more valuable at Dell because of its superior organizational capital.

2.2 Theoretical Model

The model is a straightforward variant of Hayashi and Inoue (1991), who derived an expression for the value of a firm with multiple capital goods, and follows the derivation in Bond and Cummins (2000). Similar to what I have in mind, Hall (1993a) used Hayashi and Inoue's model to estimate the rate of return to R&D. The novel twist in our application is the idea that intangibles are like adjustment costs, which can, in turn, be estimated econometrically.

In each period, the firm chooses investment in each type of capital good: $\mathbf{I}_t = (I_{1t}, \ldots, I_{Nt})$, where j indexes the N different types of capital goods and t indexes time.[4] This is equivalent to choosing a sequence of capital stocks $\mathbf{K}_t = (K_{1t}, \ldots, K_{Nt})$, given $\mathbf{K}_{t-1}$, to maximize V_t, the cum-dividend value of the firm, defined as:

$$V_t = \mathrm{E}_t \left\{ \sum_{s=t}^{\infty} \beta_s^t \Pi(\mathbf{K}_s, \mathbf{I}_s, \epsilon_s) \right\}, \tag{1}$$

where E_t is the expectations operator conditional on the set of information available at the beginning of period t; β_s^t discounts net revenue in period s back to time t; Π is the revenue function net of factor payments, which includes the productivity shock ϵ_s as an argument. Π is linear homogeneous in (K_s, I_s) and the capital goods are the only quasi-fixed factors — or, equivalently, variable factors have been maximized out of Π. For convenience in presenting the model, I assume that there are no taxes and the firm issues no debt and has no current assets, although these considerations are incorporated in the empirical work.

[4]The firm index i is suppressed to economize on notation except when it clarifies the variables that vary by firm.

The firm maximizes equation (1) subject to the series of constraints:

$$K_{j,t+s} = (1-\delta_j)K_{j,t+s-1} + I_{j,t+s} \quad s \geq 0 \tag{2}$$

where δ_j is the rate of physical depreciation for capital good j. In this formulation, investment is subject to adjustment costs but becomes productive immediately. Furthermore, current profits are assumed to be known, so that both prices and the productivity shock in period t are known to the firm when choosing I_{jt}. Other formulations — such as one where there is a production and/or a decision lag — are possible but this is a more parsimonious specification.

Let the multipliers associated with the constraints in equation (2) be $\lambda_{j,t+s}$. Then the first-order conditions for maximizing equation (1) subject to equation (2) are

$$-\left(\frac{\partial \Pi_t}{\partial I_{jt}}\right) = \lambda_{jt} \quad \forall j = 1, \ldots, N \tag{3}$$

and

$$\begin{aligned} \lambda_{jt} &= \left(\frac{\partial \Pi_t}{\partial K_{jt}}\right) + (1-\delta_j)\beta_{t+1}^t E_t\left[\lambda_{j,t+1}\right] \quad \forall j = 1, \ldots, N \\ &= E_t\left[\sum_{s=0}^{\infty} \beta_s^t (1-\delta_j)^s \left(\frac{\partial \Pi_{t+s}}{\partial K_{j,t+s}}\right)\right]. \end{aligned} \tag{4}$$

Combining equations (3) and (4) and using the linear homogeneity of $\Pi(\mathbf{K}_t, \mathbf{I}_t, \epsilon_t)$,

$$\begin{aligned} \sum_{j=1}^{N} \lambda_{jt}(1-\delta_j)K_{j,t-1} + \epsilon_t &= \Pi_t + \beta_{t+1}^t E_t\left[\sum_{j=1}^{N} \lambda_{j,t+1}(1-\delta_j)K_{jt}\right] \\ &= E_t\left[\sum_{s=0}^{\infty} \beta_{t+s}^t \Pi_{t+s}\right] \\ &= V_t. \end{aligned}$$

Hence, the value of the firm can be expressed as the sum of the installed values of the beginning-of-period capital stocks, which according to equation (2) are equal to the difference between the current capital stock and current investment. Since there are three types of capital in the empirical work, the specific equation considered is

$$V_t = \lambda_K(K_t - I_t) + \lambda_{KIT}(KIT_t - IT_t) + \lambda_{KIP}(KIP_t - IP_t) + \epsilon_t \tag{5}$$

where investment in tangible capital (excluding IT), information technology, and intellectual property are I, IT, and IP; the capital stock (excluding IT) is denoted by K, and the IT and IP capital stocks are distinguish by appending IT and IP.

According to equation (3), the multipliers on each capital stock are the gross marginal cost of an additional unit of capital, which is equal to the price of capital including adjustment costs. To be more concrete, posit an adjustment cost function, C, that is additively separable from the net revenue function:

$$\lambda_{jt} = p_j + \frac{\partial C}{\partial I_j}. \tag{6}$$

In this equation, it is possible to distinguish between the purchase price of capital and marginal adjustment costs, which are additional outlays that are needed to make investment productive. This separation is attractive because adjustment costs — such as training workers to use new equipment and integrating new and old equipment — create intangible capital.[5] Moreover, when it comes to empirical research, there's a well-developed literature on estimating adjustment costs econometrically, whereas

[5] For example, Hempell (2003) finds broad evidence that firms complement IT spending with training programs for their employees (see also Bresnahan, Brynjolfsson, and Hitt 2002). According to Hempell's empirical results, firms that invest intensively in both training and IT perform significantly better than competitors that do not.

there is no practical way to directly measure the value of intangible capital using available data. In fact, the estimated marginal adjustment costs are equal to the return on intangible capital in equilibrium. To see this, note that firms will invest until the gross marginal cost of an additional unit of capital in equation (6) is equal to the marginal product of capital, defined by the Euler equation (4). Therefore, the equilibrium return on intangible capital can be equated with adjustment costs.

