Intangible Capital and the Investment-q Relation

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Abstract: Including intangible capital in measures of investment and Tobin's q produces a stronger investment-q relation. Specifically, regressions of investment on q produce higher R^2 values and larger slope coefficients, both in firm-level and macroeconomic data. Including intangible capital also produces a stronger investment-cash flow relation. These results hold across a variety of firms and periods, but some results are even stronger where intangible capital is more important. These findings change our assessment of the classic q theory of investment, and they call for the inclusion of intangible capital in proxies for firms' investment opportunities.

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Tobin's q is a central construct in finance and economics more broadly. Early manifestations of the q theory of investment, including by Hayashi (1982), predict that Tobin's q perfectly measures a firm's investment opportunities. As a result, Tobin's q has become the most widely used proxy for investment opportunities, making it "arguably the most common regressor in corporate finance" (Erickson and Whited, 2012).

Despite the popularity and intuitive appeal of q theory, its empirical performance has been disappointing.[1] Regressions of investment rates on proxies for Tobin's q leave large unexplained residuals. Extra variables like cash flow help explain investment, contrary to the theory's predictions. One potential explanation is that q theory, at least in its earliest forms, is too simple. Several authors, spanning from Hayashi (1982) to Gala and Gomes (2013), show that we should expect a perfect linear relation between investment and Tobin's q only in very special cases. A second possible explanation is that we measure q with error, which has spawned a sizeable literature developing techniques to measure q more accurately and correct for measurement-error bias.[2]

This paper's goal is to reduce one type of measurement error in q and gauge how the investment-q relation changes. One challenge in measuring q is quantifying a firm's stock of capital. Physical assets like property, plant, and equipment (PP&E) are relatively easy to measure, whereas intangible assets like brands, innovative products, patents, software, distribution systems, and human capital are harder to measure. For example, U.S. accounting rules treat research and development (R&D) spending as an expense rather than an investment, so the knowledge created by a firm's own R&D almost never appears as an asset on its balance sheet.[3] That knowledge is nevertheless part of the firm's economic capital: it was costly to obtain, it is owned by the firm,[4] and it produces future expected benefits. Corrado and Hulten (2010) estimate that intangible capital makes up 34% of firms' total capital in recent years, so the measurement error that results from from omitting intan-

[1]See Hassett and Hubbard (1997) and Caballero (1999) for reviews of the investment literature. Philippon (2009) gives a more recent discussion.

[2]See Erickson and Whited (2000, 2002, 2012); Almeida, Campello, and Galvao (2010); and Erickson, Jiang, and Whited (2013). Erickson and Whited (2006) provide a survey.

[3]We review the U.S. accounting rules on intangible capital in Section 1.

[4]A firm can own the knowledge directly using patents or indirectly using proprietary information contracts with employees. A firm owns its brand via trademarks. Human capital is not owned by the firm, although firm-specific human capital or employee non-compete agreements can make human capital behave as if partially owned by the firm. Eisfeldt and Papanikolaou (2013, 2014) analyze the unique ownership characteristics of organization capital.

gible capital is arguably large. We develop measures of q and investment that include both physical and intangible capital, and we show that these measures produce a stronger empirical investment-q relation. Our results have important implications for how researchers choose proxies for investment opportunities, and for how we evaluate the classic q theory of investment.

Our q measure, which we call total q, is the ratio of firm operating value to the firm's total capital stock, which equals the sum of its physical and intangible capital. Similarly, our measure of total investment is the sum of physical and intangible investments divided by the firm's total capital. A firm's intangible capital is the sum of its knowledge capital and organizational capital. We interpret R&D spending as an investment in knowledge capital, and we apply the perpetual inventory method to a firm's past R&D spending to measure its current stock of knowledge capital. We similarly interpret a fraction of past sales, general, and administrative (SG&A) expenses as investments in organizational capital. Our measure of intangible capital builds on the measures of Falato, Kadryzhanova, and Sim (2013), Eisfeldt and Papanikolaou (2013, 2014), and Zhang (2014), which in turn build on the macro measures of Corrado, Hulten, and Sichel (2009) and Corrado and Hulten (2010, 2014). One innovation in our measure is that we include firms' externally acquired intangible assets, which do appear on the balance sheet. While our measure imposes some strong assumptions on the data, we believe an imperfect proxy is better than simply setting intangible capital to zero— the typical implicit assumption in the literature. Also, one benefit of our measure is that it is easily computed for the full Compustat sample, and we show that our conclusions are robust to several variations on our measure.

Our analysis begins with OLS panel regressions of investment rates on proxies for q and cash flow, similar to the classic regressions of Fazzari, Hubbard, and Petersen (1988). We compare a specification that includes intangible capital in investment and q to the more typical specification that regresses physical investment (CAPX divided by PP&E) on "physical q," the ratio of firm value to PP&E. The specifications with intangible capital deliver an R^2 that is 37–55% higher. In a horse race between total q and physical q, total q remains strongly positively related to the total investment rate, whereas physical q becomes slightly negatively related. These results imply that total q is a better proxy for investment opportunities than is the usual physical q.

The OLS regressions suffer from two well known problems. The first is that the slopes on q are biased due to measurement error in q. Second, the OLS R^2 depends not just on how well q explains investment, but also on how well our q proxies explain the true, unobservable q. To obtain unbiased slopes and measure how close our q proxies are to the true q, we re-estimate the investment models using Erickson, Jiang, and Whited's (2013) linear cumulant estimator. This estimator produces a statistic τ^2 that measures how close our q proxy is to the true, unobservable q. Specifically, τ^2 is the R^2 from a hypothetical regression of our q proxy on the true q. We find that τ^2 is 9–20% higher when one includes intangible capital in the investment-q regression, implying that total q is a better proxy for true q than physical q is.

The cumulant estimator also produces unbiased slopes on q. Compared to the specifications with physical capital, the specifications including intangible capital produce estimated q-slopes that are 169–174% higher. These slopes are difficult to interpret, even after correcting for measurement-error bias. Several papers interpret the q-slopes as the inverse of a capital adjustment-cost parameter. Whited (1994) shows, however, that this interpretation is flawed.

Of more interest are the estimated slopes on cash flow. The classic q theory predicts a zero slope on cash flow after conditioning on q. Fazzari, Hubbard, and Petersen (1988) and others find positive slopes on cash flow, which they interpret as evidence of financial constraints. Erickson and Whited (2000) show that these slopes become insignificant after correcting for measurement error in q. These papers measure cash flow as profits net of R&D and SG&A outlays. Like Nakamura (2003), we argue that these outlays are investments rather than operating expenses, so one should add them back to obtain a more economically meaningful measure of cash flow available for investment. After making this adjustment, we find cash-flow slopes that are almost an order of magnitude larger. This result is inconsistent with the classic q theory of investment. More general theories, however, including by Hennessy and Whited (2007), predict positive cash-flow slopes even when firms invest optimally and face no financial constraints.

Our main results so far are that including intangible capital results in a stronger investment-q relation, and also a stronger investment-cash flow relation. Next, we show that these results are consistent across firms with high and low amounts of intangible capital, across the early and late sub-periods, and across almost all industries. As expected, though, some results are stronger where intangible capital is more important. For example, the increase in R^2 from including intangible capital is more than three times larger in the quartile of firms with the highest proportion of intangible capital, compared to the lowest quartile. The increase in R^2 is slightly higher, although not consistently so, in the later half of the sample, when firms use more intangible capital. The increase in R^2 is larger in the high-tech and health-care industries than in the manufacturing industry. Several important studies on q and investment use data only from manufacturing firms.[5] Our findings imply that including intangible capital is important even in the manufacturing industry, but is especially important if one looks beyond manufacturing to the industries that increasingly dominate the economy.

Next, we show that many of these results also hold in macroeconomic time-series data. Our macro measure of intangible capital is from Corrado and Hulten (2014) and is conceptually similar to our firm-level measure. Including intangible capital in investment and q results in an R^2 value that is 17 times larger and a slope on q that is nine times larger. Almost all the improvement comes from adjusting the investment measure rather than adjusting q. Our increase in R^2 is even larger than the one Philippon (2009) obtains from replacing physical q with a q proxy estimated from bond data. Philippon's bond q is still a superior proxy for physical investment opportunities and performs better when we estimate the model in first differences.

To help explain these results, we provide a simple theory of optimal investment in physical and intangible capital. The theory predicts that total q is the best proxy for total investment opportunities, whereas physical q is a noisy proxy even for physical investment opportunities. These predictions help explain why our regressions produce higher R^2 and τ^2 values when we use total rather than physical capital. The theory also predicts that a regression of physical investment on physical q will produce downward-biased slopes on q, which is consistent with our estimated q-slopes.

Two main messages emerge from our analysis. First, researchers using Tobin's q as a proxy for investment opportunities should include intangible capital in their proxies for q, investment, and

[5] Almeida and Campello (2007) and Almeida, Campello and Galvao (2010), and Erickson and Whited (2012)

cash flow. We provide proxies that are easily computed for the full Compustat universe. Second, including intangible capital changes our assessment of the classic q theories that predict a linear investment-q relation. On the one hand, including intangible capital produces higher R^2 values, meaning the theories fit the data better. On the other hand, cash-flow coefficients become much larger, contrary to the theories' predictions.

This is not the first paper to examine the relation between intangible investment and q. Almeida and Campello (2007) use q, cash flow, and asset tangibility to forecast R&D investment. Eisfeldt and Papanikolaou (2013) find a positive relation between investment in organization capital and q. Closer to our specifications, Baker, Stein, and Wurgler (2002) construct investment measures that combine CAPX, R&D, and SG&A, and they relate them to q. Chen, Goldstein and Jiang (2007) use q to forecast the sum of physical investment and R&D. All these papers use a q proxy that is close to what we call physical q. Besides having a different focus,[6] our paper is the first to fully include intangible capital not just in investment, but also in q and cash flow.

There is also a sizable literature that studies the impact of intangible investment on firms' valuations. For example, Megna and Klock (1993) and Klock and Megna (2001) show that intangible capital is an important component of semiconductor and telecommunication firms' market valuations. Similarly, Chambers, Jennings and Thompson (2002) and Villalonga (2004) find that firms with larger stocks of intangible capital exhibit stronger performance and market valuations. Nakamura (2003) examines the effect of aggregate intangible investment on the U.S. stock market.

This paper also contributes to the broader finance literature on intangible capital. Brown, Fazzari, and Petersen (2009) show that shifts in the supply of internal and external equity finance drive aggregate R&D investment. Falato, Kadyrzhanova and and Sim (2013) document an empirical link between intangible capital and firms' cash holdings, and they argue that the link is driven by debt capacity. Eisfeldt and Papanikolaou (2013) show that firms with more organization capital have higher average stock returns. Li and Liu (2012) estimate a structural model to examine the relation between expected stock returns asset tangibility. Ai, Croce and Li (2013) study the spread

[6] Almeida and Campello (2007) mainly examine how asset tangibility affects investment levels through borrowing capacity. Eisfeldt and Papanikolaou (2013) focus on the cross-section of expected returns. Baker, Stein, and Wurgler (2002) mainly ask whether investment is sensitive to stock mispricing. Chen, Goldstein and Jiang (2007) focus on whether private information in prices affects the investment-price sensitivity.

between returns on physical and intangible capital in a general equilibrium production framework. McGrattan and Prescott (2000), Hall (2001), and Hansen, Heaton and Li (2005) all use models to infer the quantity of intangible capital from financial price data. In contrast, we measure intangible capital directly from accounting data.

The paper proceeds as follows. Section 1 describes the data and our measure of intangible capital. Section 2 presents results from OLS regressions, and section 3 presents results that correct for measurement-error bias. Section 4 compares results for different types of firms and years. Section 5 contains results for the overall macroeconomy. Section 6 presents our theory of investment in physical and intangible capital. Section 7 explores the robustness of our empirical results, and section 8 concludes.

1 Data

This section describes the data in our main firm-level analysis. Section 5 describes the data in our macro time-series analysis.

The sample includes all Compustat firms except regulated utilities (SIC Codes 4900–4999), financial firms (6000–6999), and firms categorized as public service, international affairs, or non-operating establishments (9000+). We also exclude firms with missing or non-positive book value of assets or sales, and also firms with less that \$5 million in physical capital, as is standard in the literature. We use data from 1975 to 2010, although we use earlier data to estimate firms' intangible capital. Our sample starts in 1975, because this is the first year that FASB requires firms to report R&D.[7] We winsorize all regression variables at the 1% level to remove extreme outliers.

1.1 Tobin's q

To measure physical q, we follow Fazzari, Hubbard and Petersen (1988), Erickson and Whited (2012), and others who measure q as

[7] See FASB, "Accounting for Research and Development Costs," Statement of Financial Accounting Standards No. 2, October 1974.

$$q^{phy} = \frac{Mktcap + Debt - AC}{PP\&E}, \tag{1}$$

where $Mktcap$ is the market value of outstanding equity, $Debt$ is the book value (a proxy for the market value) of outstanding debt (Compustat items $dltt + dlc$), AC is the current assets of the firm, such as cash, inventory, and marketable securities (Compustat item *act*), and $P\&PE$ is the book value of property, plant and equipment (Compustat item *ppegt*). All of these quantities are measured at the beginning of the period. Section 7 explores other common ways of measuring physical q.

