

Intangible Capital and the Investment- q Relation

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Abstract: Including intangible capital in measures of investment and Tobin's q results in a stronger investment- q relation. Specifically, regressions of investment on q produce higher R^2 values, larger slopes, and hence lower implied adjustment costs in both firm-level and macroeconomic data. Estimation results also indicate that including intangible capital produces a q proxy that is closer to the true, unobservable q . These results hold across a variety of firms and periods, but they are stronger where intangible capital is more important, for example, in the high-tech industry and recent years. Our results imply that the simplest q theories of investment match the data better than was previously believed, and that researchers should include 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 a firm’s 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 and, taking early q theories literally, imply implausibly large capital adjustment costs. 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 would explain both the large unexplained residuals and large implied adjustment costs. This possibility has spawned a sizable literature developing techniques to measure q more accurately and correct for measurement-error bias.²

This paper’s goal is to address 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 difficult to measure. Our current accounting system, which was originally designed for an economy dominated by heavy manufacturing, is poorly suited for an economy increasingly dominated by intangible capital. For example, accounting rules treat research and development (R&D) spending as an expense rather than an investment, so the knowledge created by R&D does not typically appear as an asset on the firm’s 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 benefits

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

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

³If a company acquires another company, the acquired company’s R&D capital can appear indirectly on the balance sheet as goodwill.

⁴A 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

on average. 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 we evaluate existing q theories of investment, and for how researchers choose proxies for investment opportunities.

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 stocks. Similarly, our measure of total investment is the sum of physical and intangible investments divided by the firm's total capital. Our measure of intangible capital builds on the measure of Falato, Kadryzhanova, and Sim (2013), which in turn builds on the work of Corrado, Hulten, and Sichel (2009) and Corrado and Hulten (2010). 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.⁵ While our q measure imposes some strong assumptions on the data, one benefit is that it is easily computed from Compustat data for a large panel of firms.

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 44-57% 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 negatively related and almost loses statistical significance. These results indicate that total q is a better proxy for investment opportunities than is the usual physical q .

The OLS regressions suffer from a well known measurement-error bias. We correct this bias using by using the Erickson and Whited (2000, 2002) measurement-error consistent GMM estimators

human capital or employee non-compete agreements can make human capital behave as if partially owned by the firm.

⁵Eisfeldt and Papanikolaou (2013) apply a similar method to SG&A data to measure organizational capital.

and the instrumental variable (IV) estimators from Biorn (2000) and Arellano and Bond (1991). Compared to the specifications with physical investment and q , the specifications including intangible capital produce an estimated slope of investment on q that is 54–216% higher, and they also generate higher slopes on cash flow. In the simplest manifestation of q theory, the slope on q equals the inverse of the capital adjustment cost parameter. According to this benchmark theory, including intangible capital reduces our adjustment cost estimates by 35–68%. A common concern about investment- q regressions is that they produce unreasonably large capital adjustment cost estimates.⁶ We show that including intangible capital mitigates this concern and changes our estimates of an important financial friction. One caveat is that the slope on q is difficult to interpret in more general q theories, as Erickson and Whited (2000), Gala and Gomes (2013), and others have shown.

The GMM estimators produce a useful test statistic, τ^2 , measuring how close our q proxies are to the unobservable true 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 8–21% higher when one includes intangible capital in the investment- q regression, again implying that total q is a better proxy for investment opportunities than is the usual physical q . Our new q proxy is still not perfect, though: total q explains only 49–73% of the variation in true q , depending on the estimator used.

Our main result so far is that including intangible capital results in a stronger investment- q relation. This result is consistent across firms with high and low amounts of intangible capital, in the early and late parts of our sample, and across industries. As expected, however, our result is stronger where intangible capital is more important. The increase in R^2 from including intangible capital is roughly twice as large in firms with a higher proportion of intangible capital. 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 is roughly twice as large in the high-tech and consumer industries compared to the manufacturing and energy industries. The pattern in τ^2 across subsamples is similar. We also find that including intangible capital changes estimated slopes on q by more in subsamples where intangible capital is more important, with a few exceptions. This

⁶This point is made in Summers (1981) and Philippon (2009) among many others.

result suggests that capital adjustment cost estimates based on physical capital alone are likely to be more biased where intangible capital is more important. Several important studies⁷ on q and investment use data only on manufacturing firms. Our results 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 macro 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, a slope on q that is 9 times larger, and hence implied adjustment costs that are 88% lower. Almost all the improvement comes from adjusting the investment measure rather than 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, although our slope increase is smaller than Philippon's. Philippon's bond q is still a superior proxy for physical investment opportunities and performs better when we estimate the model in first differences.

We provide a simple theory of optimal investment in physical and intangible capital. The model predicts that marginal q equals total q , which provides a rationale for the total q measure. It also predicts that the total investment rate is perfectly explained by total q and time fixed effects, providing a rationale for our regressions using total capital. In contrast, the usual regression of physical investment on physical q is predicted to generate a lower R^2 and downward-biased slopes. This prediction helps explain why we find lower R^2 values larger implied adjustment costs when we exclude intangible capital.

To summarize, 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 and also in investment. Second, we show that the q theories predicting a linear investment- q relation perform much better empirically than was previously believed. Once we correct an important source of measurement error, the theory fits the data better and implies more reasonable capital adjustment costs.

⁷Almeida and Campello (2007) and Almeida, Campello and Galvao (2010), and Erickson and Whited (2012)

Besides contributing to the previously discussed literatures on investment, Tobin's q , and measurement error, this paper also contributes to the 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 Sim (2013) document a strong empirical link between intangible capital and firms' cash holdings; they argue that the link is driven by debt capacity. Eisfeldt and Papanikolaou (2013) show that firms with more organizational capital have higher average stock returns, suggesting this type of intangible capital makes these firms riskier to shareholders.

This is not the first paper to forecast intangible investment using q . Almeida and Campello (2007) use physical q , cash flow, and asset tangibility to forecast R&D investment. Their focus is on how asset tangibility affects investment levels through borrowing capacity. Slightly closer to our specifications, Chen, Goldstein and Jiang (2007) use physical q to forecast the sum of physical investment and R&D. Their focus is on whether private information in prices affects the investment-price sensitivity. Besides having a different focus, our paper is the first to include all the types of intangible capital in both investment and q .

There is also a sizable literature that studies the impact of intangible investments on q . For example, Megna and Klock (1993) and Klock and Megna (2001) study the impact of intangible capital on q in the semiconductor and telecommunications industries, respectively. These studies find that intangible capital is an important component of 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. Hall (2001) uses a capital-adjustment model to infer the aggregate stock of intangible capital from data on prices and physical capital.

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 shows subsample 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 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 firms with less than \$5 million in physical capital, as is standard in the literature. We use data from 1972 to 2010, although we use earlier data to calculate the stock of intangible capital. We winsorize all regression variables at the %0.5 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

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

where $Mktcap$ is the market value of outstanding equity, $Debt$ is the book value (a proxy for the market value) of outstanding debt, AC is the current assets of the firm, such as inventory and marketable securities, and $P\&PE$ is the book value of property, plant and equipment. All of these quantities are measured at the beginning of the period. Another less common method, used for example in Rauh (2006) and Chava and Roberts (2008), is to measure q as the market-to-book ratio. Erickson and Whited (2000, 2012) show that this proxy is less effective at forecasting investment, a result that we confirm in unreported regressions.

Our measure of total q includes both physical and intangible capital. Our measure of total q is

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

$Intan$ is the stock of intangible capital, described 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, 0.88, the measures produce quite different results in investment regressions.

1.2 Intangible Capital and Investment

Because Generally Accepted Accounting Principles classify investments in intangible assets as expenses,⁸ the stock of intangible assets is typically not captured on firms' balance sheets. Fortunately, we can construct a proxy for the stock of intangible capital by accumulating past investments in intangible assets as reported on firms' income statements.

Our measure closely follows Falato, Kadyrzhanova and Sim's (2013). A firm's stock of intangible capital, $Intan$, is the sum of its knowledge capital and organizational capital. A firm acquires knowledge capital by spending on R&D. We accumulate capital flows from R&D expenses using the perpetual inventory method:

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

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. We choose $\delta_{R\&D} = 15\%$ following Hall, Jaffe and Tranchenberg (2001). Results are robust to using alternate depreciation rates. We interpolate missing values of R&D following Hall (1993), who shows that doing so results in an unbiased measure of R&D capital. We use Compustat data back to 1950 to compute (3), but our regressions only include observations after 1972, the first year when Compustat R&D coverage exceeds 40%.

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). The logic is that at least part of

⁸FASB, "Accounting for Research and Development Costs," Statement of Financial Accounting Standards No. 2, October 1974.

SG&A spending represents investments in organizational capital through advertising, spending on distribution systems, employee training, and payments to strategy consultants. We follow Corrado, Hulten, and Sichel (2009) and consider only 20% of SG&A to be investments in intangible capital. We interpret the remaining 80% as operating costs that support the current period’s profits. Our results are not sensitive to using values other than 20%.⁹ We apply a depreciation rate of $\delta_{SG\&A} = 0.20$, following Lev and Radhakrishnan (2005).

