Volume Title: Measuring Capital in the New Economy

Volume Author/Editor: Carol Corrado, John Haltiwanger and Dan Sichel, editors

Volume Publisher: University of Chicago Press

Volume ISBN: 0-226-11612-3

Volume URL: http://www.nber.org/books/corr05-1

Conference Date: April 26-27, 2002

Publication Date: August 2005

Title: A New Approach to the Valuation of Intangible Capital

Author: Jason G. Cummins

URL: http://www.nber.org/chapters/c10618

Chapter pages in book: (47 - 72)

2

A New Approach to the Valuation of Intangible Capital

Jason G. Cummins

2.1 Introduction

In most circumstances, there are no direct measures of the return on intangible capital. As a result, researchers have relied primarily on the equity market to infer the value of intangibles. This valuation method 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, Robert 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 approach to measuring intangibles, it should be used with considerable caution. According to this method, Yahoo!'s intangibles were worth more than $100 billion in 2000. However, they were worth less than one-third of that amount in 2003. To be sure, this drop does not necessarily pose a problem for the equity market approach. Yahoo!'s market capitalization may reflect changes in

Jason G. Cummins is a senior economist in the Division of Research and Statistics at the Federal Reserve Board.

Baruch Lev has been instrumental in shaping my thinking about intangible assets. I thank him for his guidance and for providing me with the data set on information technology investment that he and Suresh Radhakrishnan put together. I am also indebted to Stephen Bond, whose collaboration laid the foundation for this research. Daniel Cooper provided research assistance. Ned Nadiri, the editors, conference participants, and Darrel Cohen all provided helpful comments and suggestions. I/B/E/S International Inc. provided the data on earnings expectations. The views presented are solely mine and do not necessarily represent those of the Board of Governors of the Federal Reserve System or its staff members.

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 from the 1970s as showing that energy price shocks effectively destroyed a great deal of capital.

expected profits or expected returns or both. But this example illustrates a potential pitfall of relying on the equity market to reveal the value of intangible capital. This value will be mismeasured to the extent that asset prices depart from their intrinsic values.

The main drawback of the equity market 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 underlying assumption of the equity market approach—that markets are strongly efficient. 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 market participants know so little about the value of intangibles?

To create an alternative proxy for the intrinsic value of the firm, I construct the discounted value of expected profits from analysts' forecasts. I/B/E/S has collected data on profit forecasts for a large sample of companies since 1982. The analysts forecast profits for one and two years ahead as well as the growth rate of profits out to a five-year horizon. In making 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 analysts expect intangibles to contribute materially to a company's bottom line over a five-year period, then their forecasts should reflect the value of these intangibles.

Of course, analysts' forecasts are not foolproof. After all, the majority of analysts appear to have overestimated the growth rates of intangible-intensive companies in the late 1990s. And analysts offer little guidance about how to discount these forecasts. In fact, the discounted value of expected profits may be just as poor a proxy for a firm's intrinsic value as the stock market is. 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 the biases of analysts and any mistakes in the way the forecasts are discounted.

The econometric setup explicitly recognizes that the two proxies measure the firm's intrinsic value with different kinds of error. Ultimately, identification of the model's parameters depends on whether there are informative instrumental variables that are uncorrelated with the measurement errors 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 compiled a data set that distinguishes firms' expenditures on tangible capital, information technology (IT), and intellectual property (IP). Relying on these data, I use the stock-market- and analyst-based measures of the firm's intrinsic value to estimate the return on each type of capital. Perhaps the most interesting finding is that organizational capital created by IT generates a sizable, albeit imprecisely estimated, return. Despite its magnitude, the estimated return is considerably smaller than comparable estimates in previous studies. To build a bridge to the previous research, I show that much larger estimates can be obtained with ordinary least squares (OLS), a method that ignores the possibility that the value of the firm and its investment policy are simultaneously determined.

2.2 The Valuation of Intangible Capital

2.2.1 Intangible Capital: An Instrumental Definition

I distinguish between two types of intangibles: IP 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 this narrow definition suggests. 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 forebears. 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 two-part taxonomy suits my empirical model and the data. The data warrant brief explanation. 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. Such a stock may seem essentially arbitrary—companies offer little guidance, for example, about how R&D and advertising depreciate—but the stock of property, plant, and equipment is a similarly unpalatable concept, even though researchers have become sufficiently inured to it.[2]

As a practical matter, one must also distinguish between IP 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 has grown

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

modestly, from 3.9 percent in 1980–89 to 4.1 percent in 1990–97. The comparable figures for R&D are 2.3 percent and 2.9 percent (Nakamura 1999). Hence, if intangibles create extraordinary gains in firm value, then arguably the most plausible driver is organizational capital, not IP.

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 IT and that of uninstalled IT.[3] Suppose a company purchases database software. By itself, database software does not generate any value. At a minimum, the software must 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.

Another example helps illustrate the definition. Dell's value depends on a unique organizational design that sells build-to-order computers directly to customers. Dell's tangible capital stock differs little from that of Hewlett-Packard (HP), one of its main competitors, because both companies assemble computers. The reason that any given piece of tangible capital is more valuable at Dell than at HP relates to Dell's unique business model and routines, organizational capital that combines the usual factors of production in a special way. Hewlett-Packard cannot simply replicate Dell's tangible capital stock and become as profitable as Dell. Hence, it does not 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 as stand-alones is nearly impossible (see, e.g., Lev 2001).