Our measure of total q includes both physical and intangible capital:

$$q^{tot} \equiv \frac{Mktcap + Debt - AC}{PP\&E + Intan} = q^{phy} \frac{PP\&E}{PP\&E + Intan}. \tag{2}$$

$Intan$ is the firm's stock of intangible capital, defined in the next sub-section. Section 6 provides a theoretical rationale for adding together physical and intangible capital in q^{tot}. A simpler but less satisfying rationale is that existing studies measure capital by summing up many different types of *physical* capital into PP&E; our measure simply adds one more type of capital to that sum. Equation (2) shows that q^{tot} equals q^{phy} times the ratio of physical to total capital. While the correlation between physical and total q in our sample is quite high, 0.81, the measures produce quite different results in investment regressions.

1.2 Intangible Capital and Investment

We briefly review the U.S. accounting rules for intangible capital before defining our measure, $Intan$. The accounting rules depend on whether the firm develops the intangible asset internally or purchases it externally, for example, by acquiring another firm.

Intangible assets developed within a firm are expensed on the income statement and almost never appear on the balance sheet.[8] For example, a firm's spending to develop knowledge, patents, or

[8]See FASB, "Accounting for Research and Development Costs," Statement of Financial Accounting Standards No. 2, October 1974. An internally developed asset may be capitalized on the balance sheet once in development stage, but this rarely occurs in practice. Furthermore, firms have an incentive to not capitalize these assets, since

software is expensed as R&D. Advertising to build brand value is a selling expense within SG&A. Employee training to build human capital is a general or administrative expense within SG&A.

In contrast, intangible assets purchased externally are capitalized on the balance sheet as Intangible Assets, which equals the sum of Goodwill and Other Intangible Assets. If the asset is "separately identifiable," such as a patent, copyright, or client list, then the asset is booked at its fair market value in Other Intangible Assets. If the asset is not separately identifiable, such as human capital or non-patented knowledge, then the asset appears as part of Goodwill on the balance sheet. In both cases, the firm is required to amortize or impair the intangible asset over time.

We define the firm's total stock of intangible capital, denoted $Intan$, to be the sum of its internally developed and externally acquired intangible capital. We measure external intangible capital as Intangible Assets from the balance sheet (Compustat item *intan*). We set this value to zero if missing. We keep Goodwill in Intangible Assets in our main analysis, because Goodwill does include the fair cost of acquiring certain important intangible assets. Since Goodwill may be contaminated by non-intangibles, such as a market premium for physical assets, we later exclude Goodwill from external intangibles and show that our conclusions are robust. Our mean (median) firm acquires only 19% (3%) of its intangible capital externally, but there are a few firms that acquire a large fraction externally. For example, 35% of Google's intangible capital in 2013 had been externally acquired.[9]

Measuring the stock of internally developed intangible capital is difficult, since it appears nowhere on the balance sheet. Fortunately, we can construct a proxy by accumulating past intangible investments, as reported on firms' income statements. While more accurate proxies for intangible capital may be available for small subsets of firms, our measure has the virtue of being easily computed for the full Compustat sample. The stock of internal intangible capital is the sum of its knowledge capital and organizational capital, which we define next.

A firm develops knowledge capital by spending on R&D. We accumulate past R&D outlays using

expensing them lowers taxes.

[9]Google in 2013 had $18B in (externally acquired) balance sheet intangibles and an estimated $32B of internally created intangible capital. For comparison, Google's PP&E was $24B, its total assets were $111B, but $73B of these were current assets including cash.

the perpetual inventory method:

$$G_{it} = (1 - \delta_{R\&D})G_{it-1} + R\&D_{it}, \tag{3}$$

where G_{it} is the end-of-period stock of knowledge capital, $\delta_{R\&D}$ is its depreciation rate, and $R\&D_{it}$ is real expenditures on R&D during the year. For $\delta_{R\&D}$, we use the Bureau of Economic Analysis's (BEA) industry-specific R&D depreciation rates, which range from 10% in the pharmaceutical industry to 40% for computers and peripheral equipment.[10] We use Compustat data back to 1950 to compute (3), but our regressions only include observations starting in 1975. Starting in 1977, we set R&D to zero when missing, following Lev and Radhakrishnan (2005) and others.[11]

Next, we measure the stock of organizational capital by accumulating a fraction of past SG&A expenses using the perpetual inventory method as in equation (3). Eisfeldt and Papanikolaou (2013, 2014) use a similar approach. The logic is that at least part of SG&A spending represents investments in organizational capital through advertising, spending on distribution systems, employee training, and payments to strategy consultants. Eisfeldt and Papanikolaou (2012, 2013) use 10-K filings, survey evidence, and firm characteristics to provide detailed support for treating SG&A spending as investment. We follow Hulten and Hao (2008), Eisfeldt and Papanikoloau (2014), and Zhang (2014) in counting only 30% of SG&A spending as investments in intangible capital. We interpret the remaining 70% as operating costs that support the current period's profits. Section 7 shows that our conclusions are robust to using values other than 30%, including a value estimated from the data. We follow Falato, Kadryzhanova, and Sim (2013) in using a depreciation rate of $\delta_{SG\&A} = 0.20$, and in Section 7 we show that our conclusions are robust to alternate depreciation rates. We replace missing values of SG&A with zeros.[12]

[10] The BEA began capitalizing R&D in satellite accounts in 1994, and in core NIPA accounts in 2013. The BEA's R&D depreciation rates are from the analysis of Li (2012). Following the BEA's guidance, we use a depreciation rate of 15% for industries not in Li's Table 4. Our results are virtually unchanged if we apply a 15% depreciation rate, the value used by Falato, Kadryzhanova, and Sim (2013), to all industries.

[11] We start in 1977 to give firms two years to comply with the 1975 R&D reporting requirement. If we see a firm with R&D equal to zero or missing in 1977, we assume the firm was typically not an R&D spender before 1977, so we set any missing R&D values before 1977 to zero. Otherwise, before 1977 we interpolate between the most recent non-missing R&D values. Starting in 1977, we make exceptions in cases where the firm's assets are also missing. These are likely years when the firm was privately owned. In such cases, we interpolate R&D values using the nearest non-missing values.

[12] As for R&D, we make exceptions in years when the firm's assets are also missing. For these years we interpolate

One challenge in applying the perpetual inventory method in (3) is choosing a value for G_{i0}, the capital stock in the firm's first non-missing Compustat record, which often coincides with the IPO. We estimate G_{i0} using data on firms' founding years, R&D spending in the first Compustat record, and average pre-IPO R&D growth rates. With those data, we can estimate each firm's R&D and SG&A spending in each year between the founding and appearance in Compustat. We apply a similar approach to SG&A. Appendix A provides additional details. Section 7 shows that a simpler measure assuming $G_{i0} = 0$ produces an even stronger investment-q relation than our main measure. That simpler measure is also reasonable proxy for investment opportunities.

Our measure of total investment includes investments in both physical and intangible capital. Specifically, we define the total investment rate as

$$\iota^{tot} = \frac{CAPEX + R\&D + 0.3 \times SG\&A}{PP\&E + Intan}. \tag{4}$$

This definition assumes 30% of SG&A represents an investment, as we assume in estimating capital stocks. Following Erickson and Whited (2012) and many others, we measure the physical investment rate as $\iota^{phy} = CAPEX/PP\&E$. The correlation between ι^{tot} and ι^{phy} is 0.87.

In Section 7 we show that our conclusions are robust to several alternate ways of measuring intangible capital and physical q.

1.3 Cash Flow

Erickson and Whited (2012) and others define cash flow as

$$c^{phy} = \frac{IB + DP}{PP\&E}, \tag{5}$$

where IB is income before extraordinary items and DP is depreciation expense. This is the pre-depreciation free cash flow available for physical investment or distribution to shareholders.

One shortcoming of c^{phy} is that it treats R&D and SG&A as expenses, not investments. For that reason, we call c^{phy} the physical cash flow. In addition to c^{phy}, we use an alternate cash flow

SG&A using the nearest non-missing values.

measure that recognizes R&D and part of SG&A as investments. Specifically, we add intangible investments back into the free cash flow, less the tax benefit of the expense:

$$c^{tot} = \frac{IB + DP + (R\&D + 0.3 \times SG\&A)(1-\kappa)}{PP\&E + Intan} \tag{6}$$

where κ is the marginal tax rate.[13] When available, we use simulated marginal tax rates from Graham (1996). Otherwise, we assume a marginal tax rate of 30%, which is close to the mean tax rate in the sample. The correlation between c^{tot} and c^{phy} is 0.75.

1.4 Summary Statistics

Table 1 contains summary statistics. We compute the intangible intensity as a firm's ratio of intangible to total capital. The mean (median) intangible intensity is 44% (46%), indicating that intangible capital makes up almost half of firms' total capital. Knowledge capital makes up only 18% of intangible capital on average, so organizational capital makes up 82%. The median firm has no knowledge capital, since the typical firm does not report any R&D expenditure. The average q^{tot} is mechanically smaller than q^{phy}, since the denominator is larger. There is less dispersion in q^{tot} than q^{phy} even if we scale the standard deviations by their respective means. Both q proxies exhibit significant skewness, which will be a requirement of the cumulant estimator we apply in Section 3. Total investment exceeds physical investment on average, meaning one typically underestimates firms' investment rates by ignoring intangible capital. This result is not mechanical, since ι^{tot} adds intangibles to both the numerator and denominator.

Figure 1 plots the time-series of average intangible intensity. We see that intangible capital is increasingly important: the intensity increases from 40% in 1975 to 48% in 2010. As expected, high-tech and health-care firms are heavy users of intangible capital, while manufacturing firms use less.[14] Somewhat surprisingly, even manufacturing firms have considerable amounts of intangible capital; their intangible intensity in 2010 is 31%, down from 34% in 1975.

[13] Since accounting rules allow firms to expense intangible investments, the effective cost of a dollar of intangible capital is only $(1-\kappa)$.

[14] We use the Fama-French five-industry definition. Details are in Section 4.

2 OLS Results

Table 2 contains results from OLS panel regressions of investment on q, cash flow, and firm and year fixed effects. The dependent variables in Panels A and B are, respectively, the total and physical investment rates, ι^{tot} and ι^{phy}. While the estimated slopes suffer from measurement-error bias, the R^2 values help judge how well our q measures proxy for investment opportunities. We focus on R^2 in this section and interpret the coefficients on q after correcting for bias in the next section. To help compare R^2 across specifications, we include the R^2 values' bootstrapped standard errors clustered by firm in parentheses.

Most papers in the literature regress ι^{phy} on q^{phy}, as in column 2 of Panel B. That specification delivers an R^2 of 0.233, whereas a regression of ι^{tot} on q^{tot} (Panel A column 1) produces an R^2 of 0.319, higher by 0.086 or 37%. In other words, total q explains total investment better than physical q explains physical investment. We are not aware of a formal statistical test for comparing R^2 values when the dependent variable differs, but the 0.086 increase we find is much larger than the 0.005 standard errors for the individual R^2 values. Including intangibles produces a higher R^2 for two reasons. First, comparing columns 1 and 2, we see that q^{tot} is better than q^{phy} at explaining both total investment (panel A) and physical investment (panel B). More importantly, R^2 values are uniformly larger in panel A than panel B, indicating that total investment rates are better explained by all q variables, including q^{tot}. One reason is that total investment is smoother over time than physical investment, largely because CAPX is lumpy compared to SG&A and R&D.[15]

When we run a horse race between total and physical q in column 3 of Panel A, the sign on q^{phy} flips to negative and becomes less statistically significant, implying that physical q contains little additional information about total investment opportunities once we account for q^{tot}. When we run that same horse race using physical investment (column 3 of Panel B), we see that both q variables enter with high significance, meaning total q contains additional information about physical investment opportunities beyond the information in q^{phy}.

Columns 4–6 repeat the same specifications while controlling for cash flow. The patterns in R^2 are similar. For example, the specification with physical capital (column 5 of panel B) produces an

[15] The within-firm volatility of physical (total) investment is 20.2% (15.4%)

R^2 of 0.238, whereas the specification with total capital (column 4 of panel A) delivers an R^2 of 0.368, 55% higher.

Taken together, these results imply that total q is a better proxy for total investment opportunities than physical q is. Total q is even a slightly better proxy for physical investment opportunities, although physical q still contains additional information.

3 Bias-Corrected Results

We argue that total q is a better proxy for true q than physical q is. However, we recognize that total q is still a noisy proxy, so all the OLS slopes in the previous section suffer from measurement-error bias. We now estimate the previous models while correcting this bias. We do so using Erickson, Jiang, and Whited's (2013) higher-order cumulant estimator, which supercedes Erickson and Whited's (2002) higher-order moment estimator.[16] The cumulant estimator provides unbiased estimates of β in the following errors-in-variables model:

$$\iota_{it} = a_i + q_{it}\beta + z_{it}\alpha + u_{it} \quad (7)$$

$$p_{it} = \gamma + q_{it} + \varepsilon_{it}, \quad (8)$$

where q_{it} is the true, unobservable q, p is a noisy proxy for q, and z is a vector of perfectly measured control variables.[17] In addition to delivering unbiased slopes, the estimator also produces two useful test statistics. The first, ρ^2, is the hypothetical R^2 from (7). Loosely speaking, ρ^2 tells us how well true, unobservable q explains investment, with $\rho^2 = 1$ implying a perfect relation. The second statistic, τ^2, is the hypothetical R^2 from (8). It tells us how well our q proxy explains true q, with $\tau^2 = 1$ implying a perfect proxy. The closer τ^2 is to one, the smaller is the gap between the OLS and bias-corrected slope, and the smaller is the gap between the OLS R^2 and cumulant ρ^2.