Let's return to the Dell-HP example to fix ideas. A quick and dirty way to characterize the difference between Dell and HP would be to say that the level of MFP is higher at Dell. But this isn't very informative because it wouldn't explain *why* Dell produces more with less. By contrast, the valuation equation (5) shows that it's possible to trace the sources of Dell's superior valuation to its intangible capital, specifically the intangible capital associated with its previous investments in IT and IP. New software, say, is more valuable at Dell because of the way its used. While this type of finding is more informative than attributing any and all differences to MFP, admittedly it still leaves something to be desired. In particular, this approach fails to explain *how* software became more valuable at Dell; estimating (5) doesn't provide a blueprint for creating value. To gain further insight on this point considerably better data and detailed case studies are necessary.

Interpretation of the estimates of equation (5) is more complicated than it might seem at first glance. Notice that the multipliers are assumed constant. However, the value of intangible capital could differ over time and across firms; indeed, the comparison of Dell and HP suggests that this is a realistic possibility. Regrettably, the empirical framework is not rich enough to accommodate this consideration. In practice, the problem is not as bad as it might seem, since I control for firm- and time-specific effects.

Nevertheless, to the extent that the multipliers are not constant after controlling for these effects, the empirical estimates of the multipliers will be averages across firms and time.[6] Hence, extreme caution must be exercised in interpreting the estimates as structural parameters; rather, the estimates are revealing about the *average* return of intellectual property and organizational capital. Lastly, it should be recognized that this limitation is not unique to my setup. On the contrary, my setup is closely related to production or cost function estimation, where it is also assumed that the parameters are constant across firms and time, in spite of the debatable case for such an assumption.

3 Estimation of the Empirical Valuation Equation

Estimation of the empirical valuation equation (5) would be straightforward if there were data on the intrinsic value of the firm and the error term was an innovation. As I will discuss in turn, each of these conditions is unlikely to hold. As a result, ordinary least squares estimates will be biased. Identification is still possible in certain circumstances using generalized method of moments. However, the GMM approach does have some notable drawbacks which I discuss in the final subsection.

Two primary issues must be confronted when it comes to estimating equation (5):

- The intrinsic value of the firm is unobservable.

  What I have called the equity market approach explicitly assumes that the stock market value of the firm, V^E, equals the intrinsic value of the firm, V. Alternatively,

[6]Cross-sectional estimation wouldn't sidestep this problem entirely because the estimates would still be averages across firms. Moreover, cross-sectional estimation is inadvisable since there are no controls for firm-specific effects.

one could argue that any market mismeasurement is orthogonal to the firms' current capital stocks and investments. Since either condition is at least suspect, I propose an alternative that arguably rests on firmer footing.

- The productivity shock ϵ — think of a new product or process — is unobservable to the econometrician and it affects both the value of the firm and its investment policy.

  As a result, OLS estimates will be biased. Alternatively, I use the system-GMM estimator proposed by Blundell and Bond (1998, 2000). They show that the system-GMM estimator performs well when there are fixed effects and the endogenous variables have near unit roots, as is true of all three types of capital.

3.1 Unobservable Value of the Firm

The most widely-used proxy for the intrinsic value of the firm is its stock market value. According to one view of the stock market, this makes good sense since share prices reflect the discounted value of expected future distributions from the firm to its shareholders. If this is the case, there are two possible explanations for share price movements: changes in expected future profitability that support future dividend payments, or changes in investors' required rates of returns. Hence, share prices of intangible-intensive companies may have been rising until 2000 on advance news of unprecedented profit growth. Another possibility consistent with this view is that investors decided that the stock market was much less risky than they previously believed. For example, Siegel (1999) argues that the safest long-term investment vehicle has been stocks, not bonds. Accordingly, investors may have realized that they were irrationally fearful of stocks. In an environment in which stocks are not really all that risky, rational investors will bid up stock prices. In other words, the equity premium was too high in the past but it's just right now.[7]

Another view of the stock market cautions that share prices may sometimes have a life of their own, away from the intrinsic level represented by the discounted value of future distributions. The theoretical possibility that share prices deviate from their intrinsic value because of a rational bubble has long been recognized.[8] Outside of this particular paradigm, there is an abundance of models in which share prices are influenced by noise traders, fads or other psychological factors. While I cannot explain the disconnect between asset prices and their intrinsic values, simple observation of the behavior of — to name just two examples in addition to the ones already discussed — tulip prices in 1634-37 and Japanese share prices in 1989, suggests that such behavior is difficult to dismiss on empirical grounds. In which case, the recent stock market boom and at least partial bust may be another example of such anomalies. Indeed, Shiller (2000) argues that investors have not rationally learned that the stock market is less risky than they previously thought. Rather, he details a whole host of reasons why investors have been, and continue to be, irrationally exuberant.

It is important to highlight the key distinction between these two different views of the stock market. In the first, market efficiency is treated as a maintained hypothesis. In the second, market *in*efficiency is treated as a maintained hypothesis. To illustrate the implications of this, pick a stream of expected profits. The first theory tells us what

[7]McGrattan and Prescott (2000) use this argument to conclude that "it is troubling that economic theory failed so miserably to account for historical asset values and returns while, at the same time, it does so well in accounting for current observations." The "current observations" in their study date from the beginning of 2000, so apparently economic theory needs some work to explain the subsequent downturn (see also Kiley 2000).

[8]A rational bubble occurs when the expected discounted future price does not converge to zero in the limit. There are both theoretical and empirical arguments that can be used to rule out rational bubbles (see, e.g., Campbell, Lo, and MacKinlay 1997, chapter 7). Hence, rational bubbles are unlikely to offer a persuasive explanation for financial market behavior.

the (possibly time-varying) discount rate (i.e., the return) must be in order to justify the observed stock price. The second theory tells us that there is some reason outside the basic model — bubbles, noise traders, fads, or the like — why the stock price differs from its intrinsic value. It's very difficult to determine which of these explanations is preferable because they both rely on unobservable factors to explain the very same data. To have any degree of confidence in either explanation, one must exploit the testable implications of the dynamic stochastic structure of the unobservable factors. To do so I set out a model based on joint research with Stephen Bond (2000, 2002).