This definition of organizational capital contrasts sharply with the tendency in the literature to think about intangible capital as being much like any other quasi-fixed factor of production. In that mold, firms buy intangibles as they would buy machinery. But intangibles, by and large, are different from other factors because companies cannot order or hire intangibles. Rather, intangible capital typically results from the distinctive way companies combine the usual factors of production. Treating intangibles as inputs misses this point altogether.

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 is not exhaustive because some intangibles are not associated with specific ex-

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

penditures. For example, a good idea—in Dell's case, selling computers over the Internet—can be thought of as a type of intangible capital. Nevertheless, most intangibles are closely associated with some sort of outlay; after all, at least some investment is usually needed to make a good idea profitable.

My definition of organizational capital may seem similar to the more familiar concept of multifactor productivity (MFP) or IT-biased technical change. Indeed, organizational capital is like IT-biased technical change in that it boosts the marginal product of IT capital. However, the concepts differ in a critical respect: Organizational capital is costly to create; in contrast, IT-based technical change and MFP require no specific outlays, and for that reason they are called "manna from heaven." Organizational capital should also be distinguished from embodied technical change. Whereas embodied technical change characterizes the capabilities of a particular asset—disk drives are more efficient and reliable than they used to be—organizational capital depends on how the firm uses an asset. In the example discussed 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 Dell's superior organizational capital.

2.2.2 Theoretical Model

The model is a straightforward variant of the one developed by Hayashi and Inoue (1991), who derived an expression for the value of a firm with multiple capital goods; it follows the derivation in Bond and Cummins (2000b). Using a method similar to mine, B. Hall (1993a) relied on Hayashi and Inoue's model to estimate the rate of return on R&D. The novel twist in my application is the idea that intangibles are like adjustment costs and therefore can be estimated econometrically.

In each period, the firm chooses to invest 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 decision 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

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

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; and Π is the revenue function net of factor payments, which includes the productivity shock ε_s as an argument. Π is linear homoge-

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

neous in $(\mathbf{K}_s, \mathbf{I}_s)$, 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 the firm pays no taxes, issues no debt, and has no current assets, although these considerations are incorporated into the empirical work.

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

$$(2) \qquad \mathbf{K}_{j,t+s} = (1 - \delta_j)\,\mathbf{K}_{j,t+s-1} + \mathbf{I}_{j,t+s}\; s \geq 0,$$

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, I assume that current profits are known so that the firm, when choosing I_{jt}, knows both the prices and the productivity shock in period t. Other formulations such as one including a production lag, a decision lag, or both are possible, but this specification is more parsimonious.

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

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

and

$$(4) \qquad \lambda_{jt} = \left(\frac{\partial \Pi_t}{\partial K_{jt}}\right) + (1 - \delta_j)\beta^t_{t+1} E_t(\lambda_{j,t+1}) \quad \forall j = 1, \ldots, N$$

$$= E_t\left[\sum_{s=0}^{\infty} \beta^t_s (1 - \delta_j)^s \left(\frac{\partial \Pi_{t+s}}{\partial K_{j,t+s}}\right)\right].$$

Combining equations (3) and (4) and using the linear homogeneity of $\Pi(\mathbf{K}_t, \mathbf{I}_t, \varepsilon_t)$, I get the following result:

$$\sum_{j=1}^{N} \lambda_{jt}(1 - \delta_j)K_{j,t-1} + \varepsilon_t = \Pi_t + \beta^t_{t+1} E_t\left[\sum_{j=1}^{N} \lambda_{j,t+1}(1 - \delta_j)K_{jt}\right]$$

$$= E_t\left(\sum_{s=0}^{\infty} \beta^t_{t+s} \Pi_{t+s}\right) = V_t.$$

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 the current investment. Because three types of capital are included in the empirical work, the specific equation considered is

$$(5) \qquad V_t = \lambda_K(K_t - I_t) + \lambda_{\mathrm{KIT}}(\mathrm{KIT}_t - \mathrm{IT}_t) + \lambda_{\mathrm{KIP}}(\mathrm{KIP}_t - \mathrm{IP}_t) + \varepsilon_t,$$

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

According to equation (3), the multiplier on each capital stock is 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, I 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, the purchase price of capital is distinguishable from marginal adjustment costs, which are additional outlays needed to make investment productive. This separation is attractive because adjustment costs such as the costs of training workers to use new equipment and of integrating new and old equipment create intangible capital.[5] Moreover, regarding empirical research, we have a well-developed literature on estimating adjustment costs econometrically, whereas we have no practical way of directly measuring the value of intangible capital from available data. In fact, the estimated marginal adjustment costs are equal to the return on intangible capital in equilibrium. That is, 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 equation (4), also known as the Euler equation. Therefore, the equilibrium return on intangible capital can be equated with adjustment costs.