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. Falato, Kadryzhanova, and Sim (2013) assume the firm has been investing at the constant rate $R\&D_{i1}$ forever, so $G_{i0} = R\&D_{i1}/\delta_{R\&D}$. Eisfeldt and Papanikolaou (2013) use a modified approach that assumes the investment level has been growing at some constant rate forever. By assuming the firm has been alive forever, both methods tend to over-estimate firms’ initial capital stocks. We use a modified approach that incorporates data on firms’ founding years and recognizes that capital spending increases faster for younger firms. Specifically, we set G_{i0} to $R\&D_{i1}$ times a coefficient that depends on the firm’s age in year zero. We compute these coefficients assuming the firm’s pre-Compustat R&D spending grows at the average rate for Compustat firms of the same age. We apply a similar approach to SG&A spending. Appendix A provides additional details and tabulates the age-specific coefficients.

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

$$i^{tot} = \frac{CAPEX + R\&D + 0.2 \times SG\&A}{PP\&E + Intan}. \quad (4)$$

In contrast, the physical investment rate most commonly used in the literature is $i^{phy} = CAPEX/PP\&E$. The correlation between i^{tot} and i^{phy} is 0.87.

⁹We obtain similar results using a range from 0–40%.

1.3 Cash Flow

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

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

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. In addition to c^{phy} , we use an alternate cash flow measure that recognizes R&D and part of SG&A as investments rather than operating expenses. Specifically, we add intangible investments back into the free cash flow, less the tax benefit of the expense:¹⁰

$$c^{tot} = \frac{IB + DP + (R\&D + 0.2 \times SG\&A)(1 - \kappa)}{PP\&E + Intan} \quad (6)$$

where κ is the marginal tax rate. 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 0.81.

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 and median intangible intensities are 42%, indicating that intangible capital makes up almost half of firms' total capital. Knowledge capital makes up 48% of intangible capital on average, so organizational capital makes up 52%. The average q^{tot} is mechanically smaller than q^{phy} , since the denominator is larger. There is less volatility in q^{tot} than q^{phy} even if we scale the standard deviations by the respective means. Total investment exceeds physical investment on average. This result is not mechanical, since q^{tot} adds intangibles to both the numerator and denominator. By ignoring intangible investments, one typically underestimates firms' investment rates.

¹⁰Since the firm expenses intangible investments, the effective cost of a dollar of intangible capital is only $(1 - \kappa)$

Figure 1 plots the time-series of average intangible intensity. We see that intangible capital is increasingly important: the intensity increases from 27% in 1972 to 47% in 2010. As expected, high-tech firms are heavy users of intangible capital, while manufacturing firms use less. Somewhat surprisingly, even manufacturing firms have considerable and growing amounts of intangible capital; their intangible intensity increases from 27–36% between 1972–2010.

2 OLS Results

Table 2 contains results from OLS panel regressions of investment on q with 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.

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 0.276, whereas a regression of ι^{tot} on q^{tot} (Panel A column 1) produces an R^2 of 0.398, 44% higher. In other words, total q explains total investment better than physical q explains physical investment. There are two reasons for the increase in R^2 . First, comparing columns 1 and 2 in Panel B, we see that q^{tot} explains even physical investment slightly better than does q^{phy} . 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} . It also turns out that q^{tot} does a better job than q^{phy} at explaining total investment (columns 1 and 2 of Panel A). 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 much 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, although q^{tot} has the higher t -statistic. Columns 4–6 repeat the same specifications while controlling for cash flow; the pattern in R^2 values is similar. Taken together, these results imply that total q is a better proxy for total investment opportunities than is physical

q . Total q is even a slightly better proxy for physical investment opportunities, although physical q still contains additional information.

We have also run similar (unreported) horse race regressions with other definitions of q , delivering similar results. For example, Eberly, Rebelo and Vincent (2012) do not subtract current assets from the numerator of q . Chen, Goldstein and Jiang (2007) calculate q as the market value of equity plus book value of assets minus the book value of equity scaled by book assets. These alternative definitions perform similarly to, or worse than, physical q .

3 Bias-Corrected Results

We now estimate the previous models while correcting the measurement-error bias in OLS. We compare results from three estimators. Besides producing unbiased slopes that are easier to interpret, some of these estimators produce measures of how close our q proxies are to the true, unobservable q . We briefly describe the estimators below and provide additional details in Appendix B. Our main conclusions are consistent across the various estimators, but we include them all for completeness.

The first estimator we use is the measurement-error consistent two-step GMM estimator of Erickson and Whited (2000, 2002), which we denote EW GMM. This estimator chooses parameter values that minimize the distance between actual and predicted higher-order moments in investment, our noisy proxy for q , and their interaction. We consider four variants of the estimator. The Geary (1942) and GMM4 estimators use up to third and fourth moments, respectively; for each type, we estimate the model in levels and first differences. The EW GMM estimator produces a statistic ρ^2 that measures the R^2 from a hypothetical regression of investment on true, unobservable q . It also produce a statistic τ^2 measuring the R^2 from a hypothetical regression of our q proxy on the true q . A q measure with a higher τ is therefore a better proxy for true q . The EW GMM estimator has been superceded by Erickson, Jiang, and Whited's (2013) higher-order cumulant estimator, which has the same asymptotic properties but better finite-sample properties. We plan to use the cumulant estimator in the future.

The second and third estimators are IV estimators advocated by Almeida, Campello and Galvao

(2010). Both 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. These estimators have the advantage of being better understood and easier to implement numerically. However, Erickson and Whited (2012) find that they can produce the same biased results as OLS regressions if the measurement error is serially correlated, which is possible in our setting.

Estimation results are in Table 3. Each column shows results from a different estimator. For comparison, the first column shows results using OLS with firm and time fixed effects. Panel A shows results using total capital (l^{tot} , q^{tot} , and c^{tot}), and Panel B shows results using physical capital (l^{phy} , q^{phy} , and c^{phy}).

First, we discuss results from Erickson and Whited’s (2012) identification diagnostic test, which tests the joint null hypothesis that the slope on q is zero, and that the proxy for q is non-skewed. The model is not well identified if this null is true. All results are for the EW GMM estimator using up to fourth moments. For the data in levels (first differences), the test for Panel B’s physical capital specification rejects the hypothesis of no identification in 82% (62%) of the 39 years in our data, while in the total capital specifications it rejects in 85% (62%) of the years. It therefore seems that the identifying assumptions for the EW GMM estimator hold at least as well using total capital as they do with physical capital alone.

The τ^2 estimates are uniformly higher in Panel A than Panel B, indicating that total q is a better proxy for the true, unobservable q than is physical q . Depending on the estimator used, the increase in τ^2 ranges from 8–21%. Total q is still a noisy proxy, however: our highest τ^2 is 0.728, indicating that total q explains only 72.8% of the variation in true q .

The ρ^2 estimates are also uniformly higher in Panel A than Panel B, depending on the GMM estimator used. This result indicates 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 ranges from 32–54% depending on the estimator. The ρ^2 estimates in Panel A range from 0.598 to 0.703, indicating that q explains 60–70% of the variation in investment. This result helps us evaluate how the simplest linear investment- q theory fits the data. The theory explains most of the variation in investment, but there is still considerable variation left unexplained. The theory fits the data considerably better when one includes intangible capital in investment and q .

Next, we consider the estimated slopes on q . Comparing panels A and B, the coefficients on q are larger in Panel A for every estimator used. The increase in coefficient from Panel B to Panel A ranges from 54–216%. This result has interesting economic implications, because the simplest q theories predict that the inverse of the estimated slope on q equals the marginal capital adjustment cost parameter.¹¹ According to these benchmark theories, our estimated adjustment costs are 35–68% lower when we use total capital rather than just physical capital in our measures. Previous papers¹² have concluded that adjustment costs from investment- q regressions are unreasonably large. We find more reasonable estimates after correcting an important source of measurement error, which builds confidence in these simple q theories. An important caveat is that alternate, more general q theories do not provide a clean mapping between our regression slope and adjustment cost parameters. An important priority for future research is to estimate these alternate theories using measures of investment and q that include intangible capital.

Finally, we discuss the estimated slope coefficients on cash flow. The simplest q theories predict a slope of zero. Recent theories, however, have shown that these slopes are hard to interpret, as non-zero slopes may arise from many sources, only one of which is financial constraints. 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 frictions.

We find significantly positive slopes on cash flow for five out of seven estimators in each panel. Comparing Panels A and B, the slopes on cash flow are typically larger when we include intangible capital. This result is expected: when intangible investment is high, c^{tot} will exceed c^{phy} as a result

¹¹Hayashi (1982), among others, makes this prediction. The prediction typically follows from three key assumptions: perfect competition, constant returns to scale, and quadratic capital adjustment costs. We provide our own theory in Section 6.

¹²For example, see Summers (1981), Shapiro (1986), and Philippon (2009).

of adding the tax-adjusted intangible investment back into cash flow. However, 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 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 to intangible capital investment as free cash flow.