Suppose the stock market reveals the intrinsic value of the firm with some error, so that

$$V_t^E = V_t + \mu_t, \tag{7}$$

where μ_t is the measurement error in the equity valuation V_t^E, regarded as a measure of the intrinsic value V_t. Substituting V_t^E for V_t in equation (5) then gives the empirical valuation equation when there are noisy share prices:

$$V_t^E = \lambda_K(K_t - I_t) + \lambda_{KIT}(KIT_t - IT_t) + \lambda_{KIP}(KIP_t - IP_t) + (\mu_t + \epsilon_t). \tag{8}$$

Let's consider the effect of measurement error in the model's dependent variable, and ignore the difficulty presented by the unobservable productivity shock which is considered in the following section. The conventional wisdom is that measurement error of this type biases the standard errors but not the coefficient estimates (see, e.g., Hausman 1991). However, this is untrue when the measurement error is correlated with the explanatory variables.

To illustrate the argument, consider a simplified version of equation (8) in which the firm has only IT capital. The coefficient estimate on IT capital, call it b_{KIT}, will consist of the true return on IT, β_{KIT}, and the bias caused by measurement error:

$$p \lim b_{KIT} = \beta_{KIT} + \beta_{\mu,KIT},$$

where $\beta_{\mu,KIT}$ is the coefficient estimate from a hypothetical regression of the measurement error on IT capital: $\beta_{\mu,KIT} = \text{COV}(\mu, KIT)/\text{VAR}(KIT)$. Clearly, there's no bias if $\text{COV}(\mu, KIT) = 0$; the measurement error is uncorrelated with the regressor and the conventional wisdom about measurement error in the dependent variable is correct. However, if the stock market overestimates the value of IT-intensive companies, then $\beta_{\mu,KIT} > 0$ and, therefore, the return to IT investment will be upward biased. Since my sample is skewed toward the kind of companies commonly thought the have been overvalued compared to fundamentals — companies in the 1990s with big IT budgets — it seems reasonable to suspect that this upward bias could be substantial. However, if the stock market were to underestimate the value of IT-intensive companies, the bias would go in the other direction. Indeed, this type of downward bias would imply that the true return to investment exceeded the estimated return during periods like the 1970s when the stock market was arguably undervalued compared to fundamentals. Although it is not possible to sign the bias based on a priori reasoning in the multivariate case, the estimated returns to IP and tangible capital are also likely to be biased. However, the IT and IP coefficients seem likely to be severely affected because the stock market appears to have overestimated the value of intangible-intensive companies in the 1990s.

As an alternative to using the stock market to infer the value of intangibles, I rely on analysts' profit forecasts. Intangible assets create value only to the extent that they are expected to generate profits in the future. Professional analysts are paid to forecast the future profits of the firms they track — and leading analysts are paid very well indeed for performing this role. Thus it is possible to ask whether analysts are forecasting profit growth in line with the intangible asset growth that seems to be implied by stock market valuations. Though the popular press regularly lambastes analysts for being far too optimistic, the answer is 'no'.[9] After introducing the data in the next section, I show that analysts' forecasts of future profits are informative.

Combining these forecasts with a simple assumption about the discount rates β^t_{t+s}, I construct an alternative estimate of the present value of current and future net revenues as

$$\hat{V}_t = E_t \left(\Pi_t + \beta^t_{t+1} \Pi_{t+1} + \ldots + \beta^t_{t+s} \Pi_{t+s} \right). \tag{9}$$

I then use this estimate in place of the firm's stock market valuation. Clearly the estimate $\hat{V}_t$ will also measure the firm's intrinsic value, V_t, with some error ν. The potential sources of measurement error include truncating the series after a finite number of future periods, using an incorrect discount rate, and the fact that analysts forecast net profits rather than net revenues. The resulting empirical valuation equation is:

$$\hat{V}_t = \lambda_K (K_t - I_t) + \lambda_{KIT} (KIT_t - IT_t) + \lambda_{KIP} (KIP_t - IP_t) + (\nu_t + \epsilon_t). \tag{10}$$

[9] Armed with a time-varying, firm-specific discount rate, one can equate any stream of profit forecasts to the observed stock price at every observation; without additional restrictions there are, in fact, an infinite number of paths of time-varying discount rates that can equate the two. The key point is that extreme assumptions would be required to obtain the V^E's in the sample from the analysts' forecasts of future profits. Share prices in my sample appear to be high not only in relation to current profits, but also in relation to the best available forecasts of likely future profits.

As discussed in the following section, identification will depend on whether the measurement error ν is uncorrelated with suitably lagged values of instruments, for example, capital stocks. This seems plausible since the current measurement error from using analysts' forecasts is unlikely to be correlated with lags of the capital stock. Ultimately, however, this is an empirical question that will be investigated using tests of overidentifying restrictions.

3.2 Unobservable Productivity Shock

Despite some important differences, the empirical valuation equations (8) and (10) resemble a production function. This similarity is unfortunate because, as Griliches and Mairesse (1999) say, "In empirical practice, the application of panel methods to micro-data have produced rather unsatisfactory results." Mairesse and Hall (1996) show that attempts to control for unobserved heterogeneity and simultaneity — both likely sources of bias in the OLS results — have produced implausible estimates of production function parameters. To be more specific, in my setup I assume that the unobservable productivity shock consists of a firm-specific, a time-specific, and an idiosyncratic component. In this case, the application of GMM estimators, which take first differences to eliminate unobservable firm-specific effects and use lagged instruments to correct for simultaneity in the first-differenced equations, has produced especially unsatisfactory results.

Blundell and Bond (1998, 2000) show that these problems are related to the weak correlation between the regressors and the lagged levels of the instruments. This results in weak instruments in the context of the first-differenced GMM estimator. Bond and Blundell show that these biases can be dramatically reduced by incorporating more informative moment conditions that are valid under quite reasonable conditions. Essentially, their approach is to use lagged first-differences as instruments for equations in levels, in addition to the usual lagged levels as instruments for equations in first-differences. The result is the so-called system-GMM estimator, which I use as the preferred estimator. This is implemented using DPD98 for GAUSS (Arellano and Bond 1998).[10]

There are two types of diagnostic tests for the empirical models. First, I report the p-value of the test proposed by Arellano and Bond (1991) to detect first- and second-order serial correlation in the residuals. The statistics, which have a standard normal distribution under the null, test for nonzero elements on the second off-diagonal of the estimated serial covariance matrix. Second, I report the p-value of the Sargan statistic (also know as Hansen's J-statistic), which is a test of the model's overidentifying restrictions; formally, it is a test of the joint null hypothesis that the model is correctly specified and that the instruments are valid.