Returning to the Dell-HP example, one might be tempted to characterize the difference between Dell and HP by saying that the level of MFP is higher at Dell than at HP. But this characterization is not sufficiently informative because it does not explain *why* Dell produces more with less. In contrast, the valuation equation (5) shows that it is 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 it is used. Although this approach is more informative than the one that attributes any difference to MFP, admittedly it still falls short. In particular, this approach fails to explain *how* software became more valuable at Dell; estimating (5) provides no blueprint for creating value. To gain further insight, we need considerably better data and more-detailed case studies.

Interpreting the estimates of equation (5) is more complicated than it

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 do competitors that forgo such investment.

may seem at first glance. Although the multipliers are assumed to be constant, the value of intangible capital can vary over time and across firms; indeed, the comparison of Dell with HP suggests that this variance 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 may seem because 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, econometricians must exercise extreme caution when interpreting the estimates as structural parameters, which they are not; rather, the estimates reveal the *average* return on IP and organizational capital. Finally, this limitation is not unique to my formulation. On the contrary, my formulation is closely related to production- or cost-function estimation, in which the parameters are assumed to be constant across firms and time despite the debatable case for such an assumption.

2.3 Estimating the Empirical Valuation Equation

Estimating the empirical valuation equation (5) would be straightforward if data on the intrinsic value of the firm were available and the error term were an innovation. As I will discuss in turn, neither of these conditions is likely to hold. As a result, estimates based on OLS will be biased. Identification is still possible in certain circumstances with generalized method of moments (GMM). However, the GMM approach does have some notable drawbacks, which I discuss in the final subsection.

Two primary issues affect the estimation of equation (5):

- The econometrician cannot observe the intrinsic value of the firm. 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, one can argue that any market mismeasurement is orthogonal to the firm's current capital stocks and investments. Because both of these conditions are at least suspect, I propose an alternative that arguably rests on firmer footing.
- The econometrician also cannot observe the productivity shock, ε, such as a new product or process, but this shock affects both the value of the firm and its investment policy. As a result, OLS estimates will be biased. Instead of OLS, 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.

6. Cross-sectional estimation does not sidestep this problem entirely because the estimates will still be averages across firms. Moreover, cross-sectional estimation is inadvisable because it does not control for firm-specific effects.

2.3.1 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 approach makes good sense because share prices reflect the discounted value of expected future distributions from the firm to shareholders. If they do, share price movements can be explained in one of two ways: as changes in expectations about future profits, changes that support future dividend payments; or as fluctuations in investors' required rates of return. Hence, from the early 1990s to 2000, the rise in share prices of intangible-intensive companies may have been due to advance news of unprecedented profit growth. Alternatively, prices may have increased because investors decided that the stock market was much less risky than they had previously believed. As a result, they reduced their required rates of return. For example, Siegel (1998) argues that stocks, not bonds, have been the safest long-term investment vehicle. Accordingly, investors may have realized that they were irrationally fearful of stocks. When stocks are seen as posing little risk, rational investors will bid up stock prices. In other words, they will decide that the equity premium was too high in the past but that it is just right now.[7]

Another view of the stock market cautions that share prices may sometimes have a life of their own, apart from the intrinsic level represented by the discounted value of future distributions. Observers have long recognized the theoretical possibility that share prices deviate from their intrinsic values because of a rational bubble.[8] Outside this particular paradigm, numerous models show that noise traders, fads, or other psychological factors influence share prices. Although I cannot explain the disconnect between asset prices and their intrinsic values, I can cite two well-known examples of this phenomenon: tulip prices in 1634–37 and Japanese share prices in 1989. These anomalies in price behavior are difficult to dismiss on empirical grounds. The recent stock market boom and at least partial bust may be another such anomaly. Indeed, Shiller (2000) argues that investors have not learned that the stock market is less risky than they had previously thought. Rather, for a whole host of reasons, investors have been and continue to be "irrationally exuberant."

Highlighting the key distinction between these two views of the stock market is important. Whereas the first view treats market efficiency as a

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 help in explaining 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. Both theoretical and empirical arguments can be used to rule out rational bubbles (see, for example, Campbell, Lo, and MacKinlay 1997, chap. 7). Hence, rational bubbles are unlikely to offer a persuasive explanation for behavior of financial markets.

maintained hypothesis, the second treats market *in*efficiency as a maintained hypothesis. To illustrate the implications of this distinction, I pick a stream of expected profits. The first theory tells us what the (possibly time-varying) discount rate (that is, the return) must be to justify the observed stock price. The second theory tells us that the stock price differs from its intrinsic value for some reason outside the basic model—bubbles, noise traders, fads, or the like. It is very difficult to determine which of these explanations is preferable because they both rely on unobservable factors to explain the same data. If one is to have any confidence in either explanation, one must exploit the testable implications of the dynamic stochastic structure of the unobservable factors. Toward this end, I created a model based on joint research with Stephen Bond (2000a, 2000b, 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 with noisy share prices:

$$V_t^E = \lambda_K(K_t - I_t) + \lambda_{\mathrm{KIT}}(\mathrm{KIT}_t - \mathrm{IT}_t) + \lambda_{\mathrm{KIP}}(\mathrm{KIP}_t - \mathrm{IP}_t) + (\mu_t + \varepsilon_t). \tag{8}$$

Let us consider the effect of measurement error on 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, for example, Hausman 2001). However, this wisdom is false when the measurement error is correlated with the explanatory variables.