4 Cross-Sectional and Time-Series Differences

So far we have pooled together all observations. Next, we compare results across firms and years. We re-estimate the previous models in subsamples formed using three variables. First, we form low- and high-intangible subsamples, where low- (high-) intangible firms have below- (above-) median intangible intensity in a given year. Recall that intangible intensity is the ratio of a firm’s intangible to total capital stock. Second, we examine the early (1972–1993) and late (1994–2010) parts of our sample. Third, we form industry subsamples. To avoid small subsamples in our GMM analysis, we use Fama and French’s 5-industry definition, and we present results only for the three largest industries: “Manuf,” which includes manufacturing and energy firms (we drop utility firms); “Cnsmr,” which includes consumer durables, nondurables, wholesale, retail, and some services; and “HiTec,” which includes business equipment, telephone, and television transmission. We refer to these industries as simply manufacturing, consumer, and high-tech. For each subsample we estimate a total-capital specification using ι^{tot} , q^{tot} , and c^{tot} . An adjacent column presents a physical-capital specification using ι^{phy} , q^{phy} , and c^{phy} . Where possible, we tabulate the difference in R^2 , ρ^2 , and τ^2 between the physical- and total-capital specifications.

OLS results for the intangible and year subsamples are in Table 4. OLS results for industry subsamples are in Table 5. The top panels includes just q , whereas the bottom panels add cash flow as a regressor. Using total capital rather than physical capital alone produces higher R^2 values in all subsamples. The increase in R^2 ranges from 0.067–0.193, i.e., from 33–68%.

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 0.138 (43%) in the

high-intangible subsample, compared to 0.067 (33%) in the low-intangible subsample. We see mixed results for the year subsamples. Without controlling for cash flow, the increase in R^2 is slightly higher in later subsample, whereas controlling for cash flow in Panel B delivers the opposite result. This result is somewhat surprising, as intangible capital is more prevalent in recent years (Figure 1). Including intangible capital increases the R^2 by 0.061 (29%) in the manufacturing industry, compared to 0.120 (50%) in the consumer industry and 0.136 (38%) in the high-tech industry. This result makes sense, as the manufacturing industry uses the least of intangible capital (mean intensity = 23%), the consumer industry uses an intermediate amount (mean intensity = 35%), and the high tech industry uses the most (mean intensity = 47%). 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.

Next, we correct for measurement bias in the OLS subsample regressions. Since our main results in Section 3 are consistent across estimators, in this section we use a single estimator, the fourth-order GMM estimator of Erickson and Whited (2000, 2002). Results are in Tables 6 and 7, which have a similar structure as Tables 4 and 5. With only a few exceptions,¹³ our key results are consistent across all subsamples and specifications: τ^2 is higher when we include intangible capital, indicating that total q is a better proxy for true q ; ρ^2 is higher when we include intangible capital, indicating a stronger investment- q relation; and estimated slopes on q are higher when we include intangible capital, implying lower capital adjustment costs. The increases in slopes are especially dramatic, ranging from 36–482%.

As in the OLS regressions, including intangible capital is more important in certain firms and years. For example, the increase in τ^2 is larger in later years (0.128) than earlier years (0.042), and it is larger in the consumer (0.080) and high tech industries (0.185) than the manufacturing industry (0.035). Somewhat surprisingly, while the increase in τ^2 is large for both low- and high-intangible firms, it is larger for the low-intangible firms (0.206 vs. 0.173). This difference in differences is not large, however. In most subsamples, the percent increase in the estimated slope on q from including

¹³In the manufacturing and consumer industries, τ^2 is lower if we use total capital and control for cash flow. If we exclude cash flow as a regressor in those same industries, however, the result reverses. In the manufacturing industry, ρ^2 is slightly smaller if we use total capital and exclude cash flow from the model, but the result reverses if we include cash flow.

intangible capital is larger in subsamples with more intangible capital, as expected. For example, the slope increases 36% in the low-intangible subsample, compared to 206% in the high-intangible subsample.

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. As expected, though, this result is typically stronger where intangible capital is more important.

5 Macro Results

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 i^{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

$$q^{tot} = \frac{V}{K^{phy} + K^{intan}} = q^{phy} \times \frac{K^{phy}}{K^{phy} + K^{intan}} \quad (7)$$

and total investment as

$$i^{tot} = \frac{I^{phy} + I^{intan}}{K^{phy} + K^{intan}} = i^{phy} \times \frac{K^{phy}}{K^{phy} + K^{intan}} \times \frac{I^{phy} + I^{intan}}{I^{phy}}. \quad (8)$$

where q^{phy} and i^{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 (7)], and the latter ratio has changed slowly and consistently over time.¹⁴ Of significantly larger importance is the change from physical to total investment, which requires changing both the numerator and the denominator in (8). 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 at 0.43.

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

¹⁴The 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.

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 8 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 the variables 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.

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 and the Investment- q Relation

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 . Our second goal is to illustrate what can go wrong when one omits intangible capital and simply regresses physical investment on physical q . Our theory is deliberately simple in order to make the economic mechanism as clear as possible. At the end of the section we discuss related theories and assess whether our predictions will extend to more general settings. All proofs are in Appendix C.

We extend 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.) At each instant t the firm chooses the investment rates I_{1t} and I_{2t} in two types of capital and the amount of labor L_t that maximize the present value of expected future cash flows:

$$V(K_{1t}, K_{2t}, \varepsilon_t, p_{1t}, p_{2t}) = \max_{L_{t+s}, I_{1,t+s}, I_{2,t+s}} \int_0^\infty E_t[\pi(K_{t+s}, L_{t+s}, \varepsilon_{t+s}) - c(I_{1,t+s}, I_{2,t+s}, K_{t+s}, p_{1,t+s}, p_{2,t+s})]e^{-rs} ds \quad (9)$$

subject to

$$dK_1 = (I_1 - \delta K_1) dt \quad (11)$$

$$dK_2 = (I_2 - \delta K_2) dt. \quad (12)$$

Operating profits π depend on the total amount of capital $K \equiv K_1 + K_2$, labor L , a constant wage rate w , and a random variable ε :

$$\pi(K, L, \varepsilon) = F(L, K, \varepsilon) - wL. \quad (13)$$

Since profits depend on total capital K but not on K_1 and K_2 individually, the two capital types are perfect substitutes in production. This 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 as perfect substitutes. We assume the production function F is linearly homogenous in K and L . The cost of investment c equals

$$c(I_1, I_2, K, p_1, p_2) = \frac{\gamma_1}{2} K \left(\frac{I_1}{K} \right)^2 + \frac{\gamma_2}{2} K \left(\frac{I_2}{K} \right)^2 + p_1 I_1 + p_2 I_2. \quad (14)$$

The first two terms of c represent adjustment costs, and the last two terms denote the purchase/sale cost of new capital. The capital prices p_1 and p_2 , along with profitability shock ε , fluctuate over time according to a general stochastic diffusion process

$$dx_t = \mu(x_t) dt + \Sigma(x_t) dB_t, \quad (15)$$

where $x_t = [\varepsilon_t \ p_{1t} \ p_{2t}]'$. We assume all firms face the same capital prices p_{1t} and p_{2t} , but the shock ε can vary across firms.

Next we present the three main predictions from the theory.

Lemma 6.1. *Marginal q equals average q , the ratio of firm value to the total capital stock:*

$$\frac{\partial V_t}{\partial K} = \frac{V_t}{K_{1t} + K_{2t}} \equiv q^{tot}(\varepsilon_t, p_{1t}, p_{2t}). \quad (16)$$

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 .

The firm chooses the optimal investment rate by equating marginal q and the marginal cost of investment. For physical capital, this equality is $\partial V_t / \partial K_1 = \partial c(\cdot) / \partial I_1$. Applying this condition to our cost function (14) yields the following optimal investment rates in the two capital types:

$$\iota_t^{phy} \equiv \frac{I_{1t}}{K_{1t} + K_{2t}} = \frac{1}{\gamma_1} (q_t^{tot} - p_{1t}) \quad (17)$$

$$\iota_t^{intan} \equiv \frac{I_{2t}}{K_{1t} + K_{2t}} = \frac{1}{\gamma_2} (q_t^{tot} - p_{2t}). \quad (18)$$

Intuitively, the firm invests more in a type of capital when the benefits of investing (q^{tot}) are higher, when its adjustment cost γ is lower, and when the capital price is lower. Summing the two investment rates above generates our next main prediction.

Lemma 6.2. *The total investment rate ι^{tot} is linear in q^{tot} and the capital prices:*

$$\iota_t^{tot} \equiv \frac{I_{1t} + I_{2t}}{K_{1t} + K_{2t}} = \left(\frac{1}{\gamma_1} + \frac{1}{\gamma_2} \right) q_t^{tot} - \frac{p_{1t}}{\gamma_1} - \frac{p_{2t}}{\gamma_2}. \quad (19)$$

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

$$\iota_{it}^{tot} = a_t + \beta q_{it}^{tot} + \eta_{it} \quad (20)$$

will produce an R^2 of 100% and a slope coefficient β equal to $1/\gamma_1 + 1/\gamma_2$.

This result provides a rationale for regressing total investment on total q , as we do earlier in the paper. Time fixed effects are needed to soak up the time-varying capital prices p in (19).