3.3 Limitations of the Empirical Approach

If the GMM-based empirical approach were successfully implemented, then that would be the end of the story in most applications. However, intangible assets pose a special problem. According to my model, intangibles are associated with specific investments but clearly that's not the whole story; sometimes intangibles are not associated with any identifiable outlay. In that case, at least some of the intangibles end up in the error term as an omitted variable or as part of the unobservable productivity shock.

[10] In all specifications, time effects are captured by including year dummies in the estimated specifications.

To fix ideas, suppose the fixed effect in the unobservable productivity shock represents intangible capital. If the fixed effect embeds intangible capital in this way, the econometric cure may be worse than the disease. In particular, first-differencing would sweep out the effect of fixed intangible capital. As a result, the possibility that intangible capital determines the *level* of the firm's intrinsic value would be completely missed.

To take another interesting example, MFP is normally thought of as a black box but perhaps this box is full of what researchers mean by intangibles. Indeed, many of the examples used to illustrate the role that intangibles play in organizations have the flavor of MFP. That is, intangible capital comes from a good idea like selling computers over the Internet in Dell's case; or, a unique corporate culture created by CEOs like Jack Welch or Bill Gates. Be that as it may, most intangible assets appear to be created by investment, as argued in the introduction. After all, Dell cannot sell computers over the Internet without its own computers, and Microsoft spends more than $5 billion annually on R&D and advertising.

In summary, by pursuing an estimation strategy like GMM with instruments that are arguably orthogonal to the error term, one might recover something closer to the direct impact of any asset on market value. However, one will by construction miss the role of omitted intangibles or intangibles that underlie the productivity shock. Thus, such IV strategies can be informative, but they cannot provide the full set of answers about the role of intangibles.

In fact, Brynjolfsson, Hitt, and Yang (2000, 2002) have taken this argument one step further: They say that the effect of intangible capital can be indirectly inferred from

OLS estimates of the return to IT capital. Two points are worth making about this argument, the first methodological and the second empirical.

First, OLS cannot be used to separate out all the direct and indirect effects of intangible capital. In particular, the return to, or the stock of, intangible capital cannot be inferred from the biased OLS coefficient on IT capital. When intangible capital is an omitted variable and IT capital is the only other type of capital, a straightforward analysis of omitted variable bias reveals that the coefficient on IT capital is

$$p \lim b_{KIT} = \beta_{KIT} + \beta_{KIC}\beta_{KIC,KIT},$$

where β_{KIC} is the return to intangible capital and $\beta_{KIC,KIT}$ is the coefficient estimate from a hypothetical regression of the omitted intangible KIC on IT capital: $\beta_{KIC,KIT} = \mathrm{COV}(KIC, KIT)/\mathrm{VAR}(KIT)$. For example, if \$1 of IT capital is associated with more than \$1 of omitted intangible capital, $\beta_{KIC,KIT} > 1$.

Using firm-level data, Brynjolfsson et al. estimate b_{KIT} using OLS and find that each dollar of IT capital is associated with about ten dollars of market value. They interpret this finding as revealing the existence of a "large *stock* of intangible assets that are complementary with IT spending (emphasis added)." However, that conclusion depends on assumptions about little understood relationships. Specifically, to say anything about the value of intangible capital, one has to know the return to IT capital. And to say anything about the return to intangibles or the size of the stock of intangibles, the value of intangible capital must be broken into its constituent components. Brynjolfsson et al. solve these problems by assuming that there are no adjustment costs, in which case the returns to IT and intangible capital are equal to unity ($\beta_{KIT} = \beta_{KIC} = 1$), and the stock of intangible capital associated with IT capital can be backed out. According to this argument, the stock market doesn't literally value \$1 of IT capital at \$10. Rather, the estimate is a "marker" for the existence of a large stock of IT-related intangibles.

The second concern is empirical: the results in Brynjolfsson et al. (2000) contradict their interpretation of the estimate on IT capital. When the authors added a variable that measures organizational intangibles, ORG, to the regressions, β_{KIT} is almost totally unaffected.[11] If the additional variable better measures intangibles, as the authors argue persuasively, then b_{KIT} should have fallen significantly because it's a "marker" for intangibles. Since the estimate was about unchanged, b_{KIT} must be biased for another reason, like the stock market mismeasurement or simultaneity bias that I've highlighted. If that is the case, it is advisable to adopt an empirical technique that corrects for the bias.

4 Data

4.1 Sources and definitions

The limiting factor in terms of the data is the availability of information about IT outlays. For IT expenditures I use a data set compiled by Lev and Radhakrishnan (this volume) from *Information Week*, which is in turn based on surveys by the Gartner Group. The total sample is an unbalanced panel of firms that appeared in the *Information Week* 500 list between 1991 and 1997 and for which Compustat and IBES data are available.

The variables used in the empirical analysis are defined as follows:

[11] In their subsequent paper, Brynjolfsson et al. (2002) did not include the telling regression from their first paper. Instead, they interacted ORG with employment. Although the interpretation of the effect of ORG is complicated this interaction, the take away point remained the same: the estimate on IT capital did not change significantly when ORG interacted with employment was included in the regression.

- V^E is the sum of the market value of common equity (defined as the number of common shares outstanding multiplied by the end-of-fiscal-year common stock price) and the market value of preferred stock (defined as the firm's preferred dividend payout divided by S&P's preferred dividend yield obtained from Citibase).