To illustrate the argument, I 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:

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

where $\beta_{\mu,\mathrm{KIT}}$ is the coefficient estimate from a hypothetical regression of the measurement error on IT capital: $\beta_{\mu,\mathrm{KIT}} = \mathrm{COV}(\mu, \mathrm{KIT})/\mathrm{VAR}(\mathrm{KIT})$. Clearly, no bias occurs if $\mathrm{COV}(\mu, \mathrm{KIT}) = 0$; 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 $\beta_{\mu,\mathrm{KIT}} > 0$, and therefore the return on IT investment will be upwardly biased. Because my sample is skewed toward those companies commonly thought to have been overvalued compared with fundamentals—companies in the 1990s with big IT budgets—this bias could be substantial. If the stock market underestimates the value of IT-intensive companies, the bias will go in the other direction. Indeed, this type of downward bias implies that the true return on investment exceeded the estimated return during periods like the 1970s, when the stock market was arguably undervalued compared with fundamentals. In addition, one cannot sign the bias based on a priori reasoning in the multivariate case, but the estimated returns on 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.

Rather than 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, one can 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 ways of introducing measurement error include truncating the series after a finite number of future periods, using an incorrect discount rate, and using analysts' forecasts, which project net profits rather than net revenues. The resulting empirical valuation equation is

$$\hat{V}_t = \lambda_k(K_t - I_t) + \lambda_{\mathrm{KIT}}(\mathrm{KIT}_t - \mathrm{IT}_t) + \lambda_{\mathrm{KIP}}(\mathrm{KIP}_t - \mathrm{IP}_t) + (\nu_t + \varepsilon_t). \tag{10}$$

As discussed in the following section, identification will depend on whether the measurement error ν is uncorrelated with suitably lagged values of instruments such as capital stocks. This event seems plausible because the current measurement error obtained with analysts' forecasts is unlikely to

9. Armed with a time-varying, firm-specific discount rate, one can equate any stream of profit forecasts to observed stock prices at every observation; without additional restrictions an infinite number of paths of time-varying discount rates 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 in relation not only to current profits but also to the best available forecasts of likely future profits.

be correlated with lags of the capital stock. Ultimately, however, this question is an empirical one that can be investigated with tests of overidentifying restrictions.

2.3.2 Unobservable Productivity Shock

Despite some important differences, empirical valuation equations (8) and (10) resemble production functions. 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 model I assume that the unobservable productivity shock consists of a firm-specific, a time-specific, and an idiosyncratic component. In this case, applying 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 insignificant correlation 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. I then use DPD98 for GAUSS to perform the estimation (Arellano and Bond 1998).[10]

I conduct 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 known 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.

2.3.3 Limits of the Empirical Approach

If the GMM-based empirical approach is successfully implemented then that is the end of the story in most applications. However, intangible assets

10. In all specifications, I capture time effects by including year dummies in the estimated specifications.

pose a special problem. According to my model, intangibles are associated with specific investments, but clearly that is 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.

To fix ideas, let us suppose the fixed effect in the unobservable productivity shock represents intangible capital. If the fixed effect embeds intangible capital in this way, the econometric solution may be worse than the problem. In particular, taking first differences will 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 will be completely missed.

Let us 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—in Dell's case—selling computers over the Internet or from a unique corporate culture created by a chief executive officer like Jack Welch or Bill Gates. Nevertheless, most intangible assets appear to be created by investment, as I 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, if one were to pursue an estimation strategy like GMM with instruments that were arguably orthogonal to the error term, one might recover something closer to the direct impact of any asset on market value. However, one would by construction miss the role of omitted intangibles or intangibles that underlie the productivity shock. Thus, such instrumental variable strategies could be informative, but they could not 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 on IT capital. Two points are worth making about this argument: the first is 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 on, or the stock of, intangible capital cannot be inferred from the biased OLS coefficient on IT capital. When intangible capital (IC) 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

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

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

Using firm-level data, Brynjolfsson and others (2000, 2002) estimate b_{KIT} with 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 must know the return on IT capital. And to say anything about the return on intangibles or the size of the stock of intangibles, one must break the value of intangible capital into its constituent components. Brynjolfsson and others solve these problems by assuming that adjustment costs are zero, 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 does not literally value one dollar of IT capital at ten dollars. 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, Hitt, and Yang (2000) contradict the authors' interpretation of the estimate on IT capital. When the authors add 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 fall significantly because it is a marker for intangibles. Because the estimate is about unchanged, b_{KIT} must be biased for another reason, like the stock market mismeasurement or simultaneity bias that I have highlighted. If it is biased for another reason, then one is wise to adopt an empirical technique that corrects for the bias.

2.4 Data

2.4.1 Sources and Definitions

The limiting factor in our empirical analysis is the availability of data on IT outlays. For IT expenditures I use a data set compiled by Lev and Radhakrishnan (chap. 3 in 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 I/B/E/S data are avail-

11. In their subsequent paper, Brynjolfsson, Hitt, and Yang (2002) do not include the telling regression from their first paper. Instead, they interact ORG with employment. Although the interpretation of the effect of ORG is complicated in this interaction, the take-away point remains the same: The estimate on IT capital does not change significantly when ORG interacts with employment in the regression.

able. To be sure, this is a nonrandom sample, because the *Information Week* 500 contains firms with large IT budgets. However, it is worth pointing out that the biggest purchasers of IT are generally not the biggest sellers of IT. For example, General Electric and General Motors usually topped the 500 list. Given the nature of the sample selection, the empirical results should be used to draw conclusions about only the types of large firms in the sample.