The result also tells us that the OLS slope β is an unbiased estimator of the total inverse adjustment cost, $1/\gamma_1 + 1/\gamma_2$. This prediction provides one potential reason why we find larger slopes of total investment on total q in Section 3: our slope is not the inverse adjustment cost parameter, but the sum of two inverse adjustment cost parameters. This prediction highlights the difficulty in interpreting these slopes, a point made by Erickson and Whited (2000) and others. If we had assumed a different investment cost of the form

$$c(I_1, I_2, K, p_1, p_2) = \frac{\gamma}{2}K \left(\frac{I_1 + I_2}{K} \right)^2 + p_1 I_1 + p_2 I_2, \quad (21)$$

then our model would make the usual prediction that $\beta = 1/\gamma$. With this alternate setup, we could interpret Section 3's larger slopes on total q as evidence of a lower adjustment cost parameter γ .

We now use our 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.

Lemma 6.3. *The physical investment rate equals*

$$l_{it}^{phy} \equiv \frac{I_{1,i,t}}{K_{1,i,t}} = \frac{1}{\gamma_1} q_{it}^{phy} - \frac{p_{1t}}{\gamma_1} \frac{K_{it}}{K_{1,i,t}}. \quad (22)$$

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

$$l_{it}^{phy} = \tilde{a}_t + \tilde{\beta} q_{it}^{phy} + \tilde{\eta}_{it} \quad (23)$$

will produce an R^2 less than 100% and a slope $\tilde{\beta}$ that is biased away from $1/\gamma_1$.

Equation (22) follows from multiplying both sides of equation (17) by $K_{it}/K_{1,i,t}$. Time fixed effects \tilde{a}_t will not absorb the term $\frac{p_{1t}}{\gamma_1} \frac{K_{it}}{K_{1,i,t}}$ in equation (22), because $K_{it}/K_{1,i,t}$ is not necessarily

constant across firms. As a result, the error term $\tilde{\eta}_{it}$ can be nonzero, producing an R^2 less than 100% in regression (23). Equation (22) implies that the error term in regression (23) equals

$$\tilde{\eta}_{it} = -\frac{p_{1t}}{\gamma_1} \left(\frac{K_{it}}{K_{1,i,t}} - \overline{\frac{K_t}{K_{1,t}}} \right). \quad (24)$$

This disturbance is cross-sectionally¹⁵ correlated with the regressor q_{it}^{phy} through the term $K_{it}/K_{1,i,t}$ in (24), because $q_{it}^{phy} = q_{it}^{tot} K_{it}/K_{1,i,t}$. Since the error term is correlated with the regressor in (23), the estimated slope coefficient is biased away from $1/\gamma_1$.

Will adjustment cost estimates from regression (23) be too high or too low? Signing the bias is difficult since q^{tot} and q^{phy} are not available in closed form. We solve the model numerically¹⁶ and show that, for reasonable parameter values, the OLS slope $\tilde{\beta}$ is a downward-biased estimator of $1/\gamma_1$. In other words, regression (23) typically over-estimates the adjustment cost parameter γ_1 . The reason for the negative bias in $\tilde{\beta}$ is that the regression's error term $\tilde{\eta}_{it}$ in (24) has an almost perfect negative correlation with the regressor q_{it}^{phy} , which makes sense given that $K_{it}/K_{1,i,t}$ appears in both variables, albeit with a negative sign in $\tilde{\eta}_{it}$.

To summarize, our simple theory predicts that total q is the best proxy for total investment opportunities, whereas physical q is a noisy proxy 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 upward-biased adjustment cost estimates.

Existing theories shed light on how sensitive these predictions are to our specific assumptions. Using a dynamic, deterministic investment model with multiple capital goods, Wildasin (1984) shows that only under stringent assumptions will the total investment rate be linear in a total q measure that, like ours, simply adds together the different capital goods. Hayashi and Inoue (1990) also analyze an investment model with multiple capital goods, and they show that investment and q may be related through a potentially nonlinear aggregator of the various capital goods. Several

¹⁵The regression with time fixed effects is equivalent to demeaning q_{it}^{phy} and q_{it}^{tot} 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 $\tilde{\eta}_{it}$ that matters for determining bias.

¹⁶Details on the numerical solution are in Appendix D.

theories of investment in a single capital good, including recently Gala and Gomes (2013), show that Tobin's q and investment are weakly linked except in very special cases.

In sum, a linear relation between total investment and what we call total q obtains only in special cases, including the one we consider in this section. It is therefore all the more surprising that we find a strong linear relation between investment and q in the data, at least when we include intangible capital in our measures. This discussion also emphasizes the importance of testing more general q theories using measures of investment and q that include intangible capital. Since the benchmark linear investment- q relation changes considerably when we include intangible capital, we speculate that the more general relation will also change.

7 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, our measures deliver higher R^2 values, larger coefficients on q , and hence lower implied adjustment costs in regressions of investment on q . These results hold true in both firm-level and macro data. Firm-level estimation results also indicate that our measure of total q is closer to the unobservable true q than is the standard physical q measure. These results hold true across several types of firms and years, but they are especially strong where intangible capital is most important, for example, in the high-tech industry and in recent years.

Our results have two main implications. First, our results indicate that the q theory of investment, or at least the version predicting a linear relation between investment and Tobin's q , performs better empirically than was previously believed. Once we correct an important source of measurement error, the theory fits the data better and implies more reasonable capital adjustment costs. Second, researchers using Tobin's q as a proxy for firms' total 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.

Appendix A: Measuring Firms' Initial Capital Stock

This appendix explains how we estimate a firm's stock of knowledge and organizational capital in its first non-missing Compustat record. We describe the steps for estimating the initial knowledge-capital stock; the method for organizational capital is similar. Broadly, for each firm i we estimate R&D spending in each year of life between the firm's founding and its first non-missing Compustat record, denoted year zero. Our main assumption is that the firm's R&D grows at the average rate for Compustat firms of the same age. We then apply the perpetual inventory method to these forecasted R&D values to obtain the initial stock of knowledge capital in year zero.

The specific steps are as follows:

1. Obtain firms' founding date from Jay Ritter's database, available on Ritter's web site.
2. Compute age since founding for all non-missing Compustat records.
3. Using the full Compustat dataset, compute the average log change in R&D in each yearly age category.
4. For firms with missing founding date in Ritter's data, estimate the founding date 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). For each firm i , we now have $R\&D_{i1}$, the first non-missing R&D value for firm i , and we also have Age_{i1} the firm's age since founding in the year corresponding to $R\&D_{i1}$.
5. For each age between 1 and Age_{i1} , we assume the log change in R&D equals the average value from step 3 above.
6. Using $R\&D_{i1}$ and the estimated changes from the previous step, estimate the past values of R&D for firm i 's ages 1 to $Age_{i1} - 1$.
7. Apply the perpetual inventory method in equation (3) to the estimated R&D spending from the previous step to obtain G_{i0} , the stock of knowledge capital. Equivalently, set G_{i0} equal to $R\&D_{i1}$ times an age-specific multiplier. We plot the age-specific multipliers below:

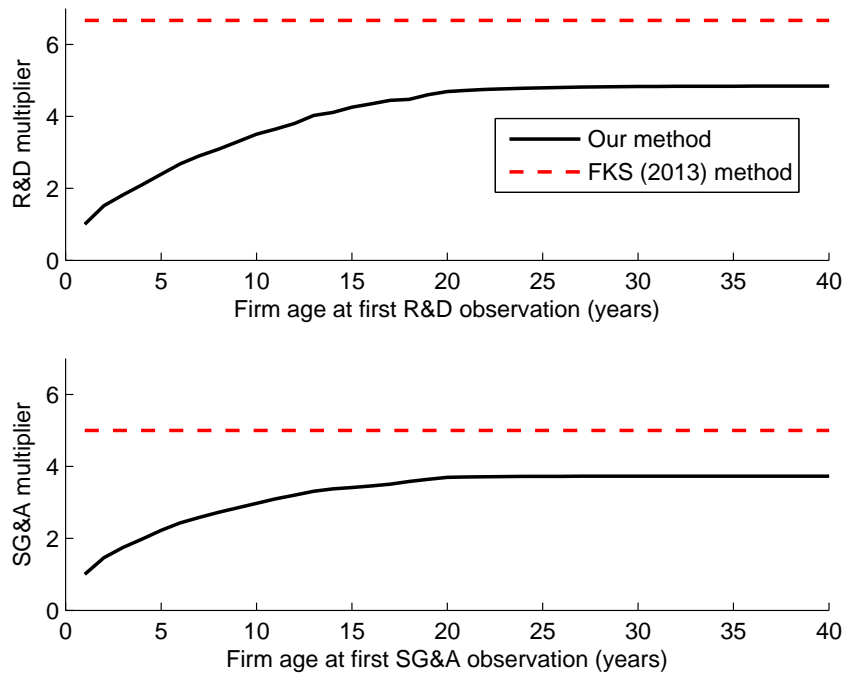


Figure A1. This figure plots the age-specific multipliers used to estimate the stock of knowledge capital (top panel) and organizational capital (bottom panel) in firms' first non-missing Compustat record. The solid line indicates our multiplier, and for comparison the dashed line indicates the multiplier assumed by the method of Falato, Kadryzhanova, and Sim (2013). The latter multiplier equals one divided by the assumed depreciation rate.