- $\hat{V}$ is the present value of analysts' profit forecasts. Let Π_{it} and $\Pi_{i,t+1}$ denote firm i's expected profits in periods t and $t+1$ formed using beginning-of-period information. Let g_{it} denote firm i's expected growth rate of profits in the following periods formed using beginning-of-period information. Notice, the stock market valuation of the firm, V^E, is dated at time $t-1$ so the market information set contains these forecasts. Then I calculate the implied level of profits for periods after $t+1$ by growing out the average of Π_{it} and $\Pi_{i,t+1}$ at the rate g_{it}. Let this average be $\bar{\Pi}_{it}$.[12]

  The resulting discounted sequence of profits defines $\hat{V}_{it}$:

$$\begin{aligned}\hat{V}_{it} = \quad & \Pi_{it} + \beta_t \Pi_{i,t+1} + \beta_t^2 (1+g_{it})\bar{\Pi}_{it} + \beta_t^3 (1+g_{it})^2 \bar{\Pi}_{it} \\ & + \beta_t^4 (1+g_{it})^3 \bar{\Pi}_{it} + \beta_t^5 \frac{(1+g_{it})^3 \bar{\Pi}_{it}}{\bar{r} - \bar{g}}\end{aligned}$$

  The constant discount factor reflects a static expectation of the nominal interest rate over this five year horizon; that is I use the Treasury bill interest rate in year

[12] In principle, the horizon for calculating $\hat{V}$ should be infinity. However, the analysts estimate g over a horizon of five years. Thus, in order to match the horizon for which there is information, I set the forecast horizon to five years. A terminal value correction accounts for the firm's value beyond year five. The correction assumes that the growth rate for profits beyond this five-year horizon is equal to that for the economy. Specifically, the last year of expected earnings is turned into a growth perpetuity by dividing it by $(\bar{r} - \bar{g})$; where I assume that $\bar{r}$ is the mean nominal interest rate for the sample period as a whole (about 15%, which includes a constant 8 % risk premium) and $\bar{g}$ is the mean nominal growth rate of the economy for the sample period as a whole (about 6%).

t (plus a fixed 8% risk premium as suggested by Brealey and Myers (2000) among others).

- D_t is the book value of debt which is the sum of short- and long-term obligations.
- C_t is net current assets, essentially cash-on-hand.
- I and K are capital expenditures and the current-cost net stock of property, plant, and equipment (both excluding IT). The current-cost stock is constructed with the perpetual inventory method using an industry-level rate of economic depreciation constructed from Hulten and Wykoff (1981).
- IT and KIT are IT expenditures and the current-cost net stock of IT. IT outlays are from the *Information Week* survey. The current-cost stock is constructed with the perpetual inventory method using a depreciation rate consistent with annual economic depreciation of 40%.
- IP and KIP are IP expenditures and the current-cost net stock of IP. IP expenditures are the sum of R&D and advertising. The current-cost stock is constructed with the perpetual inventory method using a depreciation rate consistent with annual economic depreciation of 25%.

The sample used for estimation includes all firms with at least four consecutive years of complete data. Four years of data are required to allow for first-differencing and the use of lagged variables as instruments. The determination whether the firm satisfies the four-year requirement is done after deleting several observations that looked like recording or reporting errors. Also, a few observations were deleted because $\hat{V} < 0$.[13]

[13] The data and programs for this study are available at www.insitesgroup.com/jason.

Table 1 describes details about the sample. The first two rows define the different proxies for the intrinsic value of the firm. The total value of the firm consists of three components: the return to equity holders, V^E or $\widehat{V}$, the return to debt holders, D, and an adjustment for net current assets, C. At both the mean and median values, the stock-market-based value is about three-quarters greater than the analyst-based value. Another notable feature of the sample is that spending on IT and IP is a large fraction of total investment spending at the mean and median values.

4.2 A Look at Analysts' Forecasts

To lay the foundation for using the analyst-based proxy for the intrinsic value of the firm, I compare the analysts' forecasts of long-term growth, g_{it}, with realizations of growth over a three-year horizon. As a first pass, the analysts expected profits to grow at an annual rate of 11.3% for the mean firm in my sample. Over a three-year horizon, profits actually grew at just a touch slower rate of 11%.

Figure 1 presents a more detailed comparison of actual and expected profit growth with each dot representing a single firm-year observation. Three features of the data are apparent. First, analysts don't forecast negative long-term growth. That's sensible, since such forecasts would be equivalent to saying that the company is essentially worthless. Second, analysts are loath to forecast very high long-term growth rates. That's sensible too. Very few companies generate profit growth in excess of 30%, and it's hard to identify ex ante those that may. Finally, actual profit growth is highly variable. Some companies do grow at very fast rates or suffer large retrenchments.

The OLS regression line describes the average relationship between the two variables. Actual and expected earnings growth are positively related — the slope of the regression line is 0.74 with a standard error of 0.15 — but realized earnings growth often differs widely from analysts' expectations.[14] Moreover, the forecasts tend to be overly optimistic on average. In addition, analysts do not issue particularly accurate long-range forecasts; evidently, a lot can happen to a company over a three year period, most of which cannot be anticipated. However, the key requirement for my purpose is not forecast accuracy, but rather the ability of analysts' forecasts to capture the expected future returns on which the firm's investment decisions are based. Judged according to this metric, analysts' forecasts appear to be reasonable and informative assessments about companies' future prospects.

5 Empirical Results

The empirical results are laid out in two stages. In Table 2, I present OLS estimates of the empirical valuation equations in levels and within groups. After establishing that these results are consistent with the sort of bias I've described, I present in Table 3 the results from two GMM estimators. First, I present a standard estimator that first-differences the empirical equations and uses lagged capital stocks as instrumental variables. For reasons described in section 3.2, the coefficient estimates are likely to be downward-biased in this case. Second, I present results from the system-GMM estimator. The diagnostic statistics indicate that system-GMM is well-behaved when using the analyst-based measure of intrinsic value and the results themselves are quite sensible.

[14] A few extreme observations have been left out of the figure in order to maintain a 1:1 aspect ratio. These observations are, however, included in fitting the regression.