[16] Cumulants are polynomials of moments. The estimator is a GMM estimator with moments equal to higher-order cumulants of investment and q. Compared to Erickson and Whited's (2002) estimator, the cumulant estimator has better finite-sample properties and a closed-form solution, which makes numerical implementation easier and more reliable. We use the third-order cumulant estimator, which dominates the fourth-order estimator in the estimation of τ^2 (Erickson and Whited, 2012; Erickson, Jiang, and Whited, 2013).

[17] The cumulant estimator's main identifying assumptions are that u and ε are independent of q, z, and each other; and that p has non-zero skewness.

For comparison, we also show results using the IV estimators advocated by Almeida, Campello and Galvao (2010). These estimators use lagged regressors as instruments for the noisy q proxy.[18] Erickson and Whited (2012) show that the IV estimators are biased if measurement error is serially correlated, which is likely in our setting. This bias is probably most severe in the usual regressions that omit intangible capital: Omitted intangible capital is an important source of measurement error, and a firm's intangible capital stock is highly serially correlated. Since the cumulant estimators are robust to serially correlated measurement error, we prefer them over the IV estimators.

Estimation results are in Table 3. All specifications include firm and year fixed effects. Columns 1–4 show results from a different estimator, with OLS results in column on for comparison. The second column show results using the cumulant estimator. Columns three and four use the IV estimators. Columns 5–8 are like columns 1–4 but control for cash flow. Panel A shows results using total capital (ι^{tot}, q^{tot}, and c^{tot}). Panel B shows results using physical capital (ι^{phy}, q^{phy}, and c^{phy}).

The τ^2 estimates are higher in panel A than panel B, indicating that total q is a better proxy for the true, unobservable q than is physical q. For example, comparing column 2 of Panels A and B, τ^2 increases from 0.492 to 0.588, a 20% increase. We are not aware of a statistical test for comparing τ^2 values, but this 0.096 increase in τ^2 is considerably larger than their individual bootstrapped standard errors, 0.007 and 0.010. Despite the improvement, total q is still a noisy proxy for true q: the 0.588 value of τ^2 implies that total q explains only 58.8% of the variation in true q. The improvements in τ^2 are smaller, roughly 9%, when we control for cash flow in columns 5–8.

The ρ^2 estimates are also higher in Panel A than Panel B, indicating that the unobservable true q explains more of the variation in total investment than it does for physical investment. In other words, the relation between q and investment is stronger when we include intangible capital in both q and investment. The increase in ρ^2 from including intangible capital is 0.056 (15%) without cash flow, 0.111 (30%) with cash flow. Both increases are large relative to the standard errors for ρ^2.

[18] Both IV estimators start by taking first differences of a linear investment-q model. Biorn's (2000) IV estimator assumes the measurement error in q follows a moving-average process up to some finite order, and it uses lagged values of the regressors as instruments to "clear" the memory in the measurement error process. Arellano and Bond's (1991) GMM IV estimator use twice-lagged q and investment as instruments for the first-differenced equation, and weights these instruments optimally using GMM.

The ρ^2 estimates in Panel A, 0.428 and 0.482, indicate that q explains 43–48% of the variation in investment. These result helps us evaluate how the simplest linear investment-q theory fits the data. The theory explains almost half of the variation in investment, so there is still considerable variation left unexplained. Judging by the higher ρ^2 values in panel A, the simple benchmark theory fits the data considerably better when one includes intangible capital in investment and q.

Next, we discuss the bias-corrected slopes on q. Comparing panels A and B, we see much larger slopes on total q than physical q for every estimator used. The increase in coefficient from Panel B to Panel A ranges from 127–189%. Interpreting these slopes is difficult. Taken literally, the simplest q theories, including the one we present in Section 6, predict that the inverse of the q-slope determines the marginal capital adjustment cost.[19] Whited (1994) and Erickson and Whited (2000) explain, though, that is impossible to obtain meaningful adjustment-cost estimates from the investment-q slopes, even within the quadratic adjustment-cost framework. The main problem is that our regression corresponds to a large class of investment cost functions, so there is no hope of identifying average adjustment costs without strong, arbitrary assumptions on the cost function. Another problem is that marginal adjustment cost has a one-to-one mapping with marginal q and is therefore independent of the investment-q slope. If one moves beyond the classic, simple, quadratic framework we describe in Section 6, it becomes even harder to interpret our slopes on q (Gala and Gomes, 2013). We simply interpret our q-slopes as determinants of the elasticity of investment with respect to q, and we note that including intangible capital makes the slopes much larger.

Finally, we discuss the estimated slope coefficients on cash flow. The simplest q theories predict a zero slope, since q should completely explain investment. The data strongly reject this prediction: We find significantly positive slopes on cash flow in all columns and both panels. Comparing panels A and B, we find that the slopes on cash flow are 6–10 times larger when we include intangible capital. This result makes sense. Recall that we add back intangible investment to move from c^{phy} to c^{tot}. As a result, when intangible investment is high, c^{tot} also tends to be high, creating a stronger overall investment-cash flow relation. We emphasize that this difference is the result of having a more economically sensible measure of investment and hence free cash flow. In other words, we

[19] Hayashi (1982) also makes make this prediction. which follows from three key assumptions: perfect competition, constant returns to scale, and quadratic capital adjustment costs.

argue that previous studies that only include physical capital have found slopes on cash flow that are too small, because they fail to classify the resources that go toward intangible capital as free cash flow available for investment. To summarize, judging by the cash-flow slopes, the simplest q theories fit the data worse when we include intangible capital. This result does not necessarily spell bad news for more recent, general theories of q and investment, which have shown that non-zero slopes on cash flow may arise from many sources. For example, Gomes (2001), Hennessy and Whited (2007), and Abel and Eberly (2011) develop models predicting significant cash-flow slopes even in the absence of financial constraints. Our results indicate that these cash-flow slopes are almost an order of magnitude larger than previously believed, once we account for intangible capital.

4 Where and When Does Intangible Capital Matter Most?

So far we have pooled together all observations. Next, we compare results across firms and years. Doing so allows us to check the robustness of our main results across subsamples, and also lets us judge where and when intangible capital matters most.

We re-estimate the previous models in subsamples formed using three variables. First, we sort firms each year into quartile subsamples based on their ratio of intangible to total capital (Table 4). Second, we form industry subsamples (Table 5). We use Fama and French's five-industry definition to avoid small subsamples in our cumulants analysis. After dropping "Other," the four industries are manufacturing, consumer, high-tech, and health.[20] Third, we examine the early (1972–1995) and late (1996–2010) parts of our sample (Table 6). For each subsample we estimate a total-capital specification using ι^{tot}, q^{tot}, and c^{tot}. The adjacent column presents a physical-capital specification using ι^{phy}, q^{phy}, and c^{phy}. We tabulate the difference in R^2, ρ^2, and τ^2 between the physical- and total-capital specifications. To help judge whether these differences are significant, we report bootstrapped standard errors clustered by firm for R^2, ρ^2, and τ^2. The top panels include just q, whereas the bottom panels add cash flow as a regressor.

[20] Manufacturing includes manufacturing and energy firms (we drop utility firms). Consumer includes consumer durables, nondurables, wholesale, retail, and some services. High tech includes business equipment, telephone, and television transmission. Health includes healthcare, medical equipment, and drugs.

First we discuss the OLS R^2 values. Our main result is quite robust: Using total capital rather than physical capital produces higher R^2 values in all ten subsamples. The increase in R^2 ranges from 0.047–0.222, or from 26–73%. This result implies that total q is a better proxy for investment opportunities in every subsample.

Including intangible capital is more important in certain types of firms and years. As expected, it is more important in firms with more intangible capital: the increase in R^2 is 0.176 (58%) in the highest intangible quartile, compared to 0.047 (26%) in the lowest quartile. We are not aware of a formal statistical test for this difference in difference in R^2 values. We can say, though, that the 0.129 (=0.176-0.047) diff-in-diff is large relative to the individual standard errors, which range from 0.009 to 0.013.

Including intangible capital increases the R^2 by 0.060 in the manufacturing industry, 0.093 in the consumer industry, 0.085 in the health industry, and 0.108 in the high-tech industry. These increases roughly line up with the industries' use of intangible capital. For example, 57% of the tech industry's capital is intangible, on average, compared to 32% in the manufacturing industry. Nevertheless, we emphasize that even manufacturing firms have considerable amounts of intangible capital and see a stronger investment-q relation when we include intangible capital.

We see mixed results for the year subsamples. Without controlling for cash flow, the increase in R^2 is slightly higher in the later subsample, whereas controlling for cash flow in panel B delivers the opposite result. The former result makes more sense, as there is more intangible capital in the later period (Figure 1).

Next we discuss results from the cumulant estimator. Our key results are largely robust across subsamples and specifications. Including intangible capital produces higher values of ρ^2 and larger slopes on q and cash flow in nine out of ten subsamples.[21]

Including intangible capital produces a higher τ^2 in subsamples with more intangible capital. This result implies that total q is a better proxy for true q in firms and years with the most intangible capital, as expected. Some of these improvements are dramatic. For example, τ^2 increases by 0.209 (48%) in the quartile with the most intangible capital, by 0.129 (35%) in the health industry, by

[21] The value of ρ^2 and the cash-flow slope are slightly lower in the health industry, but these differences do not appear to be statistically significant.

0.133 (26%) in the tech industry, and by 0.118 (25%) in the later period. Including intangible capital produces a lower τ^2, however, in subsamples with less intangible capital, such as the manufacturing industry. Some of these decreases appear to be statistically insignificant. To the extent that they are significant, physical q is a better proxy for true q in firms and years with less intangible capital. One potential explanation is that the noise in our intangible-capital measure swamps any improvement from including it in contexts where intangible capital is close to zero. Recall, though, that including intangibles produces a higher R^2 value in all ten subsamples. If the goal is to produce a good proxy for investment opportunities– and not just a proxy for true q– then including intangible capital produces improvements in all subsamples.

To summarize, our main result– that including intangible capital results in a stronger investment-q relation– is consistent across firms with high and low amounts of intangible capital, in the early and late parts of our sample, and across industries. On some dimensions (R^2, for example), including intangible capital produces a stronger investment-q relation especially in years and firms where intangible capital is more important.

5 Macro Results

One might expect q theory to work better in aggregate macroeconomic data than firm-level data, since firm-level investment is lumpy over time. So far we have analyzed firm-level data. Next we investigate the investment-q relation in U.S. macro time-series data. Our sample includes 142 quarterly observations from 1972Q2–2007Q2, the longest period for which all variables are available.

We construct versions of physical and total investment and q using macro data. Physical q and investment come from Hall (2001), who uses the Flow of Funds and aggregate stock and bond market data. Physical q, again denoted q^{phy}, is the ratio of the value of ownership claims on the firm less the book value of inventories to the reproduction cost of plant and equipment. The physical investment rate, again denoted ι^{phy}, equals private nonresidential fixed investment scaled by its corresponding stock, both of which are from the Bureau of Economic Analysis.

Data on the aggregate stock and flow of physical and intangible capital come from Carol Corrado and are discussed in Corrado and Hulten (2014). Earlier versions of these data are used by Corrado, Hulten, and Sichel (2009) and Corrado and Hulten (2010). Their measures of intangible capital include aggregate spending on business investment in computerized information (from NIPA), R&D (from the NSF and Census Bureau), and "economic competencies," which includes investments in brand names, employer-provided worker training, and other items (various sources). Similar to before, we measure the total capital stock as the sum of the physical and intangible capital stocks, we compute total q as the ratio of total ownership claims on firm value, less the book value of inventories, to the total capital stock, and we compute the total investment rate as the sum of intangible and physical investment to the total capital stock.

To mitigate problems from potentially differing data coverage, we use Corrado and Hulten's (2014) ratio of physical to total capital to adjust Hall's (2001) measures of physical q and investment. More precisely, we calculate total q as

$$q^{tot} = \frac{V}{K^{phy} + K^{intan}} = q^{phy} \times \frac{K^{phy}}{K^{phy} + K^{intan}} \tag{9}$$

and total investment as

$$\iota^{tot} = \frac{I^{phy} + I^{intan}}{K^{phy} + K^{intan}} = \iota^{phy} \times \frac{K^{phy}}{K^{phy} + K^{intan}} \times \frac{I^{phy} + I^{intan}}{I^{phy}}. \tag{10}$$

where q^{phy} and ι^{phy} are from Hall's (2001) data and K^{phy}, K^{intan}, I^{phy}, and I^{intan} are from Corrado and Hulten's (2014) data.