The solid line slopes up, meaning our method reasonably assigns the firm more capital if it is older at the time of its first Compustat record. We use estimated R&D values only to compute firms' stock of knowledge capital. We never use estimated R&D in a regression's dependent variable, for example.

Appendix B: Details on bias-free estimators

The discussions here follow Erickson and Whited (2000, 2002, 2012) and Almeida, Campello, and

Galvao (2010).

1. The Erickson and Whited (2000, 2002) GMM Estimator

We start with the classical errors in variables model. This model can be written as

$$y_i = z_i\alpha + q_i\beta + u_i \quad (25)$$

$$p_i = \gamma + q_i + \varepsilon_i \quad (26)$$

where q_i is the average q of firm i , p is an estimate of Tobin's q , and z_i is a row vector of perfectly measured regressors, including a constant. The regression error, u_i , and the measurement error, ε_i , are assumed independent of each other and of (z_i, q_i) , and the observations within a cross section are assumed i.i.d.

The first step is to re-express the model in terms of deviations from means. Define $\mu_y = [E(z_i'z_i)]^{-1}E(z_i'y_i)$ and $\mu_q = [E(z_i'z_i)]^{-1}E(z_i'p_i)$, and letting $\hat{y}_i = y_i - \mu_y z_i$, $\hat{p}_i = p_i - \mu_q z_i$ and $\hat{q}_i = q_i - \mu_q z_i$, rewrite the model as

$$\hat{y}_i = \hat{q}_i\beta + u_i \quad (27)$$

$$\hat{p}_i = \hat{q}_i + \varepsilon_i \quad (28)$$

This model provides a measure τ^2 of the quality of the proxy for q . This measure is the population R^2 of the last equation, which we can calculate as

$$\tau^2 = \frac{\mu_q' var(z)\mu_q + E(\hat{q}_i^2)}{\mu_q' var(z)\mu_q + E(\hat{q}_i^2) + E(\varepsilon_i^2)}. \quad (29)$$

Given a panel data set, we first estimate τ^2 for each cross section of our panel by substituting cross-section estimates of $E(\hat{q}_i^2)$, $E(\varepsilon_i^2)$, μ_q and $var(z)$ into Equation (29). The first two estimates are GMM estimates based on moment conditions that use third-order moments to identify the

errors-in-variables model. The assumptions on equations (25) and (26) imply:

$$E(\hat{y}_i^2) = \beta^2 E(\hat{q}_i^2) + E(u_i^2) \quad (30)$$

$$E(\hat{y}_i \hat{p}_i) = \beta E(\hat{q}_i^2) \quad (31)$$

$$E(\hat{p}_i^2) = E(\hat{q}_i^2) + E(\varepsilon_i^2) \quad (32)$$

$$E(\hat{y}_i^2 \hat{p}_i) = \beta^2 E(\hat{q}_i^3) \quad (33)$$

$$E(\hat{y}_i \hat{p}_i^2) = \beta E(\hat{q}_i^3) \quad (34)$$

$$E(\hat{y}_i^3 \hat{p}_i) = \beta^3 E(\hat{q}_i^4) + 3\beta E(\hat{q}_i^2) E(u_i^2) \quad (35)$$

$$E(\hat{y}_i^2 \hat{p}_i^2) = \beta^2 E(\hat{q}_i^4) + \beta^2 E(\hat{q}_i^2) E(\varepsilon_i^2) + E(\hat{q}_i^2) E(u_i^2) + E(\varepsilon_i^2) E(u_i^2) \quad (36)$$

$$E(\hat{y}_i \hat{p}_i^3) = \beta E(\hat{q}_i^4) + 3\beta E(\hat{q}_i^2) E(\varepsilon_i^2) \quad (37)$$

Estimation requires replacing the left hand side quantities of equations (30)-(37) with data estimates and then using GMM to find the vector of right hand side quantities $(\beta, E(\hat{q}_i^2), E(u_i^2), E(\varepsilon_i^2), E(\hat{q}_i^3), E(\hat{q}_i^4))$ that minimizes the distance between the left and right hand sides according to the minimum-variance GMM weighting matrix.

This estimation procedure requires the identifying assumptions that both β and $E(\hat{q}_i^3)$ are nonzero. If these assumptions hold then equations (33) and (34) imply that $\beta = E(\hat{y}_i^2 \hat{p}_i) / E(\hat{y}_i \hat{p}_i^2)$. If we used only equations (30)-(35) the system would be just identified. Equations (36) and (37) provide overidentifying restrictions that increase efficiency, as shown in Erickson and Whited (2006).

Erickson and Whited (2012) recommend using many different starting values for β along a grid to ensure one finds a global minima, where the grid should contain the OLS estimate of β , as well as the GEARY estimate, which is how we implement their estimator. After the estimator is run on each cross section of the data, the results are pooled using the minimum distance estimator for unbalanced panels described in Erickson and Whited (2012). The code for both the GMM estimator and for the minimum distance estimator are from Toni Whited's web site.

2. Biorn's (2000) IV Estimator

Similar to the setup of the EW GMM estimator above, we start with an error-in-variables model:

$$y_{it} = z_{it}\alpha + q_{it}\beta + u_{it} \quad (38)$$

$$p_{it} = \gamma + q_{it} + \varepsilon_{it}, \quad (39)$$

where q_{it} is the true q , p_{it} is a noisy estimate of q , and z_i is a row vector of well measured regressors, including individual fixed effects. The regression error, u_{it} , and the measurement error, ε_{it} , are uncorrelated with each other and with (z_{it}, q_{it}) , and the observations are independent across i .

By substituting (39) into (38), we can take first differences of the data to eliminate the individual effects and obtain

$$y_{it} - y_{it-1} = (p_{it} - p_{it-1})\beta + [(u_{it} - \varepsilon_{it}\beta) - u_{it-1} - \varepsilon_{it-1}\beta]. \quad (40)$$

The coefficient of interest will be biased due to the assumed correlation between the mismeasured variable and the innovations. Griliches and Hausman (1986) propose an IV approach to reduce this bias. While this IV approach does not make any distributional assumptions on the mismeasured regressor, it does require the additional assumption that the measurement error terms ε_{it} are i.i.d. over time.

Biorn (2000) relaxes the i.i.d. condition for innovations in the mismeasured equation and proposes alternative assumptions under which consistent IV estimators of the coefficient of the mismeasured regressor exist. In particular, if we allow for a vector moving average structure up to order λ (≥ 1) for the innovations then one can use the lags of the variables already included in the model as instruments to “clear” the λ period memory of the MA process in the measurement error. See Biorn (2000) for details. The identifying assumption made in this paper is that the measurement error is MA of order $\lambda \leq 3$.

3. The Arellano and Bond (1991) GMM Estimator

The discussion here follows Blundell, Bond, Devereux and Schiantarelli (1992), who were the first researchers to apply the Arellano and Bond (1991) GMM instrumental variable technique in the

context of a standard investment model for correlated firm-specific effects and mismeasurement of q . These authors use an instrumental variables approach on a first-differenced model in which the instruments are optimally weighted so as to form the GMM estimator. In particular, they use $q_{i,t-2}$ and twice-lagged investments as instruments for the first-differenced equation for firm i in period t .

A GMM estimator for the errors-in-variables model of equation (40) based on IV moment conditions takes the form

$$\hat{\beta} = [(\Delta x' Z) W_N^{-1} (Z' \Delta x)]^{-1} (\Delta x' Z) W_N^{-1} (Z' \Delta y), \quad (41)$$

where Δx is the stacked vector of observations on the first difference of the mismeasured variable and Δy is the stacked vector of observations on the first difference of the dependent variable. The instrument matrix takes the form:

$$\begin{pmatrix} x_1 & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & x_1 & x_2 & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ 0 & 0 & 0 & \dots & x_1 & \dots & x_{T-2} \end{pmatrix}.$$

An optimal choice of the inverse weight matrix W_N is a consistent estimate of the covariance matrix of the orthogonality conditions $E(Z_i' \Delta \nu_i \Delta \nu_i' Z_i)$, where $\Delta \nu_i$ are the first-differenced residuals of each individual. A two-step GMM estimator uses a robust choice $\tilde{W} = \sum_{i=1}^N Z \Delta \hat{\nu}_i \Delta \hat{\nu}_i' Z_i$ where $\Delta \hat{\nu}_i$ are one-step GMM residuals.

Again, we use the results of Biorn (2000) who shows that when one allows for an $MA(\lambda)$ structure in the measurement error, one must ensure that the variables in the IV matrix have a lead or lag of at least $\lambda + 1$ periods in the regressor. While the GMM estimator is more efficient than the IV estimator in the presence of heteroscedasticity, estimation of the optimal weighting matrix requires obtaining estimates of fourth moments so this GMM estimator can have poor small sample properties (Baum, Schaffer and Stillman (2003)).