5.1 OLS results

In the specification in the first column of Table 2, the coefficient on IT capital substantially and significantly exceeds unity as does the coefficient on IP capital. Meanwhile, the estimate of the return to tangible capital is significantly less than unity.[15] According to this first pass at the data, \$1 of IT capital is associated with about \$2 of unmeasured intangibles and \$1 of IP capital is associated with about \$1 of unmeasured intangibles. Thus my basic results parallel those reported by Brynjolfsson et al. despite the fact that I don't use the same firms or estimation period; I use different techniques for constructing the capital stocks; and I use different regressors.[16]

The basic pattern of estimates in column 1 is similar to the pattern in column 2, where $\hat{V}$ replaces V^E. In particular, using an analyst-based or a market-based definition of intrinsic value doesn't make much of a difference when estimating in levels using OLS. However, the estimates on IT capital are considerably smaller in columns 3 and 4, where net current assets are accounted for in valuing the firm. Apparently, large IT capital stocks are associated with relatively abundant net current assets — an example is Microsoft, which has a large stock of IT and has built up a huge cash cushion on its balance sheet. When this relationship is ignored, the coefficient on IT capital picks up both the effect of intangibles and the omitted effect of net current assets. Thus, to develop an accurate picture about the role of IT capital, the value of the firm has to be defined carefully.

[15] Recall from the theoretical model that the beginning of period capital stocks belong on the right hand side of the empirical valuation equation. According to equation (2) the beginning-of-period capital stocks are equal to the difference between the current capital stock and current investment. Hence, the relevant regressors are $(K_t - I_t)$ and so on.

[16] It was not possible to investigate the effects of these differences because Brynjolfsson et al. declined to share their data.

The results presented so far do not control for unobserved heterogeneity. As a result, the estimates are difficult to interpret because the firm-specific effect is surely correlated with contemporaneous capital investments. To sweep out the firm-specific effect, the within-groups estimates presented in columns 5 and 6 express all of the variables as deviations from within-firm means. In this case, the coefficients on IT are significantly negative in both specifications, and the coefficients on the other types of capital appear downward biased in the final column. These findings are not unexpected because the capital stocks are highly persistent. While unit root tests are useless for short panels, the (unreported) AR(1) coefficient estimates from regressions of the current capital stocks on their first lags are all greater than 0.92. In such situations, the received wisdom from the literature on production function estimation indicates that one should expect downward bias from within-groups estimates.[17]

5.2 GMM results

The GMM estimates are motivated by the observation that the within-groups results do nothing to control for simultaneity bias. Such bias must be important because the value of the firm (no matter how it is measured) and its investment policy are jointly determined. To see the intuition behind this point, compare the empirical valuation equation to an empirical investment equation based on Tobin's Q. In the current setup, the firm's intrinsic value is a function of the capital stock and investment, whereas the reverse is true in an equation that relates the investment rate to Tobin's Q. Put simply, increases in market value may cause investment in IT (and other types of capital), not

[17] In fact, it is not unusual for production function estimates of the capital share to go from 0.3 in levels to negative values for within-groups. The magnitude of the bias in Table 2 may seem surprisingly large by comparison, but keep in mind that production functions are estimated in logs.

the reverse. To deal with simultaneity bias (and eliminate the firm-specific effect at the same time), the first-differenced empirical valuation equations are estimated with GMM, using lagged levels of the capital stocks as instruments. These results are reported in columns 1 and 2 of Table 3.

Taking a look first at the Sargan test, the p-values in columns 1 and 2 do not indicate a decisive rejection of the model's overidentifying restrictions. That doesn't mean, however, that the instruments are informative. Indeed, in unreported results, I confirm that weak instruments cannot be rejected using the partial R^2 or first-stage F-statistic as criteria. If the instruments used in the first-differenced equations are weak, then the results should be biased in the direction of within-groups.[18] Indeed, a comparison of columns 1 and 2 of Table 3 to columns 5 and 6 of Table 2 shows that the direction and magnitude of the bias are similar in the first-differenced and within-groups estimates.

To address concerns about weak instruments, I use the system-GMM estimator in columns 3 and 4. Again, begin by looking at the Sargan test, which indicates that the model using V^E is decisively rejected while the one using $\widehat{V}$ is not. This suggests that the instruments are correlated with the market's mismeasurement of companies' intrinsic values but not with the analysts' mismeasurement of the same. Why might that be? As I have argued, intangibles are difficult to value. If, say, the lagged change in the stock of intangibles is correlated with the extent to which the market overstates the firm's intrinsic value, then the system-GMM estimator will tend to be rejected. By contrast, for reasons I've detailed, there's less reason to worry that analysts' forecast errors are correlated with the lagged change in the stock of intangibles, and this conjecture is

[18]The technical explanation for this statement depends on two things. First, weak instruments will bias 2SLS in the direction of OLS. Second, the first-differenced GMM estimator coincides with a 2SLS estimator when the fixed effects are removed with the orthogonal deviations transformation; and, OLS transformed to orthogonal deviations coincides with within groups. Therefore, weak instruments will bias this particular 2SLS estimator (which coincides with first-differenced GMM) in the direction of within groups.

born out by the Sargan test. Therefore, my preferred estimates use the analyst-based measure of the firm's intrinsic value.

In column 4, the coefficient estimates on tangible and IP capital are insignificantly different from unity (although they are significantly different from zero), and the coefficient on IT capital is significantly greater than unity. Taken at face value, the coefficient on IT capital implies that organizational capital earns a 70% annual rate of return, a figure that might seem excessive. However, two points are worth nothing. First, the evidence of excess returns is statistically weak because the 95% confidence interval encompasses returns as low as 7%. Second, in my model the return to IT capital *includes* the effect of adjustment costs; indeed, that is how organizational capital is defined in equation (6). This possibility is seldom noted because researchers usually estimate the return to IT using a static production function, which assumes that capital is in a steady-state equilibrium so that adjustment costs are zero by construction.[19]

The coefficient on IP capital is less than unity, a result consistent with earlier findings that R&D earns a somewhat less than normal rate of return (see, e.g., Hall 1993b). Perhaps firms cannot reap the full benefit of their IP investments owing to the nonexclusive nature of some types of R&D (see, e.g., Griliches 1979; Jaffe 1986; Bernstein and Nadiri 1989). However, caution is warranted in drawing such a conclusion because the 95% confidence interval encompasses returns as large as 20%, more in line with the recent findings in Hand (2002). Finally, the estimate on tangible capital (excluding IT) is slightly less than unity. This is consistent with lower rates of return on these types of