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

- 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 Standard & Poor'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 that the stock market valuation of the firm, V^E, is dated at time $t - 1$ so that the market information set contains these forecasts. Then, to calculate the implied level of profits for periods after $t + 1$, I allow the average of Π_{it} and $\Pi_{i,t+1}$ to grow at the rate g_{it}. Let this average be $\overline{\Pi}_{it}$.[12]

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

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

  The constant discount factor reflects a static expectation of the nominal interest rate over this five-year period; that is, I use the Treasury bill interest rate in year t (plus a fixed 8 percent 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.

12. In principle, the period for calculating $\hat{V}$ should be infinity. However, analysts estimate g over a period of three to five years. Thus to match the period for which information exists, 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, I create a growth perpetuity by dividing the last year of expected earnings 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 percent, 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%).

- 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). In constructing the current-cost stock, I follow the perpetual inventory method and use an industry-level rate of economic depreciation derived 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. Again, in constructing the current-cost stock, I follow the perpetual inventory method, and I use a depreciation rate consistent with annual economic depreciation of 40 percent.[13]
- IP and KIP are IP expenditures and the current-cost net stock of IP. IP expenditures are the sum of R&D and advertising. In constructing the current-cost stock, I once more follow the perpetual inventory method, and I use a depreciation rate consistent with annual economic depreciation of 25 percent.

The estimation sample includes all firms with at least four consecutive years of complete data. Four years of data are required to calculate first differences and to use lagged variables as instruments. I determine whether the firm satisfies the four-year requirement after I delete several observations that appear to be recording or reporting errors. Also, a few observations were deleted because $\hat{V} < 0$.[14]

We turn now to a description of the sample (table 2.1). The first two rows of the table 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 $\hat{V}$; the return to debt holders, D; and an adjustment for net current assets, C. At both the mean and the 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.

2.4.2 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},

13. Economic depreciation includes the effect of technological obsolescence as well as wear and tear, so a 40% depreciation rate is reasonable given the rapid advances in the quality of IT. Estimates of IT depreciation rates are scarce, but in recent studies researchers have found that the economic depreciation rate of personal computers is about 40 percent (Doms et al. 2004). More generally, the depreciation rates adopted in the NIPAs for software are considerably higher than 40 percent, and those for communications gear are considerably lower. My choice seems balanced, and the empirical results are not materially affected by alternatives in the range of 30 percent to 50 percent.

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

Table 2.1 **Descriptive statistics for variables used in empirical analysis, 1991–97 (in millions of current dollars)**

Variable	Mean	Standard deviation	First quartile	Median	Third quartile
$(V^E + D - C)$[a]	12,315	23,225	2,321	5,086	12,402
$(\hat{V} + D - C)$[b]	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

Note: In this and subsequent tables, as well as in the chart, the sample contains firms with at least four years of complete data. $N = 253$, for a total of 1,503 observations.

[a]Stock-market-based value.

[b]Analyst-based value.

with realizations of growth over a three-year period. My results show that analysts expected profits to grow at an annual rate of 11.3 percent for the mean firm in my sample. Over a three-year period, profits actually grew just a touch more slowly than estimated, at a rate of 11 percent.

A visual comparison of actual and expected profit growth is revealing (figure 2.1). Three features of the data are apparent. First, analysts do not forecast negative long-term growth. That practice is sensible because such forecasts would be equivalent to saying that the company was essentially worthless. Second, analysts are loath to forecast exceedingly high long-term growth rates—another sensible practice. Few companies generate profit growth in excess of 30 percent, and analysts cannot easily identify ex ante those that may realize such growth. Finally, actual profit growth is highly variable. Some companies grow at 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.[15] 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, and most of what happens cannot be anticipated. However, the key requirement for my purposes is not forecast accuracy but 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

15. I have left a few extreme observations out of the figure in order to maintain a 1:1 aspect ratio. However, in fitting the regression, I have included these observations.