Appendix C: Proofs

Proof of Lemma 1. Abel and Eberly (1994) show that constant returns to scale in π implies

$$\max_L \pi(K, L, \varepsilon) = H(\varepsilon) K. \quad (42)$$

We can write the investment cost function as

$$c(I_1, I_2, K, p_1, p_2) = K \left[\frac{\gamma_1}{2} \left(\frac{I_1}{K} \right)^2 + \frac{\gamma_2}{2} \left(\frac{I_2}{K} \right)^2 + \frac{I_1}{K} + p_{2t} \frac{I_2}{K} \right], \quad (43)$$

so we can write the value function as

$$V_t = \max_{i_{1,t+s}, i_{2,t+s}} \int_0^\infty E_t \{ [H(\varepsilon_{t+s}) - c(\iota_{1,t+s}, \iota_{2,t+s}, 1, p_{1,t+s}, p_{2,t+s})] K_{t+s} \}, \quad (44)$$

where $\iota_{1,t+s} \equiv I_{1,t+s}/K_{t+s}$ and $\iota_{2,t+s} \equiv I_{2,t+s}/K_{t+s}$. Since depreciation rates are constant across the two types of capital, we have

$$dK_t = (I_t - \delta K_t) dt,$$

where total investment is defined as $I = I_1 + I_2$. 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* :

$$V(K_1, K_2, \varepsilon, p_1, p_2) = V(K, \varepsilon, p_1, p_2). \quad (45)$$

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

$$V(K, \varepsilon, p_1, p_2) = K q^{tot}(\varepsilon, p_1, p_2) = (K_1 + K_2) q^{tot}(\varepsilon, p_1, p_2). \quad (46)$$

Partially differentiating this equation with respect to K_1 and K_2 yields (16).

Proof of Lemma 2. Equation (19) follows from adding equations (17) and (18). 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_1 to obtain

$$q^{tot} = c_{I_1}(I_1, I_2, K, p) = \gamma_1 \frac{I_1}{K} + p_1, \quad (47)$$

which generates (17). Details are available upon request.

Proof of Lemma 3. From (22) we have

$$\beta = 1/\gamma_1 \quad (48)$$

$$\tilde{a}_t + \eta_{it} = -\frac{p_{1t}}{\gamma_1} \frac{K_{it}}{K_{1,i,t}}. \quad (49)$$

The right-hand side of (49) can vary across firms i at any instant t , for example, because firms are endowed with different ratios $K_{i0}/K_{1,i,0}$. It follows that η_{it} can be nonzero, so regression (23) will produce an $R^2 < 1$ in general. The bias in β follows from the correlations described in the paper.

Appendix D: 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

$$\pi(K, \varepsilon) = \max_L \pi(K, L, \varepsilon) = H(\varepsilon) K \quad (50)$$

$$H(\varepsilon) = h\varepsilon^\theta$$

$$h = \alpha^{\frac{\alpha}{1-\alpha}} w^{\frac{\alpha}{\alpha-1}} - \alpha^{\frac{1}{1-\alpha}} w^{\frac{\alpha}{\alpha-1}}$$

$$\theta = \frac{1}{1-\alpha}.$$

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 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

$$q^{tot}(r + \delta) = \pi_K(K, \varepsilon) - c_K(I_1, I_2, K, p_1, p_2) + E[dq^{tot}]/dt. \quad (51)$$

Substituting in (50), (14), (17), and (18) and applying Ito's lemma yields

$$q^{tot}(r + \delta) = h\varepsilon^\theta + \frac{1}{2\gamma_1} (q^{tot} - p_1)^2 + \frac{1}{2\gamma_2} (q^{tot} - p_2)^2 + q_x^{tot} \mu(x) + \frac{1}{2} q_{xx}^{tot} \Sigma(x). \quad (52)$$

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:

$$\begin{aligned} \alpha &= 0.5, \quad w = 0.1, \quad r = 0.2, \quad \delta = 0.1, \quad \gamma_1 = 100, \quad \gamma_2 = 200 \\ \phi &= 2, \quad \sigma_\varepsilon = 0.1, \quad \sigma_p = 0.2. \end{aligned}$$

We choose a high discount rate r and adjustment costs γ so that q^{tot} is finite. For these parameter values, q^{tot} is strongly increasing in ε and weakly decreasing in p_1 and p_2 .

We simulate a large panel of data on i_{it}^{phy} and q_{it}^{phy} , then estimate the panel regression (23) by OLS. The estimated coefficient on q_{it}^{phy} is 0.0091, whereas the true value of $1/\gamma_1$ is 0.01. In other words, the OLS slope coefficient is a downward biased estimator for $1/\gamma_1$, i.e., an upwards biased estimator of γ_1 . The reason for the downward bias is that the regression disturbance $\tilde{\eta}_{it}$ in equation (24) has a correlation of roughly -0.98 with the cross-sectionally demeaned regressor q_{it}^{phy} .

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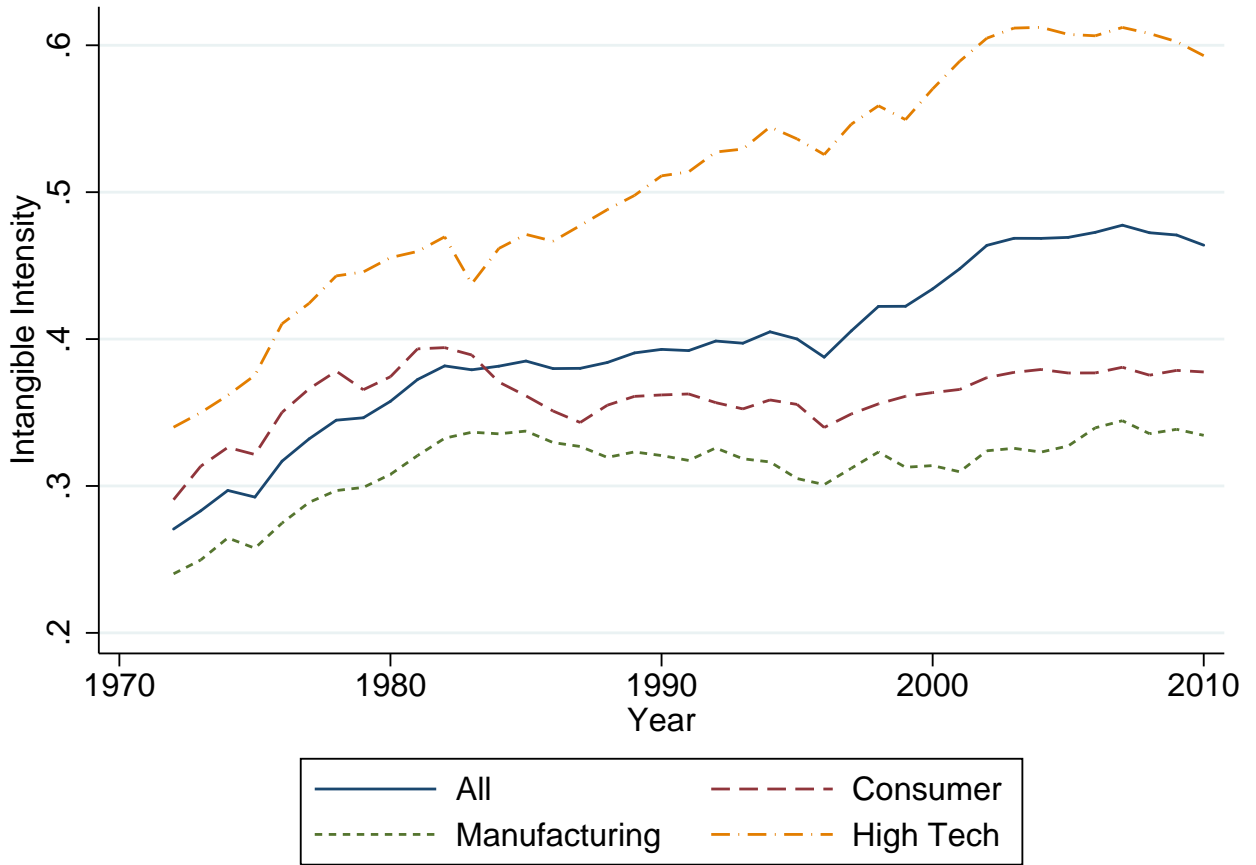


Figure 1. This figure plots the mean intangible capital intensity for all firms in our sample as well as the subset of firms in the consumer, manufacturing, and high tech industries. Intangible intensity is the fraction of a firm’s capital stock made up of intangible capital. We use the five-industry definition from Fama and French (1997).