[19]To elaborate on the implications of my approach in the context of a production function, notice that the marginal product of capital in my model is equal to the traditional user cost *plus* adjustment costs. For example, abstracting from taxes and setting the price of capital equal to unity, the equilibrium condition in my model is $\frac{\partial \Pi}{\partial KIT} = r + \delta_{KIT} + \frac{\partial C}{\partial KIT}$. So long as adjustment costs are positive, the estimated return to capital can exceed $(r + \delta_{KIT})$, the usual equilibrium required rate of return in the production function framework.

capital and with recent studies in which estimated adjustment costs are quite modest in size (see, e.g., Bond and Cummins 2002).

6 Conclusion

The dramatic rise of the stock market in the 1990s led some observers to conclude that intangible capital was an increasingly important contributor to the bottom line at many companies. However, the abrupt and sustained decline in the stock market that began in 2000 seemed to suggest just the opposite. This reversal highlights the desirability of alternative measurement strategies that would distinguish between the gyrations of the stock market and the value created by intangibles.

My empirical approach offers such an alternative strategy, with both a different perspective about what intangibles are and how researchers can estimate their return. In my model, intangible capital is not a distinct input to production like physical capital or labor; indeed, I assume that intangibles cannot be purchased in a market like a computer or a college graduate. Nor are intangibles some kind of relabeled MFP. Rather intangible capital is the glue that creates value from the usual factor inputs. This perspective naturally leads to an empirical model in which intangible capital is defined in terms of adjustment costs. As such, intangibles are the difference between the value of installed and uninstalled inputs.

In my empirical approach, I use two proxies for the intrinsic value of the firm, one based on the firm's stock market value and the other based on analysts' profit forecast. In addition, I use a GMM estimation technique to control for unobserved heterogeneity and simultaneity bias in specifications with nearly-integrated regressors. Using the analyst-based proxy and the GMM technique, there is no evidence of economically important intangibles associated with investment in intellectual property or physical capital apart from IT. However, my estimates suggest that organizational capital created by information technology generates a 70% annual rate of return.

These findings come with a caveat attached. Controlling for simultaneity bias and unobserved heterogeneity removes intangibles that may have been swept into the error term, either as omitted variables or as part of the unobservable productivity shock. Nevertheless, alternative empirical approaches are unpalatable to say the least. Indeed, my OLS estimates would seem to imply a strong role for intangibles but they are unreliable because the value of the firm and its investment policy are jointly determined. In the end, how best to characterize the heterogeneity across firms and the role that intangibles play remains an open question. Are intangibles a part of the unobservable productivity shock? Are intangibles some fixed (or quasi-fixed) factor that interact in complex ways with other inputs? The answers to these questions remain unresolved.

Finally, it's worth reflecting on whether my approach suggests ways to incorporate intangible capital in national income accounting. At a very basic level, the implications are not encouraging. Factor inputs in the national accounts have prices, albeit ones that are often difficult to measure accurately. By contrast, my approach starts with the assumption that intangibles are nearly impossible to value on a standalone basis. In particular, intangibles have unobservable *shadow* prices that depend on expectations. This setup makes the return to intangibles impossible to measure directly and uncertain by construction. These two features make intangible capital particularly ill-suited to national income accounting. Nevertheless, my approach does suggest a road map for improving the national accounts. A key ingredient for better understanding the scope of intangibles is detailed data on the types of outlays that are closely connected with intangibles. In this regard, the national accounts could be considerably improved. I focused on IT, R&D, and advertising but it would be desirable to have data on other types of outlays as well, such as education, on-the-job training programs and the like.

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Figure 1
Actual Profit Growth and Expected Long-Term Profit Growth, 1992-1997