The correlation between physical and total q is extremely high, at 0.997. The reason is that total q equals physical q times the ratio of physical to total capital [equation (9)], and the latter ratio has changed slowly and consistently over time.[22] Of significantly larger importance is the change from physical to total investment, which requires changing both the numerator and the denominator in (10). Since the ratio of capital flows has changed more than the ratio of the capital stocks, the correlation between total and physical investment is much smaller, 0.43.

[22]The macro intangible intensity increases from roughly 0.2 in 1975 to 0.3 in 2010. In contrast, Figure 1 shows the cross-sectional average intensity increasing from roughly 0.27 to 0.47 over this period. We can reconcile these facts if small firms use more intangible capital.

For comparison, we also use Philippon's (2009) aggregate bond q, which he obtains by applying a structural model to data on bond maturities and yields. Bond q is available at the macro level but not at the firm level. Philippon (2009) shows that bond q explains more of the aggregate variation in what we call physical investment than does physical q. Bond q data are from Philippon's web site.

Figure 2 plots the time series of aggregate investment and q using physical capital (left panel) and total capital (right panel). Except in a few subperiods, physical q is a relatively poor predictor of physical investment, as Philippon (2009) and others have shown. Total q seems to do a much better job of predicting total investment, although the fit is not perfect. The total investment-q relation is particularly strong during the tech boom of the late 1990's, and is particularly weak during the early period, 1975-85. As explained above, the improvement in fit comes mainly from changing the investment measure, since total and physical q are almost perfectly correlated in the time series.

Table 7 presents results from time-series regressions of investment on q. The top panel uses total investment as the dependent variable, and the bottom panel uses physical investment. The first two columns show dramatically higher R^2 values and slope coefficients in the top panel compared to the bottom. The result is similar for both total and physical q (columns 1 and 2), as expected. This result implies a much stronger investment-q relation when we include intangible capital in our investment measure. The 0.57 increase in R^2 from including intangible capital is even larger than the 0.43 increase Philippon (2009) obtains by using bond q in place of physical q (columns 2 vs. 3 in panel B).

Interestingly, the R^2 values in panel A indicate that both total and physical q explain more than three times as much variation in total investment than does bond q, which does not enter significantly either on its own (column 3) or in horse races with total or physical q (columns 4 and 5). (We do not run a horse race between total and physical q since they are almost collinear.) We obtain the opposite result when the dependent variable is physical investment: bond q explains much more of the variation in physical investment and is the only q variable that enters significantly.

Why is bond q better at explaining physical investment but worse at explaining total investment?

One potential explanation is that bond prices are less sensitive to growth opportunities than equity prices are, and intangible investment is highly sensitive to growth opportunities. Also, firms with more intangible investment typically hold less debt, so they contribute relatively little to the aggregate bond q measure.[23]

We re-estimate the regressions in first differences and, to handle seasonality, in four-quarter differences. Results are available upon request. Echoing our results above, regressions of investment on both total and physical q generate larger slopes and R^2 values when we use total rather than physical investment. The relation between physical investment and either q variable is statistically insignificant in first differences, whereas the relation between total investment and either q is always significant. In all these specifications in differences, bond q enters with much higher statistical significance, drives out total and physical q in horse races, and generates higher R^2 values.

To summarize, in macro time-series data we find a much stronger investment-q relation when we include intangible capital in our measure of investment. The increase in R^2 is even larger than the one Philippon (2009) finds when using bond q in place of physical q. While total q is better than bond q at explaining the level of total investment, bond q is better at explaining first differences, and bond q is also better at explaining the level of physical investment.

6 A Theory of Intangible Capital, Investment, and q

In this section we present a theory of optimal investment in physical and intangible capital. Our first goal is to provide a rationale for the empirical choices we have made so far. Specifically, we provide a rationale for adding together physical and intangible capital in our measure of total q, and we provide a rationale for regressing total investment on total q. More importantly, we illustrate what can go wrong when one omits intangible capital and simply regresses physical investment on physical q. The aim here is not to make a theoretical contribution,[24] but to help explain our empirical results. We therefore provide a toy model in Section 6.1 in order to make the economic

[23]Firms with above-median intangible intensity have mean (median) leverage of 22.6% (18.3%), compared to 30.1% (27.0%) for below-median firms. We measure leverage as Compustat items (dlc + dltt)/at.

[24]There are already many theories of investment and q, including theories featuring multiple capital goods. See, for example, Wildasin (1984) and Hayashi and Inoue (1991).

mechanism as transparent as possible. Section 6.2 presents a slightly richer model and shows that the main conclusions are robust. All proofs are in Appendix B.

6.1 Model with Perfect Substitutes and Analytical Predictions

We simplify and modify Abel and Eberly's (1994) theory of investment under uncertainty to include two capital goods. We interpret the two capital goods as physical and intangible capital, but they are interchangeable within the model. The model features an infinitely lived, perfectly competitive firm that holds K_{1t} units of physical capital and K_{2t} units of intangible capital at time t. (We omit firm subscripts for notational ease. Parameters are constant across firms, but shocks and endogenous variables can vary across firms unless otherwise noted.) Like Hall (2001), we assume the two capital types are perfect substitutes, so what matters is total capital $K \equiv K_1 + K_2$ and total investment $I \equiv I_1 + I_2$. A similar assumption is implicit in almost all empirical work on the investment-q relation: by using data on CAPEX or PP&E, both of which add together different types of physical capital, researchers have treated these different types of physical capital as perfect substitutes. The next subsection relaxes the perfect-substitutes assumption.

At each instant t the firm chooses the investment levels I_{1t} and I_{2t} in two types of capital and the amount of labor L_t that maximize firm value:

$$V\left(K, \varepsilon_t, p_{1t}, p_{2t}\right) = \max_{L_{t+s},\ I_{1,t+s},\ I_{2,t+s}} \int_0^\infty E_t[F\left(K_{t+s}, L_{t+s}, \varepsilon_{t+s}\right) - wL_{t+s} - \frac{\gamma}{2} K_{t+s} \left(\frac{I_{t+s}}{K_{t+s}}\right)^2 - p_{1,t+s} I_{1,t+s} - p_{2,t+s} I_{2,t+s}] e^{-rs} ds \qquad (11)$$

subject to

$$dK_i = \left(I_i - \delta K_i\right) dt, \quad i = 1, 2 \qquad (12)$$

$$I_1,\ I_2 \geq 0. \qquad (13)$$

We assume the production function F is linearly homogenous in K and L, and also depends on a shock ε. The wage w is constant. Equation (11) assumes the firm faces quadratic capital adjustment costs with parameter γ. Capital prices p_1 and p_2, along with profitability shock ε, fluctuate over time according to a general stochastic diffusion process

$$dx_t = \mu(x_t)\,dt + \Sigma(x_t)\,dB_t, \tag{14}$$

where $x_t = [\varepsilon_t \;\; p_{1t} \;\; p_{2t}]'$. All firms face the same capital prices p_{1t} and p_{2t}, but the shock ε_t can vary across firms. We assume parameter values are such that $I > 0$ always.[25]

The two capital types are perfect substitutes in production, capital adjustment costs, and depreciation. The only potential difference between them is their prices p_1 and p_2. We assume non-negative investment in (13), because otherwise the firm would optimally (yet unrealistically) take massive long-short positions. For example, if $p_1 > p_2$, the firm could sell its entire K_1 and buy an equal amount of K_2, thereby booking a profit without incurring any adjustment costs, since total investment $I = 0$.[26] Since $I_1, I_2 \geq 0$, the firm will invest zero in the capital type with the higher price. For example, if $p_1 > p_2$, then $I_1 = 0$ and $I = I_2$.

Next we present our three main predictions. The first two are admittedly close to the model's assumptions, the third less so.

Prediction 1: Marginal q equals average q, the ratio of firm value to the total capital stock:

$$\frac{\partial V_t}{\partial K} = \frac{V_t}{K_{1t} + K_{2t}} \equiv q^{tot}(\varepsilon_t, p_{1t}, p_{2t}). \tag{15}$$

This result provides a rationale for measuring q as firm value divided by the sum of physical and intangible capital, which we call total q. The value of q^{tot} depends on the shock ε and the two capital prices, p_1 and p_2. Marginal q, $\partial V_t / \partial K$, measures the benefit of adding an incremental unit of capital (either tangible or intangible) to the firm. Marginal q is not observed by the econometrician in many investment theories, making the theories difficult to estimate. Since our firm faces constant returns and perfect competition, as in Hayashi (1982) and others, marginal q equals the easily observed average q.

[25] Equivalently, we assume parameter values are such that $q^{tot} > \min(p_1, p_2)$ in all periods.

[26] Our main predictions still hold if we relax the non-negative investment constraint and introduce separate capital adjustment costs proportional to I_1^2 and I_2^2.

The firm chooses the optimal total investment rate by equating marginal q and the marginal cost of investment. Applying this condition to (11) yields our next main prediction.

Prediction 2: The total investment rate ι^{tot} is linear in q^{tot} and the minimum capital price:

$$\iota_t^{tot} \equiv \frac{I_{1t} + I_{2t}}{K_{1t} + K_{2t}} = \frac{1}{\gamma} q_t^{tot} - \frac{\min(p_{1t}, p_{2t})}{\gamma}. \tag{16}$$

If prices p_{1t} and p_{2t} are constant across firms i at each t, then the OLS panel regression

$$\iota_{it}^{tot} = a_t + \beta q_{it}^{tot} + \eta_{it} \tag{17}$$

will produce an R^2 of 100% and a slope coefficient β equal to $1/\gamma$.

This result provides a rationale for regressing total investment on total q, as we do in our empirical analysis. The time fixed effects a_t are needed to soak up the time-varying capital prices p in (16). Assuming no measurement error, the result also tells us that the OLS slope β is an unbiased estimator of the inverse adjustment cost parameter γ. As discussed earlier, we avoid making inferences about adjustment costs from our estimated q-slopes. The main reason, as Whited (1994) explains, is that there is a large class of adjustment cost functions that correspond to regression (17). We obtain the mapping above between β and γ thanks to strong simplifying assumptions about the adjustment cost function.

We now use the theory to analyze the typical regression in the literature, which is a regression of physical investment (I_1/K_1 in the model) on physical q (V/K_1 in the model). Our next result shows how omitting intangible capital from these regressions results in a lower R^2 and biased slope coefficients.

Prediction 3: The physical investment rate equals

$$\iota_{it}^{phy} \equiv \frac{I_{1,i,t}}{K_{1,i,t}} = \begin{cases} 0 & \text{if } p_1 > p_2, \\ \frac{1}{\gamma} q_{it}^{phy} - p_t^* \frac{K_{it}}{K_{1,i,t}} & \text{if } p_1 \leq p_2. \end{cases} \tag{18}$$

If prices and p_1 and p_2 are each constant across firms at each instant, then the OLS panel regression

$$\iota_{it}^{phy} = \widetilde{a}_t + \widetilde{\beta} q_{it}^{phy} + \widetilde{\eta}_{it} \tag{19}$$

will produce an R^2 less than 100% and a slope $\widetilde{\beta}$ that is biased away from $1/\gamma$.

Equation (18) follows from multiplying both sides of equation (16) by $K_{it}/K_{1,i,t}$ and recalling that the firm only buys the cheaper capital type. There are two reasons why the R^2 will be less than 100% in regression (19). First, in periods when $p_1 > p_2$, all firms' physical investment will equal zero, yet there will still be cross-sectional variation in q^{phy} and hence non-zero regression disturbances $\widetilde{\eta}_{it}$. Second, even in periods when $p_1 < p_2$, the time fixed effects $\widetilde{a}_t$ will not perfectly absorb the term $\frac{p_t^*}{\gamma}\frac{K_{it}}{K_{1,i,t}}$ in equation (19), because $K_{it}/K_{1,i,t}$ is not necessarily constant across firms. As a result, we again have non-zero disturbances and hence an R^2 less than 100%.

OLS estimates of $\widetilde{\beta}$ are biased if the disturbance $\widetilde{\eta}_{it}$ is cross-sectionally correlated with the regressor q_{it}^{phy}.[27] Equation (18) implies that the error term in regression (19) equals

$$\widetilde{\eta}_{it} = \begin{cases} -\widetilde{a}_t - \widetilde{\beta} q_{it}^{phy} & \text{if } p_1 > p_2, \\ -\frac{p_t^*}{\gamma}\left(\frac{K_{it}}{K_{1,i,t}} - \overline{\frac{K_t}{K_{1,t}}}\right) & \text{if } p_1 \leq p_2. \end{cases} . \tag{20}$$

If $\widetilde{\beta} > 0$, as we find in the data, then the cross-sectional correlation between $\widetilde{\eta}_{it}$ and q_{it}^{phy} equals -1 when $p_1 > p_2$. This negative correlation contribues to downward bias in OLS estimates of $\widetilde{\beta}$. When $p_1 < p_2$, the disturbance is again cross-sectionally correlated with q_{it}^{phy} through the term $K_{it}/K_{1,i,t}$ in (20), because $q_{it}^{phy} = q_{it}^{tot} K_{it}/K_{1,i,t}$. Since $K_{it}/K_{1,i,t}$ appears in both q_{it}^{phy} and $\widetilde{\eta}_{it}$, albeit with a negative coefficient in $\widetilde{\eta}_{it}$, it is likely that the regressor and disturbance are again negatively correlated, biasing the regression slope $\widetilde{\beta}$ downward.[28] Downward bias in $\widetilde{\beta}$ implies upward bias in γ, meaning regression (19) typically over-estimates the adjustment-cost parameter γ.