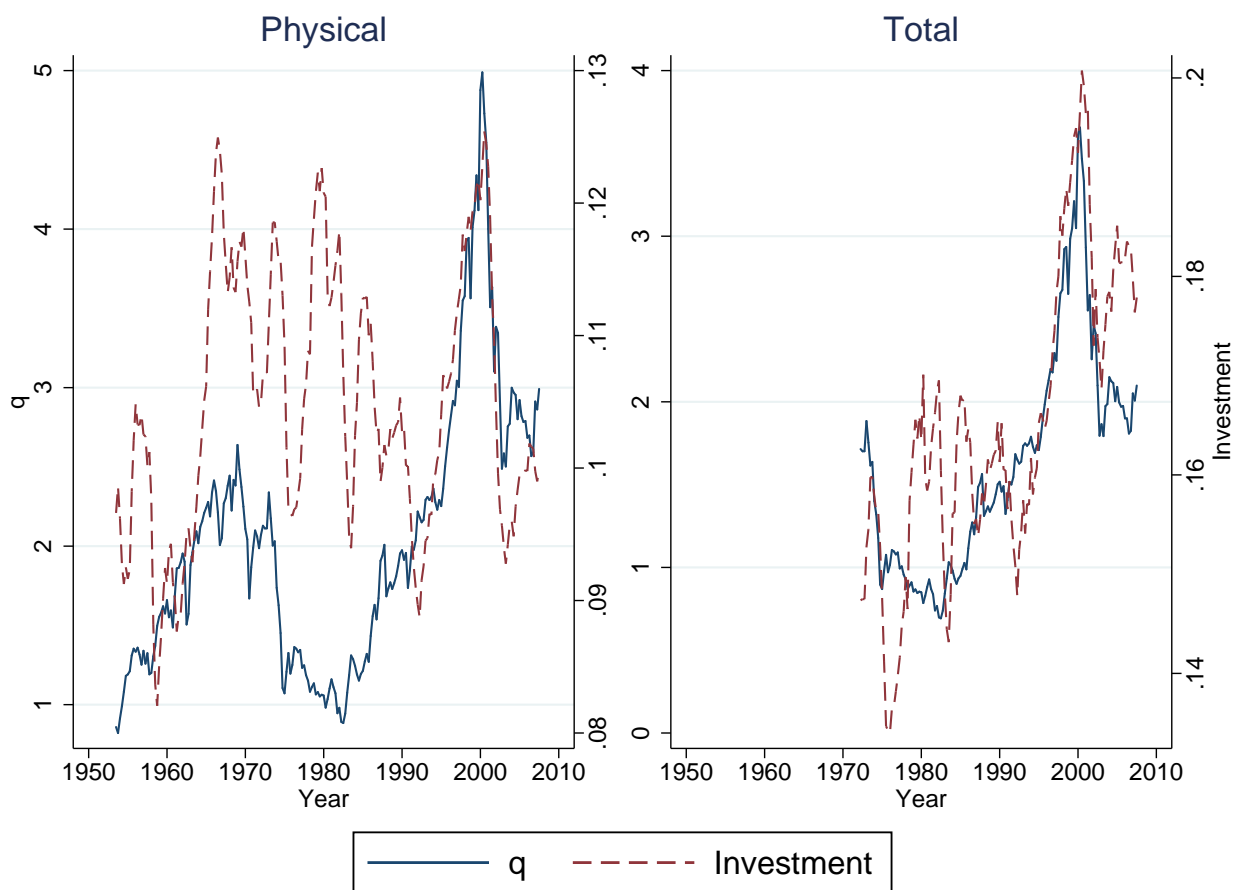


Figure 2. This figure plots Tobin's q and the investment rates for the aggregate U.S. economy. The left panel uses data from Hall (2001) and includes only physical capital in q and investment. The right panel uses data from Corrado and Hulten (2014) and includes both physical and intangible capital in 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 a sample of 69,744 yearly observations of 7,412 Compustat firms from 1972 to 2010. The physical capital stock equals $PP\&E$. We estimate the intangible capital stock by applying the perpetual inventory method to firms' intangible investments, defined as $R\&D + 0.2 \times SG\&A$. Intangible intensity equals the intangible capital stock divided by the total capital stock (physical + intangible). Knowledge capital is the part of intangible capital that comes from $R\&D$. q denotes Tobin's q , ι denotes investment divided by capital, and c denotes the cash flow rate. 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, intangible plus physical. The numerator for physical cash flow is income before extraordinary items plus depreciation expenses, and the numerator for total cash flow is the same but adds back intangible investment net a tax adjustment discussed in the text.

Variable	Mean	Median	Std	Skewness
Intangible capital stock	452	47.5	1877	9.47
Physical capital stock	1020	57.0	5556	15.57
Intangible intensity	0.42	0.42	0.22	0.11
Knowledge capital / Intangible capital	0.48	0.49	0.34	0.02
q^{phy}	3.55	0.98	8.59	5.02
ι^{phy}	0.19	0.12	0.26	5.09
c^{phy}	0.17	0.18	0.66	-1.97
q^{tot}	1.44	0.59	2.96	4.87
ι^{tot}	0.26	0.19	0.25	4.51
c^{tot}	0.21	0.18	0.26	0.70

Table 2
OLS Results

Calculations are based on a sample of Compustat firms from 1972 to 2010. All estimates are of an OLS regression of investment on a proxy for Tobin's q and cash flow with firm and year fixed effects of the form

$$l_{it} = \alpha + \beta_q q_{it} + \beta_c c_{it} + \gamma_i + \nu_t + \varepsilon_{it}.$$

q^{phy} is $(\text{MktCap} + \text{Debt} - \text{CA})/\text{PP\&E}$ and q^{tot} is $(\text{MktCap} + \text{Debt} - \text{CA})/(\text{PP\&E} + \text{INTAN})$. The dependent variable in the top panel is l^{tot} , total investment (physical + intangible) deflated by the total capital stock. c^{tot} is deflated by the total capital stock and has been adjusted for intangible capital investments. The dependent variable in the bottom panel is l^{phy} , physical investment (PP&E) deflated by the physical capital stock. c^{phy} is deflated by the physical capital stock and has not been adjusted for intangible capital expense. Robust standard errors, clustered by firm, are in parentheses under the parameter estimates. The table reports within- R^2 values.

Panel A: Total investment (l^{tot})						
q^{tot}	0.051*** (0.001)		0.058*** (0.002)	0.044*** (0.001)		0.050*** (0.002)
q^{phy}		0.016*** (0.000)	-0.003*** (0.001)		0.014*** (0.000)	-0.002*** (0.001)
c^{tot}				0.227*** (0.013)	0.273*** (0.014)	0.226*** (0.013)
R^2	0.398	0.324	0.399	0.440	0.386	0.441
N	69744	69744	69744	69744	69744	69744
Panel B: Physical investment (l^{phy})						
q^{tot}	0.048*** (0.001)		0.032*** (0.003)	0.047*** (0.001)		0.032*** (0.003)
q^{phy}		0.017*** (0.000)	0.006*** (0.001)		0.017*** (0.000)	0.006*** (0.001)
c^{phy}				0.029*** (0.005)	0.030*** (0.005)	0.029*** (0.004)
R^2	0.290	0.276	0.296	0.294	0.281	0.300
N	69744	69744	69744	69744	69744	69744

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

Table 3
Bias-Corrected Results

Calculations are based on a sample of Compustat firms from 1972 to 2010. All estimates are of a regression of investment on a proxy for Tobin's q and cash flow. GMM4 denotes the EW GMM estimator based on moments up to order 4, and GEARY denotes the third-order moment estimator from Geary (1942), where a "t" represents within-transformed data. All estimates are obtained by pooling yearly estimates via minimum distance. OLS denotes ordinary least squares with firm and year fixed effects. IV denotes instrumental variable estimation, with two and three lags of cash flow and the proxy for Tobin's q as instruments for the first difference of the proxy for Tobin's q . AB denotes estimation of this same first-differenced regression with the same instruments, but using the GMM technique in Arellano and Bond (1991). In the top panel, investment and cash flow are deflated by the total capital stock and the proxy for q is the total q described in the text. In the bottom panel, investment and cash flow are deflated by physical capital and the proxy for q is physical q . 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 . Standard errors are in parentheses under the parameter estimates.

Panel A: Total investment (i^{tot})							
	OLS	GEARY	GMM4	GEARYt	GMM4t	IV	AB
q^{tot}	0.044*** (0.001)	0.071*** (0.001)	0.060*** (0.001)	0.071*** (0.002)	0.057*** (0.001)	0.033*** (0.002)	0.035*** (0.002)
c^{tot}	0.227*** (0.012)	-0.019 (0.012)	-0.003 (0.011)	0.043*** (0.011)	0.105*** (0.010)	0.099*** (0.009)	0.100*** (0.011)
ρ^2		.703	.589	.672	.561		
τ^2		.667	.728	.527	.493		
N	69744	69744	69744	69744	69744	50070	52087
Panel B: Physical investment (i^{phy})							
	OLS	GEARY	GMM4	GEARYt	GMM4t	IV	AB
q^{phy}	0.017*** (0.000)	0.028*** (0.001)	0.019*** (0.000)	0.036*** (0.001)	0.037*** (0.001)	0.014*** (0.001)	0.015*** (0.001)
c^{phy}	0.030*** (0.005)	-0.015** (0.005)	-0.010** (0.004)	-0.003 (0.005)	-0.001 (0.005)	0.024*** (0.003)	0.025*** (0.004)
ρ^2		.532	.407	.495	.364		
τ^2		.58	.652	.437	.455		
N	69744	69744	69744	69744	69744	54141	56240

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

Table 4
Subsample Comparison: OLS Results

This table shows results from estimating Table 2's OLS regressions in subsamples. We regress investment on q and (in Panel B) cash flow. Columns labeled "Physical" use ι^{phy} , q^{phy} and c^{phy} , while columns labeled "Total" use ι^{tot} , q^{tot} and c^{tot} as defined in the notes for Table 1. The Low (High) subsample contains firms whose ratio of intangible to total capital is below (above) the year's median. The Early (Late) subsample includes years 1972–1993 (1994–2010). ΔR^2 is the change in R^2 between the Physical and Total specification. Robust standard errors, clustered by firm, are in parentheses under the parameter estimates. The table reports within- R^2 values.