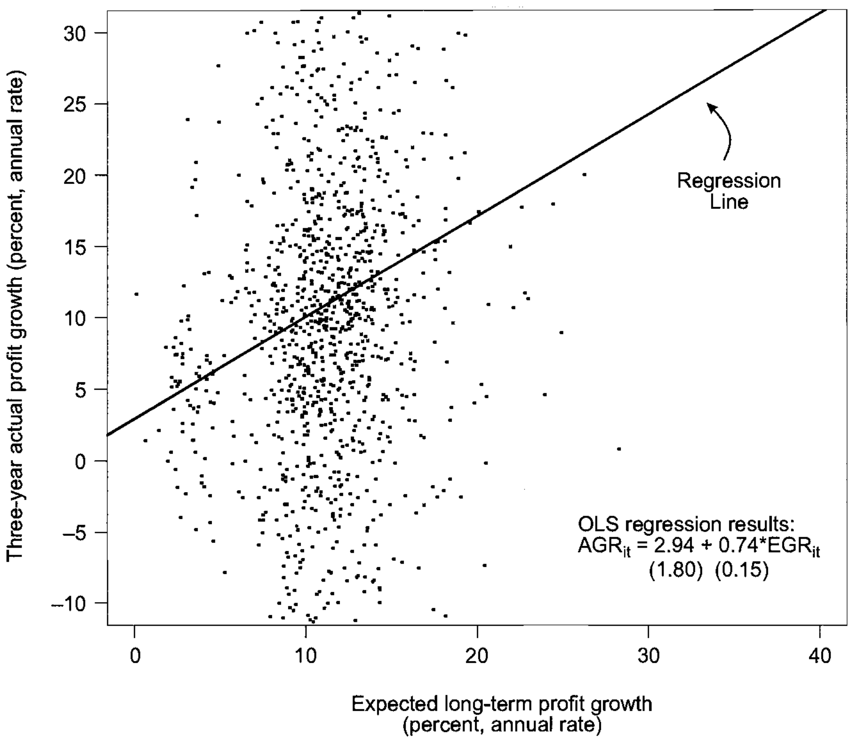

Fig. 2.1 Actual profit growth and expected long-term profit growth, 1992–97
Note: Each dot represents a single firm-year observation. In the regression equation, AGR is actual profit growth and EGR is expected profit growth; standard errors are in parentheses.

to be reasonable and informative assessments about companies' future prospects.

2.5 Empirical Results

Empirical results appear in two stages. I present OLS estimates of the empirical valuation equations in levels and within-groups (table 2.2). After establishing that these results are consistent with the sort of bias I have described, I present the results from two GMM estimators (table 2.3). First, I present a standard estimator that takes first differences in the empirical equations and uses lagged capital stocks as instrumental variables. For reasons described in section 2.3.2, the coefficient estimates are likely to be downwardly biased in this case. Second, I present results from the system-GMM estimator. The diagnostic statistics indicate that system-GMM is well behaved when the analyst-based measure of intrinsic value is used and that the results themselves are quite sensible.

Table 2.2 **OLS estimates of the valuation equations, 1992–97**

	Dependent variable					
	Level				Within-group	
	$(V_t^E + D_t)$ (1)	$(\hat{V}_t + D_t)$ (2)	$(V_t^E + D_t - C_t)$ (3)	$(\hat{V}_t + D_t - C_t)$ (4)	$(V_t^E + D_t - C_t)$ (5)	$(\hat{V}_t + D_t - C_t)$ (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)
$(\mathrm{KIT}_t - \mathrm{IT}_t)$	3.19	3.14	1.97	1.91	–6.67	–8.63
	(0.491)	(0.416)	(0.415)	(0.316)	(0.836)	(0.656)
$(\mathrm{KIP}_t - \mathrm{IP}_t)$	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)			
Serial correlation[a]						
First-order	0.070	0.066	0.143	0.169	0.930	0.886
Second-order	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

Notes: Year dummies are included (but not reported) in all specifications. Robust standard errors on coefficients are in parentheses. For estimation, $N = 253$ but we drop the first year, leaving a total of 1,250 observations.

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

Table 2.3 **GMM estimates of the valuation equations, 1992–97**

	Dependent variable			
	First-differences		System	
	$(V_t^E + D_t - C_t)$ (1)	$(\hat{V}_t + D_t - C_t)$ (2)	$(V_t^E + D_t - C_t)$ (3)	$(\hat{V}_t + D_t - C_t)$ (4)
$(K_t - I_t)$	0.399	0.007	1.75	0.846
	(0.478)	(0.197)	(0.144)	(0.135)
$(\text{KIT}_t - \text{IT}_t)$	–12.9	–11.3	0.725	1.72
	(1.33)	(1.30)	(0.390)	(0.327)
$(\text{KIP}_t - \text{IP}_t)$	9.72	3.93	0.652	0.684
	(1.80)	(1.01)	(0.273)	(0.257)
	Diagnostic tests (p-values)			
Serial correlation				
First-order	0.656	0.634	0.883	0.644
Second-order	0.345	0.488	0.326	0.463
Sargan test[a]	0.047	0.360	0.000	0.073

Notes: In the first-differences estimator, the instrumental variables are the levels of the capital stocks in periods $t - 3$ and $t - 4$. 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 capital stocks in period $t - 3$ and $t - 4$. The instrumental variables for the levels equation are the first-differences of the capital stocks in period $t - 2$. See also notes to table 2.2.

[a]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.

2.5.1 OLS Results

In the specification in the first column of table 2.2, the coefficient on IT capital substantially and significantly exceeds unity, as does the coefficient on IP capital. Meanwhile, the estimate of the return on tangible capital is significantly less than unity.[16] According to this first pass at the data, one dollar of IT capital is associated with about two dollars of unmeasured intangibles and one dollar of IP capital is associated with about one dollar of unmeasured intangibles. Thus, my basic results parallel those reported by Brynjolfsson and others even though (a) I do not use the same firms or estimation period, (b) I use different techniques for constructing the capital stocks, and (c) I use different regressors.[17]

The pattern of estimates in column (1) is similar to that in column (2),

16. 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.