[27] The regression with time fixed effects is equivalent to demeaning ι_{it}^{phy} and q_{it}^{phy} by their cross-sectional means and then regressing the demeaned variables on each other without time fixed effects. It is therefore the cross-sectional correlation between q_{it}^{phy} and $\widetilde{\eta}_{it}$ that matters for determining bias. We assume here that all variables are measured without error. Measurement error would contribute even more bias to the OLS regression.

[28] We cannot prove that this second correlation is negative, because q_{it}^{tot} is not avaiable in closed form and may be correlated with $K_{it}/K_{1,i,t}$. However, we solve the model numerically and find that, for reasonable parameter values, there is a nearly perfect negative cross-sectional correlation between and q_{it}^{phy} and $\widetilde{\eta}_{it}$ when $p_1 \leq p_2$.

How large are these biases? Appendix C describes a simple simulation of the model. Results are in Panel A of Table 8. As expected, a regression of the total investment rate on q^{tot} (equation 17) delivers a 100% R^2 and an average slope equal to $1/\gamma$. A regression of the physical investment rate on q^{phy} (equation 19) delivers an average R^2 of only 49% and an average slope that is 51% lower than $1/\gamma$, consistent with the predicted downward bias in $\widetilde{\beta}$. Given the model's simplicity, we do not push the quantitative features of our theory, but simply note that the magnitudes could be large.

To summarize, our simple theory predicts, not surprisingly, that total q is the best proxy for total investment opportunities. Less obviously, physical q is a relatively noisy proxy for physical investment opportunities. These predictions help explain why our empirical regressions produce higher R^2 and τ^2 values when we use total rather than physical capital. The theory also predicts that a regression of physical investment on physical q will produce downward-biased slopes on q and hence upward-biased estimates of the adjustment-cost parameter. This result helps explain why we typically find smaller estimated slopes on q when using physical capital alone in our actual regressions.

6.2 A Model with Imperfect Substitutes

The assumption that physical and intangible capital are perfect substitutes helps generate the closed-form predictions above, but it is probably unrealistic. We now relax this assumption by replacing the linear capital aggregator $K = K_1 + K_2$ with the nonlinear capital aggregator $\phi(K_1, K_2) = K_1^{\rho} K_2^{1-\rho}$ in equation (11). To simplify the numerical solution, we also switch from continuous to discrete time. Otherwise, the model is the same as before. The setup now resembles that of Hayashi and Inoue (1991). We numerically solve and simulate this nonlinear model with $\rho = 0.5$. We then measure ι^{tot}, ι^{phy}, q^{tot}, and q^{phy} applying the same definitions as above to the new simulated data. Finally, we run the same regressions as above. This exercise essentially assumes the world is nonlinear, but asks what happens if the econometrician were to simply add together the two capital types as if they were perfect substitutes, as we do in our empirical analysis.

Simulation results for the nonlinear model are in Panel B of Table 8. As in the simpler linear model– and also in our empirical results–, in the nonlinear model we find a higher R^2 (41% versus 1%) using total rather than physical capital. Both R^2 values in Panel B are lower than their counterparts from the linear model in Panel A. This result is expected, since we are applying simple linear measures to a nonlinear world. However, the 41% R^2 using total capital is still quite high, and it is similar to the R^2 values we find in our empirical analysis using total capital. This result suggests that our empirical measures that simply add together the two capital stocks may not be a bad approximation if the real world is nonlinear. In panel B we also see that the q-slopes are much lower in than in panel A. There is no reason these slopes should equal $1/\gamma$ in the nonlinear model, so we do not quantify the bias as we do in Panel A. The slope using total capital is 15% larger than the slope using physical capital, consistent with the larger slopes we find in our empirical analysis when we use total capital.

7 Robustness

This section shows that our main empirical conclusions are robust to several alternate ways of measuring intangible capital and physical q.

7.1 What Fraction of SG&A Is An Investment?

Arguably the strongest assumption in our intangible-capital measure is that λ=30% of SG&A represents an investment and the rest is an operating expense. Table 9 shows that our main conclusions are robust to using different values of λ ranging from zero to 100%. When λ is zero, firms' intangible capital comes exclusively from R&D. No matter what λ value we assume, we find that including intangible capital produces larger values of R^2, τ^2, and ρ^2, as well as larger slopes on q. The highest OLS R^2 obtains for $\lambda = 0.5$. The highest ρ^2 and τ^2 values obtain when $\lambda = 0.3$.

Instead of assuming 30% of SG&A is investment, we can let the data tell us what the true value of λ is. The structural parameter λ affects both the investment and q measures. We estimate λ along with the q-slope and firm fixed effects by maximum likelihood. Details are available on request. This estimation imposes two strong identifying assumptions: the simple linear investment-q model is true, and there is no measurement error in our data.[29] The estimated λ values are 0.39 in the consumer industry, 0.37 in the high-tech industry, and 0.33 in the health-care industry. All these estimates are close to our assumed value of 0.3, which is comforting. However, we do not push these λ estimates strongly, for three reasons. First, the investment-q relation is probably not the ideal setting for identifying λ. Second, the assumption of a linear investment-q model is quite strong. Finally, the λ estimate in the manufacturing industry is constrained at 1.0, which is implausibly large and likely a symptom of the previous two issues. The take-away of this subsection, though, is that our main conclusions hold regardless of the λ value we use.

7.2 Alternate Measures of Intangible Capital

In addition to varying the SG&A multiplier λ, we try eight other variations on our intangible capital measure. Table 10 lists these variations and reports the results they produce. The table presents the R^2 from an OLS regression of investment on q, and it also presents the bias-corrected slope, τ^2, and ρ^2 from the cumulant estimator. For comparison, the first two rows report our main results with physical and total capital from Tables 2 and 3.

First, we show that our main conclusions are robust to the specific value of $\delta_{SG\&A}$, the depreciation rate of organizational capital. The academic literature and BEA provide guidance on choosing R&D depreciation rates, but there is much less guidance for choosing $\delta_{SG\&A}$. Our main results use $\delta_{SG\&A}$=20% when applying the perpetual inventory method (row 2 of Table 10). When we use a 10% or 30% depreciation rate instead (rows three and four), we find a very similar OLS R^2, ρ^2, τ^2, and bias-corrected slope on q.

Row five contains results after excluding goodwill from firms' intangible capital. Recall that goodwill is a component of balance-sheet intangible capital, which is a firm's externally acquired intangible capital. On the one hand, we should include goodwill since it includes the value of intangible assets that are not "separately identifiable." On the other hand, goodwill may be contaminated by market premia for externally acquired physical assets. We find that our main results are almost identical when we exclude goodwill.

[29] It may be possible to incorporate measurement error into the structural estimation of λ. Doing so, however, is outside this paper's scope.

Row six contains results after excluding all balance-sheet intangibles, including goodwill. There is no good reason for this exclusion, but it makes our measure closer to existing measures from the literature. The OLS R^2, ρ^2, and τ^2 values are all slightly lower than in row two, which implies that excluding balance-sheet intangibles produces a poorer proxy for q and firms' investment opportunities. The values are all higher than in row one, however, so our main conclusions about the importance of including intangible capital still hold using this alternate measure.

Rows 7–9 nine address the challenge of estimating firms' stock of intangible capital before their first Compustat record, which usually coincides with their IPO. Our main analysis estimates firms' starting intangible capital using data on their founding year, and by back-filling their R&D and SG&A spending using age-specific average R&D and SG&A growth rates.

In row seven we take a much simpler approach, setting firms' intangible capital to zero when they first appear in Compustat. This simplification seems to produce an even better proxy for investment opportunities and q. Compared to row two, row seven shows higher values of R^2, ρ^2, and τ^2. This result is surprising, since firms typically do own intangible capital before their IPOs. One potential explanation is that our main measure's back-filled values of R&D and SG&A are so noisy that one is better off just setting them to zero. If researchers want a simpler but still effective proxy for investment opportunities, this alternate measure is a reasonable choice.

Row eight estimates initial capital using the method of Falato, Kadryzhanova, and Sim (2013). They take the R&D or SG&A spending from the firm's first Compustat record, then assume the firm has been alive and investing that same dollar amount forever before entering Compustat. As a result, the initial stock of knowledge capital (for example) is $R\&D_{i1}/\delta_{R\&D}$, where $R\&D_{i1}$ is the R&D amount in firm i's first Compustat record.[30] By assuming the firm has been alive forever, this method tends to over-estimate firms' initial capital stocks. Compared to row two, row eight shows slightly lower values of R^2, τ^2, and ρ^2, meaning this method produces slightly worse proxies for firms' investment opportunities and q. However, this method still produces values that are well above those in row one, so our main conclusions about the importance of including intangible capital still hold using this alternate measure.

[30]Eisfeldt and Papanikolaou (2013) use a modified approach that assumes the investment level has been growing at some constant rate forever.

In rows 9a and 9b, we use the same measures as in rows one and two, but we drop the first five years of data for each firm. Doing so reduces the importance of the initial capital stock in the perpetual inventory method. Eisfeldt and Papanikolaou (2013) perform a similar robustness check. For both physical and total capital, the values of R^2, ρ^2, and τ^2 are much lower in rows 9a and 9b than in rows one and two, implying a weaker investment-q relation for older firms. Our main conclusion still holds, though, when we compare row 9a to 9b. Using total rather than physical capital produces a stronger investment-q relation, as judged by R^2, ρ^2, τ^2, and the q-slope.

R&D data are missing in 47% of our Compustat sample. Section 1 explains how we handle these missing observations. For robustness, we compute intangible capital as in our main analysis, but we drop firm/year observations with missing R&D from our regressions. Results using physical and total capital are in rows 10a and 10b, respectively. The values of R^2, ρ^2, and τ^2 are all higher compared to rows one and two, implying a stronger investment-q relation in firms that report R&D spending, even when we only measure physical capital. Our main conclusion still holds in this subsample when we compare rows 10a and 10b: Using total rather than physical capital produces a stronger investment-q relation, as judged by R^2, ρ^2, τ^2, and the q-slope.

7.3 Alternate Measures of Physical Capital

There is no consensus in the literature on how to measure Tobin's q. Our analysis so far uses the physical q measure that is most popular in the investment-q literature, but the broader finance literature uses a variety of measure. Next, we try some of these other definitions of physical q, and we show that our total q and total investment measures outperform them all.

We survey the most recent issues of the *Journal of Finance, Journal of Financial Economics*, and *Review of Financial Studies* to find papers that measure Tobin's q. We find at least nine different definitions in the January 2013 through July 2014 issues. None of these papers, nor any other papers we have seen, includes a firm's stock of internally generated intangible capital in the denominator of q, as we do in our total q measure. Some papers, though, do include externally acquired intangibles, perhaps inadvertently. They do so by setting the denominator of q to total assets, which includes balance-sheet intangibles. Since external intangibles make up a small fraction of total intangibles

(Section 1), these alternate definitions exclude most intangible capital. We therefore call these q measures from the literature alternate proxies for physical q.

We re-estimate our main physical-capital specifications using the five most popular alternate definitions we find for Tobin's q. For each one, we redefine investment so that investment and q share the same denominator. Results and detailed definitions are in Table 11, which has a similar format as Table 10. Most of the alternate physical q measures produce a slope on q that is even larger than the one generated by our total q measure. Since those alternate measures produce worse model fit, and since it is hard in general to interpret the slopes on q, it is not clear what to make of this result. The most important result in Table 10 is that including intangible capital (row 1) generates a larger R^2, τ^2, and ρ^2 value than in any of the physical-capital specifications (rows 2–7). Even our main physical capital measure outperforms these alternate measures, with one exception.[31]

8 Conclusion

We incorporate intangible capital into measures of investment and Tobin's q, and we show that the investment-q relation becomes stronger as a result. Specifically, measures that include intangible capital produce higher R^2 values and larger slope coefficients on q, both in firm-level and macroeconomic data. We also show that the investment-cash flow relation becomes much stronger if one properly accounts for intangible investments. These results hold across several types of firms and years. The increase in R^2, however, is especially large where intangible capital is most important, for example, in the high-tech and health industries. Estimation results also indicate that our measure of total q is closer to the unobservable true q than the standard physical q measure is.

Our results have two main implications. First, researchers using Tobin's q as a proxy for firms' investment opportunities should use a proxy that, like ours, includes intangible capital. One benefit of our proxy is that it is easy to compute for a large panel of firms. Second, the results change our

[31] The lone exception is the Tobin's q measure from Kogan and Papanikolaou (2014). Their measure equals the market value of equity plus the book value of debt plus the book value of preferred equity minus inventories and deferred taxes, all divided by PP&E). Erickson and Whited (2000, 2012) also show that our main physical-capital measure outperforms alternate ones.

assessment of the classic q theory of investment, or at least the version predicting a linear relation between investment and Tobin's q. On one hand, the increase in R^2 indicates that the theory fits the data better once we address an important source of measurement error. On the other hand, cash flow becomes even more strongly related to investment, contrary to the theory's predictions.