Panel A: No Cash Flow								
	Low		High		Early		Late	
	Physical	Total	Physical	Total	Physical	Total	Physical	Total
q	0.026*** (0.002)	0.047*** (0.002)	0.015*** (0.000)	0.049*** (0.001)	0.030*** (0.001)	0.065*** (0.003)	0.015*** (0.000)	0.046*** (0.001)
R^2	0.206	0.273	0.319	0.457	0.242	0.340	0.333	0.444
ΔR^2	.067		.138		.098		.111	
N	34333	34333	35411	35411	33335	33335	36409	36409

Panel B: With Cash Flow								
	Low		High		Early		Late	
	Physical	Total	Physical	Total	Physical	Total	Physical	Total
q	0.025*** (0.002)	0.040*** (0.003)	0.015*** (0.000)	0.043*** (0.002)	0.025*** (0.002)	0.040*** (0.003)	0.015*** (0.000)	0.044*** (0.001)
c	0.112*** (0.013)	0.242*** (0.021)	0.022*** (0.005)	0.219*** (0.016)	0.161*** (0.015)	0.502*** (0.026)	-0.003 (0.005)	0.083*** (0.014)
R^2	0.227	0.319	0.322	0.498	0.284	0.477	0.333	0.451
ΔR^2	.092		.176		.193		.118	
N	34333	34333	35411	35411	33335	33335	36409	36409

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

Table 5
Industry Comparison: OLS Results

This table shows results from estimating Table 2's OLS regressions of investment on q and (in Panel B) cash flow in industry subsamples. Columns labeled "Physical" use i^{phy} , q^{phy} and c^{phy} , while columns labeled "Total" use i^{tot} , q^{tot} and c^{tot} as defined in the notes for Table 1. We use the Fama-French (1997) 5-industry definition. Columns labeled "Manufacturing" use manufacturing and energy firms. Columns labeled "Consumer" use firms in the consumer goods, retail, and service industries. Columns labeled "High Tech" use business-equipment and telecommunication firms. ΔR^2 is the change in R^2 between the Physical and Total specification. Robust standard errors, clustered by firm, are in parentheses under the parameter estimates.

Panel A: No Cash Flow						
	Manufacturing		Consumer		High Tech	
	Physical	Total	Physical	Total	Physical	Total
q	0.022*** (0.002)	0.046*** (0.003)	0.025*** (0.002)	0.058*** (0.003)	0.016*** (0.001)	0.052*** (0.001)
R^2	0.210	0.271	0.239	0.359	0.362	0.498
ΔR^2	.061		.120		.136	
N	20900	20900	18128	18128	20615	20615
Panel B: With Cash Flow						
	Manufacturing		Consumer		High Tech	
	Physical	Total	Physical	Total	Physical	Total
q	0.020*** (0.002)	0.036*** (0.004)	0.024*** (0.002)	0.049*** (0.004)	0.016*** (0.001)	0.046*** (0.002)
c	0.079*** (0.017)	0.274*** (0.032)	0.081*** (0.019)	0.267*** (0.030)	0.019*** (0.005)	0.203*** (0.019)
R^2	0.229	0.348	0.257	0.414	0.364	0.529
ΔR^2	.119		.157		.165	
N	20900	20900	18128	18128	20615	20615

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

Table 6
Subsample Comparison: Bias-Corrected Results

Calculations are based on a sample of Compustat firms from 1972 to 2010. All estimates are of a regression of investment on a proxy for Tobin's q and cash flow. We use the EW GMM estimator based on moments up to order four, pooling yearly estimates via minimum distance. Columns labeled "Physical" use l^{phy} , q^{phy} and c^{phy} , while columns labeled "Total" use l^{tot} , q^{tot} and c^{tot} as defined in the notes for table 1. The Low (High) subsample contains firms whose ratio of intangible to total capital is below (above) the year's median. The Early (Late) subsample includes years 1972–1993 (1994–2010). 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 . The Δ variables denote the difference in statistic between the Physical and Total specification. Standard errors are in parentheses under the parameter estimates.

Panel A: No Cash Flow								
	Low		High		Early		Late	
	Physical	Total	Physical	Total	Physical	Total	Physical	Total
q	0.039*** (0.001)	0.053*** (0.001)	0.018*** (0.000)	0.055*** (0.001)	0.032*** (0.001)	0.093*** (0.002)	0.015*** (0.000)	0.047*** (0.001)
ρ^2	0.388	0.406	0.383	0.485	0.298	0.480	0.368	0.479
$\Delta\rho^2$	0.018		0.102		0.182		0.111	
τ^2	0.491	0.697	0.619	0.792	0.601	0.643	0.684	0.812
$\Delta\tau^2$	0.206		0.173		0.042		0.128	
N	34333	34333	35411	35411	33335	33335	36409	36409

Panel B: With Cash Flow								
	Low		High		Early		Late	
	Physical	Total	Physical	Total	Physical	Total	Physical	Total
q	0.023*** (0.001)	0.048*** (0.002)	0.011*** (0.000)	0.064*** (0.001)	0.043*** (0.001)	0.110*** (0.002)	0.016*** (0.000)	0.052*** (0.001)
c	-0.026* (0.011)	0.028 (0.016)	-0.011** (0.004)	0.025 (0.013)	0.024 (0.015)	0.231*** (0.030)	-0.013** (0.004)	-0.040** (0.013)
ρ^2	0.332	0.545	0.431	0.637	0.444	0.687	0.387	0.573
$\Delta\rho^2$	0.213		0.206		0.243		0.186	
τ^2	0.530	0.615	0.647	0.716	0.550	0.528	0.678	0.776
$\Delta\tau^2$	0.085		0.069		-0.022		0.098	
N	34333	34333	35411	35411	33335	33335	36409	36409

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

Table 7
Industry Comparison: Bias-Corrected Results

Calculations are based on a sample of Compustat firms from 1972 to 2010. All estimates are of a regression of investment on a proxy for Tobin's q and cash flow. We use the EW GMM estimator based on moments up to order four, pooling yearly estimates via minimum distance. Columns labeled "Physical" use ι^{phy} , q^{phy} and c^{phy} , while columns labeled "Total" use ι^{tot} , q^{tot} and c^{tot} as defined in the notes for table 1. We use the Fama-French (1997) 5-industry definition. Columns labeled "Manufacturing" use manufacturing and energy firms. Columns labeled "Consumer" use firms in the consumer goods, retail, and service industries. Columns labeled "High Tech" use business-equipment and telecommunication firms. 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 . The Δ variables denote the difference in statistic between the Physical and Total specification. Standard errors are in parentheses under the parameter estimates.

Panel A: No Cash Flow						
	Manufacturing		Consumer		High Tech	
	Physical	Total	Physical	Total	Physical	Total
q	0.040*** (0.000)	0.084*** (0.000)	0.033*** (0.000)	0.104*** (0.001)	0.023*** (0.000)	0.057*** (0.001)
ρ^2	0.307	0.291	0.053	0.265	0.409	0.547
$\Delta\rho^2$	-0.016		0.212		0.138	
τ^2	0.667	0.702	0.644	0.724	0.661	0.846
$\Delta\tau^2$	0.035		0.080		0.185	
N	20900	20900	18128	18128	20615	20615

Panel B: With Cash Flow						
	Manufacturing		Consumer		High Tech	
	Physical	Total	Physical	Total	Physical	Total
q	0.017*** (0.000)	0.083*** (0.001)	0.018*** (0.000)	0.100*** (0.002)	0.018*** (0.000)	0.056*** (0.001)
c	0.039*** (0.008)	0.118*** (0.017)	0.008 (0.009)	0.140*** (0.027)	-0.016*** (0.004)	0.098*** (0.014)
ρ^2	0.387	0.579	0.310	0.639	0.406	0.671
$\Delta\rho^2$.192		0.329		0.265	
τ^2	0.672	0.628	0.561	0.467	0.656	0.747
$\Delta\tau^2$	-0.044		-0.094		0.091	
N	20900	20900	18128	18128	20615	20615

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

Table 8
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 physical investment 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*** (0.003)				0.016*** (0.003)
Physical q		0.012*** (0.002)		0.012*** (0.002)	
Bond q			0.055 (0.032)	0.033 (0.017)	0.031 (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 (0.003)				0.001 (0.002)
Physical q		0.002 (0.003)		0.001 (0.002)	
Bond q			0.061*** (0.009)	0.060*** (0.009)	0.060*** (0.009)
OLS R^2	0.047	0.035	0.462	0.465	0.466
N	141	141	141	141	141

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