17. I could not investigate the effects of these differences because Brynjolfsson and his collaborators declined to share their data.

where $\hat{V}$ replaces V^E. In particular, whether one uses an analyst-based or a market-based definition of intrinsic value does not make much difference when one estimates in levels with 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. Microsoft, for example, has a large stock of IT and has amassed a huge cash cushion on its balance sheet. When one ignores this relationship, 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 of the role of IT capital, one must define the value of the firm carefully.

So far the results have not controlled 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, I include within-group estimates presented in columns (5) and (6), which 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 downwardly biased in the final column. These findings are not surprising because the capital stocks are highly persistent. Although unit-root tests are useless for short panels, the (unreported) first-order autoregression (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-group estimates.[18]

2.5.2 GMM Results

The GMM estimates are useful because the within-group 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 with 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), but the reverse may be true, too. To deal with simultaneity bias (and eliminate the firm-specific effect at the same time), I estimate the first-

18. In fact, it is not unusual for production function estimates of the capital share to go from 0.3 in levels to negative values in within-groups. By comparison, the magnitude of the bias in table 2.2 may seem surprisingly large, but one should keep in mind that production functions are estimated in logs.

differenced empirical valuation equations with GMM, using lagged levels of the capital stocks as instruments (table 2.3).

Looking first at the Sargan test, we see that the p-values in columns (1) and (2) of the table do not indicate a decisive rejection of the model's overidentifying restrictions. This result does not mean, however, that the instruments are informative. Indeed, in unreported results, I confirm that one cannot reject weak instruments when 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.[19] Indeed, a comparison of columns (1) and (2) of table 2.3 with columns (5) and (6) of table 2.2 shows that the direction and magnitude of the bias are similar in the first-differenced and within-group estimates.

To address concerns about weak instruments, I use the system-GMM estimator in columns (3) and (4) of table 2.3. The Sargan test indicates that the model using V^E is decisively rejected while the one using $\hat{V}$ is not. This result suggests that the instruments are correlated with the market's, but not with the analysts', mismeasurement of companies' intrinsic values. Why might this correlation occur? 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. In contrast, for reasons I have discussed, we have little reason to worry that analysts' forecast errors are correlated with the lagged change in the stock of intangibles, and the Sargan test supports this conjecture. 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 72 percent annual rate of return, a figure that certainly appears sizable. However, three points are worth noting. First, the evidence of outsized returns is statistically weak because the 95 percent confidence interval encompasses returns as low as 7 percent. Second, in my model the return on 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 on

19. The technical explanation for this statement depends on two things. First, weak instruments will bias two-stage least squares (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.

IT with a static production function, which assumes that capital is in a steady-state equilibrium so that adjustment costs are zero by construction.[20] Finally, closely related to the previous point, investors and analysts cannot observe organizational capital so they must infer its value. Such inferences are difficult and subject to considerable uncertainty. Therefore, caution is warranted in interpreting the coefficient estimate on IT capital as a rate of return, which is usually defined in terms of the actual profits generated by observable capital.

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, for example, B. Hall 1993b). Perhaps firms cannot reap the full benefit of their IP investments because of the nonexclusive nature of some types of R&D (see, for example, Griliches 1979; Jaffe 1986; Bernstein and Nadiri 1989). However, one must exercise caution in drawing such a conclusion because the 95 percent confidence interval encompasses returns as large as 20 percent, a result more in line with the recent findings in Hand (2002). Finally, the estimate on tangible capital (excluding IT) is slightly less than unity. This outcome is consistent with lower rates of return on these types of capital and with recent studies in which estimated adjustment costs are quite modest in size (see, for example, Bond and Cummins 2000a).

2.6 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 highlighted 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 and provides a different perspective about what intangibles are and how researchers can estimate their return. In my model, intangible capital is not a distinct factor of production as is physical capital or labor; indeed, I assume that intangibles, unlike a computer or a college graduate, cannot be purchased in a market. Nor are intangibles some kind of relabeled MFP. Rather, intangible capital is the "glue" that creates value from the usual factor inputs.

20. To see 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 $\partial\Pi/\partial \mathrm{KIT} = r + \delta_{\mathrm{KIT}} + \partial C/\partial \mathrm{KIT}$. As long as adjustment costs are positive, the estimated return on capital can exceed $(r + \delta_{\mathrm{KIT}})$, the usual required rate of return under the equilibrium condition in production function framework.

This perspective naturally suggests 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 inputs and that of 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 forecasts. 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, I find 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 sizable return.

These findings come with a caveat. 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 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 what role intangibles play remain open questions. Are intangibles part of the unobservable productivity shock? Are intangibles some fixed (or quasi-fixed) factor that interacts in complex ways with other inputs? The answers to these questions remain unresolved.

Finally, I consider whether my approach suggests ways to incorporate intangible capital into national income accounting. At a basic level, the implications are not encouraging. Factor inputs in the national accounts have prices, but such prices are often difficult to measure accurately. In contrast, my approach starts with the assumption that intangibles are nearly impossible to value as stand-alones. In particular, intangibles have unobservable *shadow* prices that depend on expectations. This setup makes the return on intangibles impossible to measure directly and uncertain by construction. These two features render 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, such as education, on-the-job training programs, and the like.