Our results point toward several questions for future research. How can we better measure firms' intangible capital? Besides the investment-q relation, what other existing empirical results change upon including intangible capital in investment, cash flow, or q? To what degree are physical and intangible capital substitutes or complements? We have focused on the classic q theory of Hayashi (1982) and others, but it is also important to include intangible capital in tests of more recent, general theories.

Appendix A: Measuring Firms' Initial Capital Stock

This appendix explains how we estimate the stock of knowledge and organizational capital in some firm i's first non-missing Compustat record. We describe the steps for estimating the initial knowledge-capital stock; the method for organizational capital is similar. Broadly, we estimate firm i's R&D spending in each year of life between the firm's founding and its first non-missing Compustat record, denoted year one. Our main assumption is that the firm's pre-IPO R&D grows at the average rate across pre-IPO Compustat firms. We then apply the perpetual inventory method to these estimated R&D values to obtain the initial stock of knowledge capital at the end of year zero. The specific steps are as follows:

1. Define age since IPO as number of years elapsed since a firm's IPO. Using the full Compustat database, compute the average log change in R&D in each yearly age-since-IPO category. Apply these age-specific growth rates to fill in missing R&D observations before 1977.

2. Using the full Compustat database, isolate records for firms' IPO years and the previous two years. (Not all firms have pre-IPO data in Compustat.) Compute the average log change in R&D within this pre-IPO subsample, which equals 0.348. (The corresponding pre-IPO average log change in SG&A equals 0.327).

3. If firm i's IPO year is in Compustat, go to step 5. Otherwise go to the next step.

4. This step applies almost exclusively to firms with IPOs before 1950. Estimate firm i's R&D spending in each year between the firm's IPO year and first Compustat year assuming the firm's R&D grows at the average age-specific rates estimated in step one above.

5. Obtain data on firm i's founding year from Jay Ritter's website. For firms with missing founding date in Ritter's data, estimate the founding year as the minimum of (a) the year of the firm's first Compustat record and (b) firm's IPO year minus 8, which is the median age between founding and IPO for IPOs from 1980-2012 (from Jay Ritter's web site).

6. Estimate the firm i's R&D spending in each year between the firm's founding year and IPO year assuming the firm's R&D grows at the estimated pre-IPO average rate from step two

above.

7. Apply the perpetual inventory method in equation (3) to the estimated R&D spending from the previous steps to obtain G_{i0}, the stock of knowledge capital at the beginning of the firm's first Compustat record.

We use estimated R&D and SG&A values only to compute firms' initial stocks of intangible capital. For example, we never use estimated R&D in a regression's dependent variable.

Appendix B: Proofs

Proof of Prediction 1. We can write the cost of investment as

$$c\left(K_t, I_t, p_t^*\right) = K_t \left[\frac{\gamma}{2}\left(\frac{I_t}{K_t}\right)^2 + p_t^* \, \frac{I_t}{K_t}\right], \tag{21}$$

where $p_t^* \equiv \min\left(p_{1t}, p_{2t}\right)$ also follows a general diffusion process with drift and volatility that depend on x_t. Abel and Eberly (1994) show that linear homogeneity in $\pi \equiv F\left(K, L, \varepsilon\right) - wL$ implies

$$\max_L \pi\left(K, L, \varepsilon\right) = H\left(\varepsilon\right) K. \tag{22}$$

We can therefore write the value function as

$$V_t = \max_{i_{1,t+s},\, i_{2,t+s}} \int_0^\infty E_t \left\{ \left[H\left(\varepsilon_{t+s}\right) - \frac{\gamma}{2}\left(\frac{I_{t+s}}{K_{t+s}}\right)^2 + p_{t+s}^* \, \frac{I_{t+s}}{K_{t+s}} \right] K_{t+s} \right\}. \tag{23}$$

Since the objective function and constraints can be written as functions of total capital K and not K_1 and K_2 individually, the firm's value depends on K but not on K_1 and K_2 individually:

$$V\left(K_1, K_2, \varepsilon, p_1, p_2\right) = V\left(K, \varepsilon, p_1, p_2\right). \tag{24}$$

Following the same argument as in Abel and Eberly's (1994) Appendix A, firm value must be proportional to total capital K :

$$V\left(K, \varepsilon, p_1, p_2\right) = K q^{tot}\left(\varepsilon, p_1, p_2\right). \tag{25}$$

Partially differentiating this equation with respect to K_1 and K_2 yields (15).

Proof of Prediction 2. Following a similar proof as in Abel and Eberly (1994), one can derive the Bellman equation and take first-order conditions with respect to I to obtain

$$q^{tot} = c_I\left(K, I, p^*\right) = \gamma \frac{I}{K} + p^*, \tag{26}$$

which generates (16). Details are available upon request.

Appendix C: Numerical solution of the investment model

We choose specific functional forms to solve the model numerically. We assume a Cobb-Douglas production function

$$\pi(K, L, \varepsilon) = \varepsilon L^{\alpha} K^{1-\alpha} - wL,$$

so that

$$\begin{aligned} \pi(K,\varepsilon) &= \max_{L} \pi(K, L, \varepsilon) = H(\varepsilon) K \\ H(\varepsilon) &= h\varepsilon^{\theta} \\ h &= \alpha^{\frac{\alpha}{1-\alpha}} w^{\frac{\alpha}{\alpha-1}} - \alpha^{\frac{1}{1-\alpha}} w^{\frac{\alpha}{\alpha-1}} \\ \theta &= \frac{1}{1-\alpha}. \end{aligned} \tag{27}$$

We assume the exogenous variables follow uncorrelated, positive, mean-reverting processes:

$$\begin{aligned} d\ln\varepsilon_{it} &= -\phi \ln\varepsilon_{it} dt + \sigma_{\varepsilon} dB_{it}^{(\varepsilon)} \\ d\ln p_{1t} &= -\phi \ln p_{1t} dt + \sigma_{p} dB_{t}^{(p_1)} \\ d\ln p_{2t} &= -\phi \ln p_{2t} dt + \sigma_{p} dB_{t}^{(p_2)}. \end{aligned}$$

The goal here is to solve for the function $q^{tot}(\varepsilon, p_1, p_2)$. Following the approach in Abel and Eberly (1994), one can show that the Bellman equation is

$$q^{tot}(r+\delta) = \pi_K(K,\varepsilon) - c_K(I, K, p_1, p_2) + E\left[dq^{tot}\right]/dt. \tag{28}$$

Substituting in and applying Ito's lemma yields

$$q^{tot}(r+\delta) = h\varepsilon^{\theta} + \frac{1}{2\gamma}\left(q^{tot} - p^{*}\right)^{2} + q_x^{tot}\mu(x) + \frac{1}{2} q_{xx}^{tot}\Sigma(x). \tag{29}$$

We numerically solve this equation for $q^{tot}(\varepsilon, p_1, p_2)$ using the collocation method of Miranda and

Fackler (2002), which approximates q^{tot} as a polynomial in ε, p_1, and p_2 and their interactions.

We use the following parameter values to illustrate the solution:

$$\begin{aligned}\alpha &= 0.5,\ w = 0.1,\ r = 0.2,\ \delta = 0.1,\ \gamma = 100\\ \phi &= 2,\ \sigma_\varepsilon = 0.1,\ \sigma_p = 0.2.\end{aligned}$$

We choose a high discount rate r and adjustment costs γ so that q^{tot} is finite.

We simulate a large panel of data on ι_{it}^{tot}, ι_{it}^{phy}, q_{it}^{tot}, and q_{it}^{phy}, then we estimate the panel regressions (17) and (19) by OLS. We repeat the simulation 50 times to obtain average simulated R^2 and slope estimates.

To solve the nonlinear model, we scale by the nonlinear capital aggregator, $K_1^\rho K_2^{1-\rho}$, and then apply value-function iteration. We simulate annual data using the same parameters as above, except for the following discrete-time adjustments: the annual discount factor is $\beta = exp(-0.2)$, the annual depreciation rate is $\delta = 1 - exp(-0.1)$, and the annual AR1 coefficient is $exp(-2)$.

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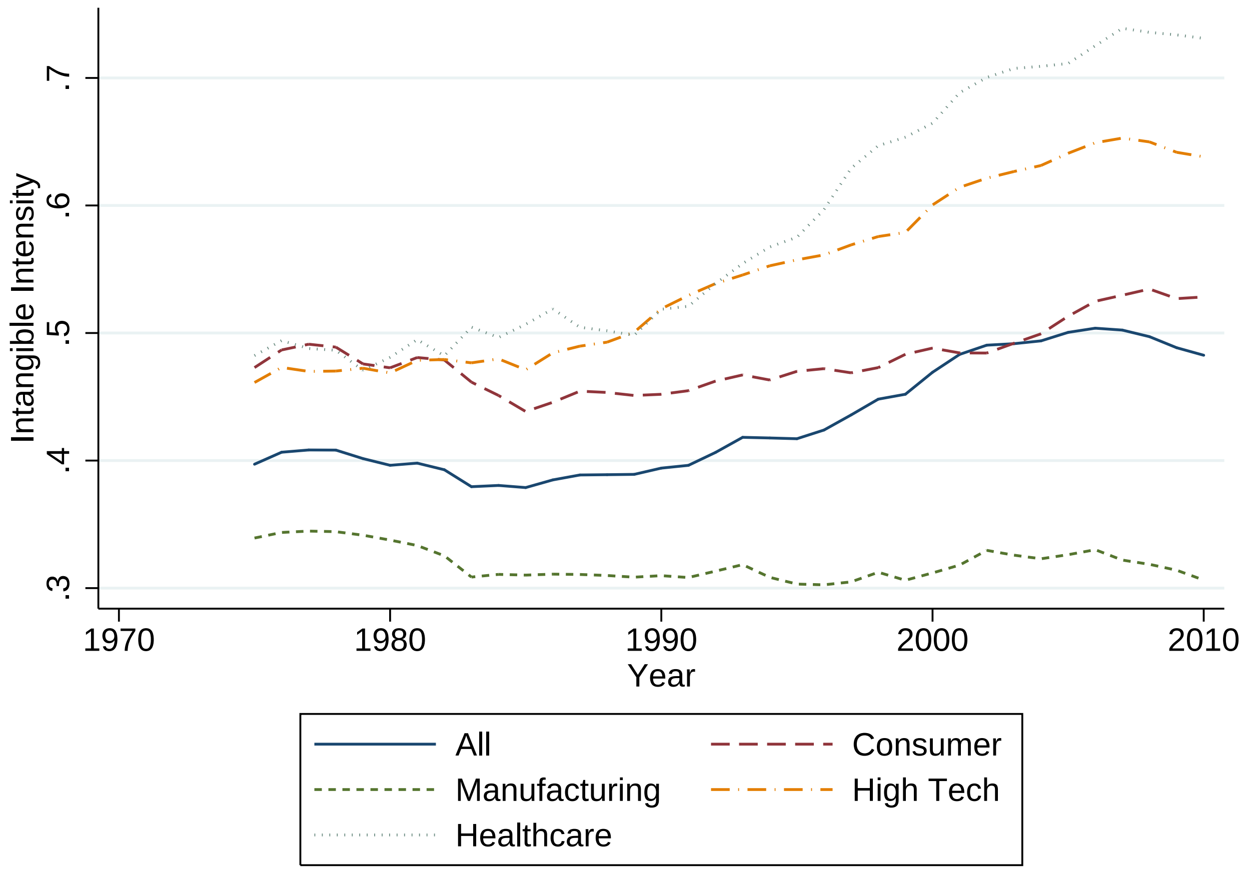

Figure 1. This figure plots the mean intangible capital intensity over time, both for our full sample and within industries. Intangible intensity is the firm's stock of intangible divided by its total stock of capital. We use the five-industry definition from Fama and French (1997) and exclude industry "Other."