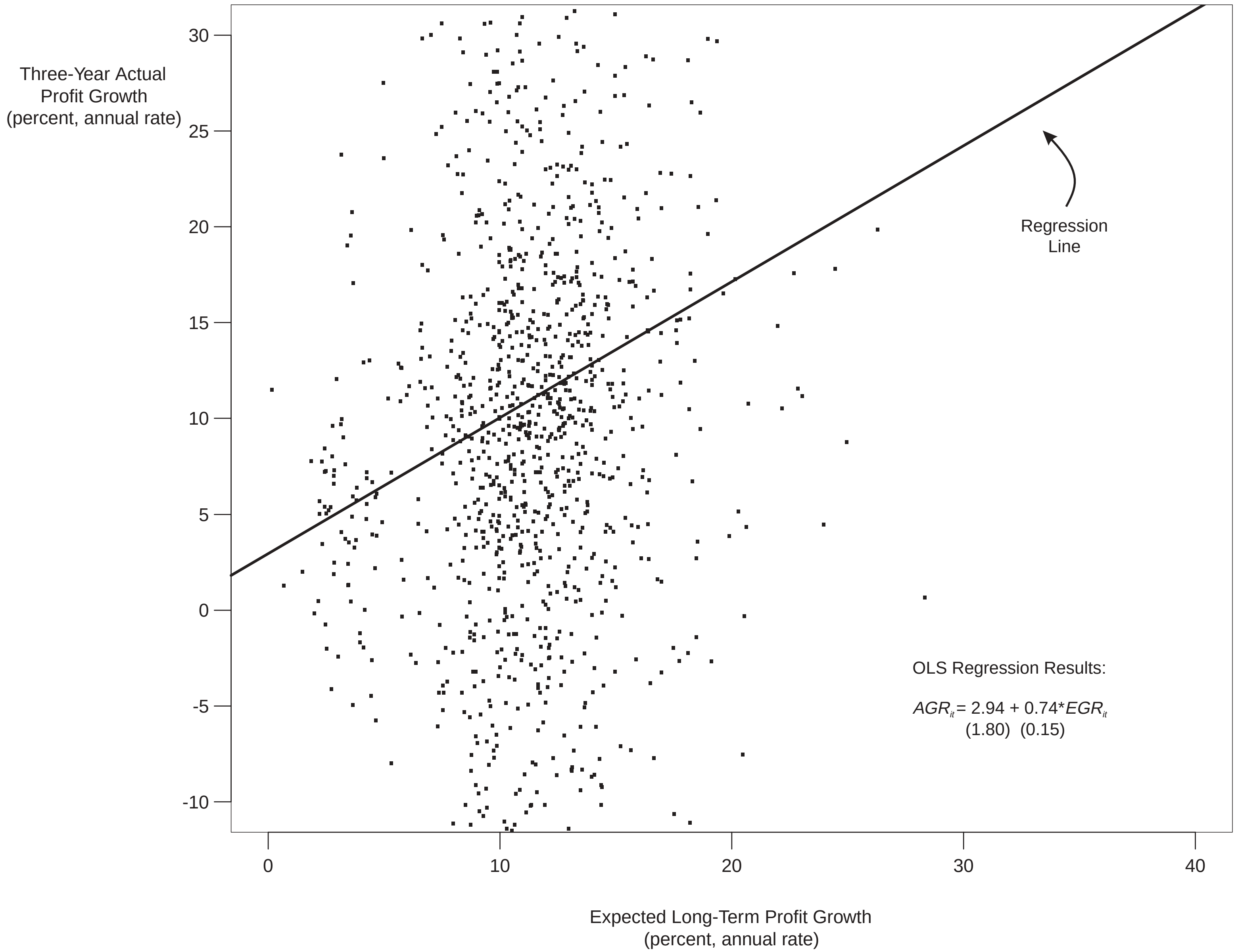

Table 1: Descriptive Statistics for Variables Used in Empirical Analysis (Millions of Current-Dollars)

Variable	mean	standard deviation	first quartile	median	third quartile
$(V^E + D - C)$	12,315	23,225	2,321	5,086	12,402
$(\hat{V} + D - C)$	7,208	15,308	1,179	2,942	7,379
K	5,822	10,107	734	2,051	6,453
KIT	922	2,013	135	337	802
KIP	1,726	4,289	0	292	1,304
I	769	1,696	107	298	729
IT	223	461	35.0	81.1	200
IP	383	997	0	53.0	255

The sample contains firms with at least four years of complete data. The number of firms in this sample is 253, for a total of 1,503 observations, and the sample period is 1991–1997.

Table 2: OLS Estimates of the Valuation Equations

	Levels				Within-Groups	
	Dependent Variable				Dependent Variable	
	$(V_t^E + D_t)$	$(\hat{V}_t + D_t)$	$(V_t^E + D_t - C_t)$	$(\hat{V}_t + D_t - C_t)$	$(V_t^E + D_t - C_t)$	$(\hat{V}_t + D_t - C_t)$
	(1)	(2)	(3)	(4)	(5)	(6)
$(K_t - I_t)$	0.753	0.482	0.821	0.550	0.892	0.182
	(0.075)	(0.064)	(0.064)	(0.048)	(0.216)	(0.169)
$(KIT_t - IT_t)$	3.19	3.14	1.97	1.91	-6.67	-8.63
	(0.491)	(0.416)	(0.415)	(0.316)	(0.836)	(0.656)
$(KIP_t - IP_t)$	2.07	1.54	1.84	1.31	2.67	0.383
	(0.211)	(0.179)	(0.179)	(0.136)	(0.685)	(0.537)
	Diagnostic Tests (p-values)					
First-Order Serial Correlation	0.070	0.066	0.143	0.169	0.930	0.886
Second-Order Serial Correlation	0.086	0.086	0.171	0.214	0.245	0.317
$\bar{R}^2$	0.451	0.401	0.474	0.457	0.107	0.171

Year dummies are included (but not reported) in all specifications. Robust standard errors on coefficients are in parentheses.

The sample contains firms with at least four years of complete data. The number of firms in this sample is 253, for a total of 1250 observations, and the estimation period is 1992–1997.

The tests for serial correlation in the residuals is asymptotically distributed as N(0,1) under the null of no serial correlation.

Table 3: GMM Estimates of the Valuation Equations

	First-Differences Dependent Variable		System Dependent Variable	
	$(V_t^E + D_t - C_t)$	$(\hat{V}_t + D_t - C_t)$	$(V_t^E + D_t - C_t)$	$(\hat{V}_t + D_t - C_t)$
	(1)	(2)	(3)	(4)
$(K_t - I_t)$	0.399	0.007	1.75	0.846
	(0.478)	(0.197)	(0.144)	(0.135)
$(KIT_t - IT_t)$	-12.9	-11.3	0.725	1.72
	(1.33)	(1.30)	(0.390)	(0.327)
$(KIP_t - IP_t)$	9.72	3.93	0.652	0.684
	(1.80)	(1.01)	(0.273)	(0.257)
	Diagnostic Tests (p-values)			
First-Order Serial Correlation	0.656	0.634	0.883	0.644
Second-Order Serial Correlation	0.345	0.488	0.326	0.463
Sargan Test	0.047	0.360	0.000	0.073

Year dummies are included (but not reported) in all specifications. Robust standard errors on coefficients are in parentheses.

The sample contains firms with at least four years of complete data. The number of firms in this sample is 253, for a total of 1250 observations, and the estimation period is 1992–1997.

In the first-differences estimator, the instrumental variables are the levels of the period $t-3$ and $t-4$ capital stocks. In the system estimator, the valuation equation in first-differences is estimated jointly with the valuation equation in levels. The instrumental variables for the first-differenced equation are the levels of the period $t-3$ and $t-4$ capital stocks. The instrumental variables for levels equation are the first-differences of the period $t-2$ capital stocks. Year dummy variables are also included as instruments in all specifications.

The tests for serial correlation in the residuals is asymptotically distributed as N(0,1) under the null of no serial correlation. The test of the overidentifying restrictions, called a Sargan test, is asymptotically distributed as $\chi^2_{(n-p)}$, where n is the number of instruments and p is the number of parameters.