References

Arellano, Manuel, and Stephen R. Bond. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58 (2): 277–97.

———. 1998. Dynamic panel data estimation using DPD98: A guide for users. Manuscript, Oxford University.

Baily, Martin Neil. 1981. Productivity and the services of capital and labor. *Brookings Papers on Economic Activity,* Issue no. 1:1–50.

Bernstein, Jeffrey I., and M. Ishaq Nadiri. 1989. Research and development and intra-industry spillovers: An empirical application of dynamic duality. *Review of Economic Studies* 56 (2): 249–69.

Blundell, Richard, and Stephen R. Bond. 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87 (1): 115–43.

———. 2000. GMM estimation with persistent panel data: An application to production functions. *Econometric Reviews* 19 (3): 321–40.

Bond, Stephen R., and Jason G. Cummins. 2000a. Noisy share prices and the *Q*-model of investment. Manuscript, New York University.

———. 2000b. The stock market and investment in the new economy: Some tangible facts and intangible fictions. *Brookings Papers on Economic Activity,* Issue no. 1:61–124.

Brealey, Richard A., and Stewart C. Myers. 2000. *Principles of corporate finance.* 6th ed. New York: McGraw-Hill.

Bresnahan, Timothy, Eric Brynjolfsson, and Lorin Hitt. 2002. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Quarterly Journal of Economics* 117 (2): 339–76.

Brynjolfsson, Eric, Lorin Hitt, and Shinkyu Yang. 2000. Intangible assets: How the interaction of information technology and organizational structure affects stock market valuations. Manuscript, MIT.

———. 2002. Intangible assets: Computers and organization capital. *Brookings Papers on Economic Activity,* Issue no. 1:137–81.

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay. 1997. *The econometrics of financial markets.* Princeton, NJ: Princeton University Press.

Doms, Mark E., Wendy E. Dunn, Stephen D. Oliner, and Daniel E. Sichel. 2004. How fast do personal computers depreciate? Concepts and new estimates. In *Tax policy and the economy,* ed. J. Poterba, Cambridge: MIT Press.

Griliches, Zvi. 1979. Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics* 10 (1): 92–116.

Griliches, Zvi, and Jacques Mairesse. 1999. Production functions: The search for identification. In *Econometrics and economic theory in the 20th century: The Ragnar Frisch Centennial Symposium,* ed. S. Strom, Cambridge: Cambridge University Press.

Hall, Bronwyn H. 1993a. Industrial research during the 1980s: Did the rate of return fall? *Brookings Papers on Economic Activity,* Issue no. 2:289–343.

———. 1993b. The stock market's valuation of R&D investment during the 1980s. *American Economic Review* 84 (1): 1–12.

Hall, Robert E. 2001. The stock market and capital accumulation. *American Economic Review* 91 (6): 1185–1202.

Hand, John R. M. 2002. The profitability and returns-to-scale of expenditures on intangibles made by publicly-traded U.S. firms, 1980–2000. Manuscript. University of North Carolina.

Hausman, Jerry A. 2001. Mismeasured variables in econometric analysis: Problems from the right and problems from the left. *Journal of Economic Perspectives* 15 (4): 57–67.
Hayashi, Fumio, and Tohru Inoue. 1991. The relation between firm growth and *Q* with multiple capital goods: Theory and evidence from panel data on Japanese firms. *Econometrica* 59 (3): 731–53.
Hempell, Thomas. 2003. Do computers call for training? Firm-level evidence on complementarities between ICT and human capital investments. Manuscript, ZEW.
Hulten, Charles R., and Frank Wykoff. 1981. Measurement of economic depreciation. In *Depreciation, inflation, and the taxation of income from capital,* ed. C. R. Hulten, Washington, DC: Urban Institute.
Jaffe, Adam. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review* 76 (4): 984–1001.
Kiley, Michael T. 2000. Stock prices and fundamentals in a production economy. Board of Governors of the Federal Reserve System. Manuscript.
Lev, Baruch. 2001. *Intangibles: Management, measurement, and reporting.* Washington, DC: Brookings Institution.
Mairesse, Jacques, and Bronwyn H. Hall. 1996. Estimating the productivity of research and development: An exploration of GMM methods using data on French and United States manufacturing firms. NBER Working Paper no. 5501. Cambridge, MA: National Bureau of Economic Research.
McGrattan, Ellen R., and Edward C. Prescott. 2000. Is the stock market overvalued? Federal Reserve Bank of Minneapolis. Manuscript.
Nakamura, Leonard. 1999. Intangibles: What put the new in the new economy? *Federal Reserve Bank of Philadelphia Business Review* (July/August): 3–16.
Prescott, Edward C., and Michael Visscher. 1980. Organization capital. *Journal of Political Economy* 88 (3): 446–61.
Shiller, Robert J. 2000. *Irrational exuberance.* Princeton, NJ: Princeton University Press.
Siegel, Jeremy. 1998. *Stocks for the long run: The definitive guide to financial market returns and long-term investment strategies.* 2nd ed. New York: McGraw-Hill.