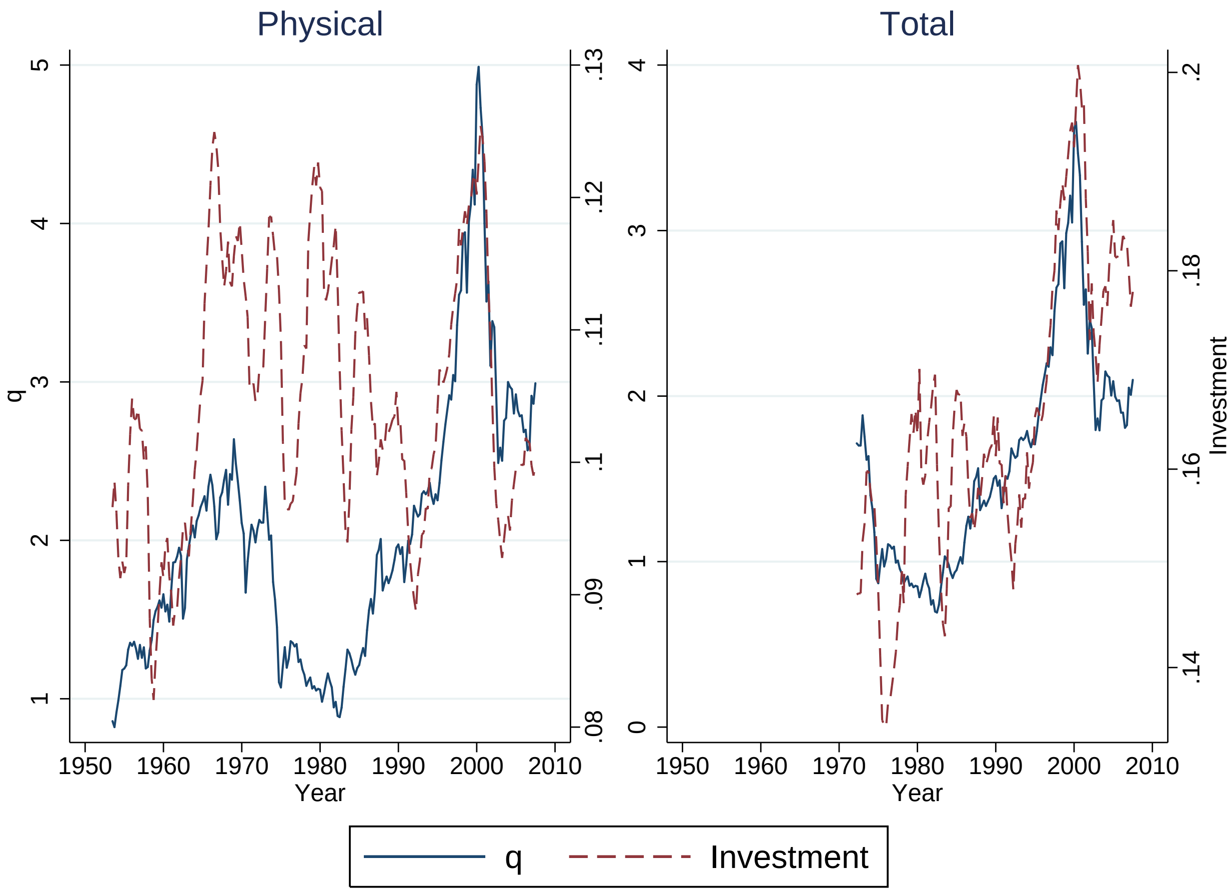

Figure 2. This figure plots Tobin's q and the investment rates for the aggregate U.S. economy. The left panel uses data from Hall (2001) and includes only physical capital in q and investment. The right panel uses data from Corrado and Hulten (2014) and includes both both physical and intangible capital in q and investment. For each graph, the left axis is the value of q and the right axis the investment rate (investment / capital)

Table 1
Summary Statistics

Statistics are based on the sample of Compustat firms from 1975 to 2010. The physical capital stock equals $PP\&E$. We estimate the intangible capital stock, $Intan$, by applying the perpetual inventory method to firms' intangible investments, defined as $R\&D + 0.3 \times SG\&A$; we then add in firms' balance-sheet intangibles. Intangible intensity equals the intangible capital stock divided by the total capital stock (PP&E+$Intan$). Knowledge capital is the part of intangible capital that comes from $R\&D$. The numerator for both q variables is the market value of equity plus the book value of debt minus current assets. The denominator for all "*phy*" variables is PP&E. The denominator for all "*tot*" variables is the total capital stock. The numerator for ι^{phy} is CAPX, and the numerator for ι^{tot} is total investment (CAPX+R&D+0.3×SG&A). The numerator for physical cash flow is income before extraordinary items plus depreciation expenses; the numerator for total cash flow is the same but adds back intangible investment net a tax adjustment.

Variable	**Mean**	**Median**	**Std**	**Skewness**
Intangible capital stock	692	59.8	3438	14.1
Physical capital stock	1237	77.9	6691	16.5
Intangible intensity	0.44	0.46	0.27	-0.03
Knowledge capital / Intangible capital	0.18	0.00	0.28	2.07
Physical q (q^{phy})	3.14	0.93	7.22	4.41
Physical investment (ι^{phy})	0.19	0.11	0.24	3.52
Physical cash flow (c^{phy})	0.15	0.16	0.62	-1.63
Total q (q^{tot})	1.07	0.56	1.83	3.71
Total investment (ι^{tot})	0.22	0.17	0.19	2.77
Total cash flow (c^{tot})	0.16	0.15	0.19	0.55

Table 2
OLS Results

Results are from OLS regressions of investment on Tobin's q, cash flow, and firm and year fixed effects. The variable q denotes Tobin's q, ι denotes investment, and c denotes cash flow. The numerator for both q variables is the market value of equity plus the book value of debt minus current assets. The denominator for all "*phy*" variables is PP&E. The denominator for all "*tot*" variables is the total capital stock, PP&E+$Intan$. The numerator for ι^{phy} is CAPX, and the numerator for ι^{tot} is total investment (CAPX+R&D+0.3×SG&A). The numerator for physical cash flow is income before extraordinary items plus depreciation expenses; the numerator for total cash flow is the same but adds back intangible investment net a tax adjustment. Bootstrapped standard errors clustered by firm are in parentheses. We report the within-firm R^2. Data are from Compustat from 1975 to 2010.

Panel A: Total investment (ι^{tot})

q^{tot}	0.054***		0.057***	0.045***		0.047***
	(0.001)		(0.001)	(0.001)		(0.001)
q^{phy}		0.012***	-0.001**		0.009***	-0.001*
		(0.000)	(0.000)		(0.000)	(0.000)
c^{tot}				0.259***	0.316***	0.259***
				(0.007)	(0.007)	(0.007)
R^2	0.319	0.242	0.320	0.368	0.318	0.368
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N	141800	141800	141800	141800	141800	141800

Panel B: Physical investment (ι^{phy})

q^{tot}	0.065***		0.041***	0.063***		0.040***
	(0.001)		(0.002)	(0.001)		(0.002)
q^{phy}		0.017***	0.008***		0.017***	0.008***
		(0.000)	(0.000)		(0.000)	(0.000)
c^{phy}				0.030***	0.032***	0.028***
				(0.003)	(0.003)	(0.003)
R^2	0.243	0.233	0.255	0.248	0.238	0.259
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N	141800	141800	141800	141800	141800	141800

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 3
Bias-Corrected Results

Results are from regressions of investment on a proxy for Tobin's q and cash flow. Columns labelled "OLS" reproduce the OLS results from Table 2. CUM denotes the cumulants estimator with firm and year fixed effects. IV denotes instrumental variable estimation, with three lags of cash flow and Tobin's q used as instruments for the first difference of Tobin's q. AB denotes estimation of this same first-differenced regression with the same instruments, but using the GMM estimator of Arellano and Bond (1991). Panel A uses the total-capital measures ι^{tot}, q^{tot}, and c^{tot}. Panel B uses the physical-capital measures ι^{phy}, q^{phy}, and c^{phy}. ρ^2 is the R^2 from a hypothetical regression of investment on true q, and τ^2 is the R^2 from a hypothetical regression of our q proxy on true q. Bootstrapped standard errors are in parentheses. Data are from Compustat from 1975 to 2010.

Panel A: Total investment (ι^{tot})

	OLS	CUM	IV	AB	OLS	CUM	IV	AB
q^{tot}	0.054***	0.097***	0.031***	0.015***	0.045***	0.096***	0.025***	0.026***
	(0.001)	(0.001)	(0.005)	(0.002)	(0.001)	(0.001)	(0.005)	(0.002)
c^{tot}					0.259***	0.148***	0.166***	0.157***
					(0.007)	(0.009)	(0.008)	(0.008)
ρ^2		0.428				0.482		
		(0.008)				(0.007)		
τ^2		0.588				0.539		
		(0.007)				(0.007)		
N	141800	141800	88700	99553	141800	141800	88700	99553

Panel B: Physical investment (ι^{phy})

	OLS	CUM	IV	AB	OLS	CUM	IV	AB
q^{phy}	0.017***	0.036***	0.012***	0.006***	0.017***	0.035***	0.011***	0.009***
	(0.000)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)
c^{phy}					0.032***	0.015***	0.026***	0.023***
					(0.003)	(0.003)	(0.002)	(0.002)
ρ^2		0.372				0.371		
		(0.007)				(0.007)		
τ^2		0.492				0.494		
		(0.010)				(0.009)		
N	141800	141800	88700	99553	141800	141800	88700	99553

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 4
Comparing Firms With Different Amounts of Intangible Capital

This table shows results from subsamples formed based on yearly quartiles of intangible intensity, which equals the ratio of a firm's intangible to total capital. Results are from regressions of investment on q, cash flow, and year and firm fixed effects. Slopes on q, as well as ρ^2 and τ^2 values, are from the cumulant estimator. R^2 is from the OLS estimator. Panel B controls for cash flow, panel A does not. Columns labeled "Physical" use the physical-capital measures ι^{phy}, q^{phy} and c^{phy}, while columns labeled "Total" use the total-capital measures ι^{tot}, q^{tot} and c^{tot}, as defined in the notes for Table 1. Δ denotes the difference between the Total and Physical specifications. Bootstrapped standard errors clustered by firm are in parentheses. Data are from Compustat from 1975-2010.

Panel A: No Cash Flow

	Quartile 1 (low)		Quartile 2		Quartile 3		Quartile 4 (high)	
	Physical	Total	Physical	Total	Physical	Total	Physical	Total
q	0.064***	0.131***	0.053***	0.106***	0.035***	0.088***	0.033***	0.088***
	(0.007)	(0.006)	(0.006)	(0.005)	(0.002)	(0.003)	(0.001)	(0.002)
R^2	0.182	0.229	0.192	0.260	0.247	0.344	0.301	0.477
	(0.009)	(0.009)	(0.011)	(0.010)	(0.012)	(0.013)	(0.010)	(0.009)
ΔR^2	0.047		0.068		0.097		0.176	
ρ^2	0.195	0.316	0.281	0.396	0.375	0.460	0.559	0.571
	(0.018)	(0.012)	(0.027)	(0.019)	(0.022)	(0.023)	(0.016)	(0.012)
$\Delta\rho^2$	0.121		0.115		0.085		0.012	
τ^2	0.691	0.587	0.505	0.493	0.485	0.518	0.440	0.649
	(0.057)	(0.026)	(0.052)	(0.023)	(0.031)	(0.023)	(0.012)	(0.014)
$\Delta\tau^2$	-0.104		-0.012		0.033		0.209	
N	35438	35438	35453	35453	35442	35442	35467	35467

Panel B: With Cash Flow

	Quartile 1 (low)		Quartile 2		Quartile 3		Quartile 4 (high)	
	Physical	Total	Physical	Total	Physical	Total	Physical	Total
q	0.065***	0.125***	0.054***	0.104***	0.034***	0.088***	0.033***	0.089***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.002)	(0.004)	(0.001)	(0.002)
c	0.185***	0.220***	0.072***	0.147***	0.011	0.110***	-0.003	0.136***
	(0.022)	(0.025)	(0.020)	(0.021)	(0.009)	(0.020)	(0.004)	(0.014)
R^2	0.208	0.269	0.212	0.317	0.255	0.401	0.303	0.525
	(0.010)	(0.010)	(0.012)	(0.010)	(0.012)	(0.013)	(0.010)	(0.009)
ΔR^2	0.061		0.105		0.146		0.222	
ρ^2	0.236	0.353	0.310	0.447	0.365	0.520	0.550	0.644
	(0.020)	(0.012)	(0.025)	(0.018)	(0.022)	(0.020)	(0.016)	(0.011)
$\Delta\rho^2$	0.117		0.137		0.155		0.094	
τ^2	0.643	0.559	0.473	0.454	0.499	0.469	0.447	0.589
	(0.060)	(0.026)	(0.046)	(0.022)	(0.028)	(0.019)	(0.012)	(0.013)
$\Delta\tau^2$	-0.084		-0.019		-0.030		0.142	
N	35438	35438	35453	35453	35442	35442	35467	35467

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5
Comparing Industries

This table shows results from industry subsamples. We use the Fama-French five-industry definition, excluding the industry "Other." Manufacturing includes manufacturing and energy firms but not utilities. Consumer includes consumer goods, retail, and service firms. High Tech includes software, business equipment, and telecommunications firms. Health Care includes health care, pharmaceutical, and medical equipment firms. Remaining details are the same as in Table 4.

Panel A: No Cash Flow

	Manufacturing		Consumer		High Tech		Health Care	
	Physical	Total	Physical	Total	Physical	Total	Physical	Total
q	0.041***	0.112***	0.042***	0.108***	0.033***	0.089***	0.038***	0.098***
	(0.002)	(0.005)	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.003)
R^2	0.186	0.246	0.214	0.307	0.354	0.462	0.258	0.343
	(0.010)	(0.009)	(0.011)	(0.012)	(0.008)	(0.011)	(0.013)	(0.014)
ΔR^2	0.060		0.093		0.108		0.085	
ρ^2	0.206	0.301	0.290	0.391	0.549	0.575	0.545	0.537
	(0.011)	(0.012)	(0.014)	(0.018)	(0.013)	(0.012)	(0.024)	(0.020)
$\Delta\rho^2$	0.095		0.101		0.026		-0.008	
τ^2	0.655	0.601	0.539	0.533	0.511	0.644	0.365	0.494
	(0.044)	(0.028)	(0.036)	(0.026)	(0.014)	(0.014)	(0.025)	(0.023)
$\Delta\tau^2$	-0.054		-0.006		0.133		0.129	
N	40280	40280	36884	36884	31680	31680	11207	11207

Panel B: With Cash Flow

	Manufacturing		Consumer		High Tech		Health Care	
	Physical	Total	Physical	Total	Physical	Total	Physical	Total
q	0.040***	0.107***	0.041***	0.110***	0.032***	0.089***	0.038***	0.098***
	(0.002)	(0.006)	(0.002)	(0.007)	(0.001)	(0.002)	(0.002)	(0.004)
c	0.083***	0.283***	0.048***	0.186***	0.001	0.106***	-0.003	-0.005
	(0.014)	(0.022)	(0.010)	(0.032)	(0.004)	(0.013)	(0.009)	(0.033)
R^2	0.202	0.317	0.236	0.390	0.355	0.495	0.258	0.364
	(0.010)	(0.009)	(0.011)	(0.012)	(0.008)	(0.011)	(0.014)	(0.015)
ΔR^2	0.115		0.154		0.140		0.106	
ρ^2	0.227	0.385	0.309	0.493	0.541	0.623	0.547	0.536
	(0.010)	(0.011)	(0.014)	(0.016)	(0.013)	(0.011)	(0.024)	(0.018)
$\Delta\rho^2$	0.158		0.184		0.082		-0.011	
τ^2	0.635	0.530	0.520	0.446	0.518	0.602	0.364	0.495
	(0.044)	(0.032)	(0.033)	(0.021)	(0.014)	(0.014)	(0.024)	(0.023)
$\Delta\tau^2$	-0.105		-0.074		0.084		0.131	
N	40280	40280	36884	36884	31680	31680	11207	11207

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6
Comparing Time Periods

This table shows results from the early (1975–1995) and late (1996–2010) subsamples. The 1995 breakpoint produces subsamples of roughly equal size. Remaining details are the same as in Table 4.

Panel A: No Cash Flow

	Early		Late	
	Physical	Total	Physical	Total
q	0.043***	0.110***	0.033***	0.091***
	(0.002)	(0.003)	(0.001)	(0.001)
R^2	0.209	0.265	0.268	0.348
	(0.008)	(0.009)	(0.007)	(0.008)
ΔR^2	0.056		0.080	
ρ^2	0.262	0.337	0.479	0.510
	(0.010)	(0.011)	(0.011)	(0.010)
$\Delta\rho^2$	0.075		0.031	
τ^2	0.615	0.583	0.477	0.595
	(0.026)	(0.022)	(0.011)	(0.011)
$\Delta\tau^2$	-0.032		0.118	
N	69753	69753	72047	72047

Panel B: With Cash Flow

	Early		Late	
	Physical	Total	Physical	Total
q	0.044***	0.108***	0.033***	0.090***
	(0.002)	(0.004)	(0.001)	(0.002)
c	0.074***	0.270***	-0.008	0.041***
	(0.009)	(0.018)	(0.004)	(0.011)
R^2	0.233	0.357	0.268	0.367
	(0.007)	(0.009)	(0.007)	(0.008)
ΔR^2	0.124		0.099	
ρ^2	0.299	0.443	0.474	0.520
	(0.010)	(0.011)	(0.011)	(0.010)
$\Delta\rho^2$	0.144		0.046	
τ^2	0.564	0.487	0.482	0.585
	(0.025)	(0.021)	(0.011)	(0.011)
$\Delta\tau^2$	-0.077		0.103	
N	69753	69753	72047	72047

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7
Time-Series Macro Regressions

Calculations are based on quarterly aggregate U.S. data from 1972Q2 through 2007Q2. In the top panel, the dependent variable is total investment (physical + intangible), deflated by the total capital stock. In the bottom panel, the dependent variable is total physical investment (PP&E) deflated by the total physical capital stock. Physical q equals the aggregate stock and bond market value divided by the physical capital stock; Hall (2001) computes these measures from the Flow of Funds. Total q includes intangible capital by multiplying physical q by the ratio of physical to total capital; the ratio is from Corrado and Hulten's (2014) aggregate U.S. data. Bond q is constructed by applying the structural model of Philippon (2009) to bond maturity and yield data; these data are from Philippon's web site. Newey-West standard errors, with autocorrelation up to twelve quarters, are reported in parentheses.

Panel A: Total investment (ι^{tot})

Total q	0.017***				0.016***
	(0.003)				(0.003)
Physical q		0.012***		0.012***	
		(0.002)		(0.002)	
Bond q			0.055	0.033	0.031
			(0.032)	(0.017)	(0.018)
OLS R^2	0.610	0.646	0.139	0.693	0.652
N	141	141	141	141	141

Panel B: Physical investment (ι^{phy})

Total q	0.003				0.001
	(0.003)				(0.002)
Physical q		0.002		0.001	
		(0.003)		(0.002)	
Bond q			0.061***	0.060***	0.060***
			(0.009)	(0.009)	(0.009)
OLS R^2	0.047	0.035	0.462	0.465	0.466
N	141	141	141	141	141

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 8
Regressions Using Simulated Data

This table shows results of regressing investment on q in simulated panel data. Panel A shows results from a linear model that assumes physical and intangible capital are perfect substitutes. Panel B shows results from a model that relaxes this assumption and aggregates the two capital types according to $K_1^{0.5}K_2^{0.5}$. We numerically solve the models, simulate large panels of data, and regress investment on q and time fixed effects. Details on both models are in Section 6. Details on the simulations are in Appendix C. Model (1) regresses total investment on total q, whereas model (2) regresses physical investment on physical q. Specifically, model (1) defines investment as $\iota^{tot} = (I_1 + I_2)/(K_1 + K_2)$ and q as $q^{tot} = V/(K_1 + K_2)$, where I_1 and I_2 are the investments in physical and intangible capital, respectively, K_1 and K_2 are the two capital stocks, and V is firm value. Model (2) defines investment as $\iota^{phy} = I_1/K_1$ and q as $q^{phy} = V/K_1$. We assume $\gamma = 100$, so the bias in $1/\gamma$ is the percent difference between the q-slope and 0.01.

Panel A: Linear Model

Regression	R^2	Slope on q	Bias in $1/\gamma$
(1) Total investment on total q	1.000	0.0100	0
(2) Physical investment on physical q	0.489	0.0049	-51%

Panel B: Nonlinear Model

Regression	R^2	Slope on q
(1) Total investment on total q	0.409	0.00035
(2) Physical investment on physical q	0.013	0.00031

Table 9
Robustness: What Fraction of SG&A Is An Investment?

Results are from regressions of investment on q and year and firm fixed effects. Slopes on q, as well as ρ^2 and τ^2 values, are from the cumulant estimator. R^2 is from the OLS estimator. The first column reproduces results from Tables 2 and 3 using our main physical capital measures, q^{phy} and ι^{phy}. The remaining columns show results using variations of the total-capital measures, q^{tot} and ι^{tot}. Each variation uses a different SG&A multiplier. The multiplier, shown in the table's top row, is the fraction of SG&A that represents an investment rather than an operating expense. Our main total-capital measures assume a 0.3 multiplier. Data are from Compustat from 1975 to 2010.

	Physical	Total Capital with Alternate SG&A Multipliers										
	Capital	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
q	0.036***	0.069***	0.080***	0.089***	0.097***	0.105***	0.112***	0.119***	0.127***	0.134***	0.139***	0.146***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.233	0.279	0.303	0.314	0.319	0.323	0.324	0.323	0.323	0.321	0.319	0.317
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ρ^2	0.372	0.407	0.419	0.424	0.428	0.429	0.429	0.430	0.431	0.430	0.428	0.426
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
τ^2	0.492	0.548	0.574	0.584	0.588	0.590	0.591	0.588	0.585	0.582	0.581	0.578
	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
N	141800	141800	141800	141800	141800	141800	141800	141800	141800	141800	141800	141800

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10
Robustness: Alternate Measures of Intangible Capital

Results are from regressions of investment on q and year and firm fixed effects. Slopes on q, as well as ρ^2 and τ^2 values, are from the cumulant estimator. R^2 is from the OLS estimator. The first two rows reproduce results from Tables 2 and 3 with our main physical-capital measures (ι^{phy} and q^{phy}) and total-capital measures (ι^{tot} and q^{tot}). Rows 2–8 show results using variations of our total-capital measure. Rows three and four use alternate values of $\delta_{SG\&A}$, the depreciation rate for organization capital. Row five excludes goodwill from balance-sheet intangibles, while row six excludes all balance-sheet intangibles. Row seven assumes firms have no intangible capital before entering Compustat. Row eight estimates firms' starting intangible capital using the method of Falato, Kadryzhanova, and Sim (2013). Rows 9a and 9b use our main measures but drop each firm's first five years of data. Rows 10a and 10b use our main measures but drop firm/year observations with missing R&D. Data are from Compustat from 1975 to 2010.

	R^2	τ^2	ρ^2	Slope on q	N
1. Physical capital (from Tables 2, 3)	0.233	0.492	0.372	0.036	141800
	(0.005)	(0.010)	(0.007)	(0.001)	
2. Total capital (from Tables 2, 3)	0.319	0.588	0.428	0.097	141800
	(0.005)	(0.007)	(0.008)	(0.001)	
3. $\delta_{SG\&A}$ =10%	0.330	0.599	0.437	0.099	141800
	(0.005)	(0.008)	(0.008)	(0.001)	
4. $\delta_{SG\&A}$ =30%	0.314	0.582	0.421	0.096	141800
	(0.005)	(0.007)	(0.008)	(0.001)	
5. Exclude goodwill	0.321	0.590	0.429	0.097	141800
	(0.005)	(0.007)	(0.008)	(0.001)	
6. Exclude balance-sheet intangibles	0.300	0.570	0.421	0.089	141800
	(0.005)	(0.009)	(0.008)	(0.001)	
7. Zero initial intangible capital	0.335	0.597	0.448	0.101	141800
	(0.005)	(0.007)	(0.008)	(0.001)	
8. FKS initial multiplier	0.289	0.561	0.398	0.095	141800
	(0.005)	(0.008)	(0.008)	(0.001)	
9. Drop first five years per firm					
a. Physical capital	0.125	0.327	0.227	0.032	82174
	(0.005)	(0.021)	(0.014)	(0.002)	
b. Total capital	0.201	0.416	0.290	0.088	82174
	(0.007)	(0.022)	(0.016)	(0.004)	
10. Exclude observations with missing R&D					
a. Physical capital	0.293	0.479	0.486	0.035	75426
	(0.007)	(0.011)	(0.013)	(0.001)	
b. Total capital	0.401	0.624	0.511	0.091	75426
	(0.009)	(0.010)	(0.013)	(0.001)	

Table 11
Robustness: Alternate Measures of Physical Capital

Results are from regressions of investment on q and year and firm fixed effects. Slopes on q, as well as ρ^2 and τ^2 values, are from the cumulant estimator. R^2 is from the OLS estimator. The first two rows reproduce results from Tables 2 and 3 with our main total-capital measures (ι^{tot} and q^{tot}) and physical-capital measures (ι^{phy} and q^{phy}) . Rows 3–7 show results using variations of our physical-capital measure. Variation 1 computes q as the market value of equity (CSHO times PRCCF, from CRSP) plus assets (AT) minus the book value of equity (CEQ+TXBD from Compustat) all divided by assets (AT). Variation 2, from Kogan and Papanikolaou (2014), computes q as the market value of equity(CSHO times PRCCF) plus book value of debt (DLTT) plus book value of preferred equity (PSTKRV) minus inventories (INVT) and deferred taxes (TXDB) divided by book value of capital (PPEGT). Variation 3 computes q as the market value of assets divided by the book value of assets (AT), where the market value of assets equals the book value of debt (LT) plus the market value of equity (PRCCF times CSHO). Variation 4 computes q as book value of assets (AT) plus the market value of equity (CSHO times PRCCF) minus book equity all over assets. Book equity is defined as total assets less total liabilities (LT) and preferred stock (PSTKRV) plus deferred taxes (TXDB) and convertible debt (DCVT). Variation 5 computes q as the book value of assets (AT) less the book value of equity (CEQ) plus the market value of equity (CSHO times PRCCF) all over the book value of assets. In each variation, the dependent variable is physical investment, measured as CAPX divided by the same denominator as in the q measure. Data are from Compustat from 1975 to 2010.

	R^2	τ^2	ρ^2	Slope on q	N
1. Total capital (from Tables 2, 3)	0.319	0.588	0.428	0.097	141800
	(0.005)	(0.007)	(0.008)	(0.001)	
2. Physical capital (from Tables 2, 3)	0.233	0.492	0.372	0.036	141800
	(0.005)	(0.010)	(0.007)	(0.001)	
3. Physical capital variation 1	0.127	0.259	0.290	0.101	137060
	(0.003)	(0.010)	(0.008)	(0.003)	
4. Physical capital variation 2	0.259	0.514	0.407	0.033	137209
	(0.006)	(0.012)	(0.008)	(0.001)	
5. Physical capital variation 3	0.127	0.261	0.290	0.100	141800
	(0.003)	(0.008)	(0.009)	(0.003)	
6. Physical capital variation 4	0.127	0.258	0.294	0.102	137209
	(0.004)	(0.009)	(0.009)	(0.003)	
7. Physical capital variation 5	0.127	0.259	0.290	0.101	141618
	(0.003)	(0.008)	(0.009)	(0.003)	