Intangible Asset Valuation: The Impact of Scalability and Economic Dependence

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Abstract

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I examine two sources of heterogeneity in the valuation of intangible assets: scalability and economic dependence. Scalability positively impacts the value of a firm's option to extend the use of existing intangible assets. Economic dependence negatively impacts the value of a firm's option to adapt its intangible assets to a different use. I develop a novel approach to categorize firms based on these characteristics and find significant variation in scalability and economic dependence in the cross section of firms. Further, I find that valuation multiples are increasing in the scalability of intangible assets and decreasing in the economic dependence of intangible assets. These results highlight the importance of considering how the properties of a firm's intangible assets impact the relation between market prices and accounting information and impact the distribution of a firm's potential future cash flows.

1. Introduction

Over the last half-century, the economic importance of capital-intensive industries with large investments in tangible assets has declined relative to the importance of industries with large investments in intangible assets (Romer 1990; Jones 2005, Lev and Gu 2016). Today, intangible assets are material to the average publicly traded firm. The term "intangible asset" however encompasses a diverse group of assets and prior research has not considered how variation in the composition of firms' intangible assets impacts the distribution of a firm's potential future cash flows. In this study, I examine two sources of heterogeneity in the valuation of intangible assets: scalability and economic dependence. I define four categories of identifiable intangible assets: technology, marketing, customer, and other. [1] I develop a novel approach to estimate the composition of firms' intangible assets across these categories and use this information to identify variation in scalability and economic dependence.[2] I then examine how scalability and economic dependence of firms' intangible assets impact a firm's real option characteristics and the relation between market measures of firm value and accounting measures of performance and book value.

I define scalability based on the expected cost to extend an asset's use. A more scalable asset has a lower expected cost to extend its use. An intangible asset that has high scalability can be used in an additional investment opportunity without having to incur costs to (1) acquire additional units of the intangible asset, (2) develop additional units of the intangible asset or (3)

[1] This study focuses on variation in composition across a firm's identifiable intangible assets, which are generally just referred to as "intangible assets" throughout the paper.

[2] As discussed in detail in Section 4, I develop purchase price allocation based, disclosure based, investment based and principal component based proxies for the composition of firms' intangible assets across the four types of intangible assets. These proxies are not reliant on a firm having recorded intangible assets on its balance sheet, but instead allow estimation of intangible asset composition across all of a firm's identifiable intangible assets independent of how the assets are accounted for under U.S. GAAP and independent of whether the assets were internally or externally acquired.

discontinue another beneficial use of the intangible asset. Consider for example touch screen technology developed and patented by a cell phone maker. Deploying that technology in additional phones or in other touch screen devices does not require the firm to develop new units of the patented technology or to discontinue previous uses of the technology. In contrast, consider a customer contract between a cell phone maker and a distributor. To extend this intangible asset, additional costs generally would need to be incurred to create a new contract or to renegotiate the existing contract.

I define economic dependence as the correlation between cash flows generated from an intangible asset's different uses (both current and potential future uses). For intangible assets with high economic dependence, a negative outcome with one use of an asset impacts the expected cash flows and net present value ("NPV") of other uses more than for intangible assets with low economic dependence. Consider again a cell phone manufacturer. If a cell phone with an exploding battery is produced using a firm's brand name (high economic dependence asset) and touch screen technology (low economic dependence asset), the NPV of other uses of the brand intangible asset is likely negatively impacted more by this negative outcome than the NPV of other uses of the touchscreen technology intangible asset.

Firm value reflects the present value of expected future cash flows (see Penman 1998 for a summary). These future cash flows, however, are uncertain at the valuation date and prior research provides evidence that value depends on the distribution of potential future cash flows.[3] Scalability positively impacts the value of a firm's option to extend the use of existing intangible

[3] For example, Hansen and Jagannathan (1997) discuss a stochastic or state-contingent discount factor where the market value today of a future uncertain payoff is represented by a model that considers payoffs and discount rates across states of nature and reflects the underlying probabilities of those states. Berk et al. (1999) show how changes in a firm's assets and growth options are associated with changes in a firm's market value and expected return. Pastor and Veronesi (2003) develop a simple model that shows how uncertainty about future profitability impacts current valuation ratios. Mitton and Vorkink (2007) and Barberis and Huang (2008) present evidence that investors value positive skew in potential future cash flows.

assets providing greater growth optionality in the event of a positive shock. Economic dependence negatively impacts the value of a firm's option to adapt its intangible assets to a different use providing less downside protection in the event of a negative shock.

Accounting can be viewed as "a system that tracks the resolution of uncertainty over time: earnings is recognized and book value added only when uncertainty is resolved." (Penman 2016). Under U.S. GAAP, recognition of potential future cash flows is generally deferred pending resolution of the uncertainty in a future period. It follows that differences in the distribution of potential future cash flows across firms will not be reflected in current accounting metrics. These differences should be observable, however, in the relation between market measures of firm value and current accounting metrics (i.e. price-to-earnings or price-to-book multiples). This motivates my two primary hypotheses; H1) firm valuation multiples are increasing in the scalability of the firm's intangible assets; and H2) firm valuation multiples are decreasing in the economic dependence of the firm's intangible assets.[4] To test my hypotheses I use a real options framework to model differences in the distribution of firms' potential future cash flows. In this framework, firm value is a non-linear function of a firm's recursion value and the value of the firm's adaptation and growth options (Berger et al. 1996, Burgstahler and Dichev 1997, Zhang 2000).[5]

Scalability and economic dependence at the firm level are expected to vary with differences in the composition of the firm's intangible assets. I develop three alternative

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[4] Valuation multiple as used herein refers to multiples that link accounting information to price (e.g., price/book, price/earnings, EV/EBIT, EV/Sales multiples)

[5] Recursion value and adaptation value as used in this study are similar to the definitions in Burgstahler and Dichev (1997). Recursion value refers to the cash flows currently generated by a firm's assets as deployed with the firm's current business strategy. The adaptation option value refers to a firm's future option to adapt its assets (sell, abandon, reposition) if the cash flows produced from the recursion value are less than the adaptation value. The growth option value refers to a firm's future option to invest additional projects or to scale the use of existing assets in current projects. A higher growth option value reflects greater probability and/or magnitude of potential positive outcomes. A higher adaptation option value reflects a smaller probability and/or magnitude of potential negative outcomes.

methods for estimating the composition of a firm's intangible assets using (1) data from purchase price allocations for Fama French 48 industry peer firms, (2) the frequency a firm discusses each type of intangible asset in its annual 10-K filing, and (3) the intensity of a firm's investment in different types of intangible assets. These methods allow estimation of intangible asset composition across all of a firm's identifiable intangible assets independent of how the assets are accounted for under U.S. GAAP and independent of whether the assets were internally or externally acquired. Empirical analysis shows significant positive correlation across the three methods, but also highlights that they are not perfect substitutes. Accordingly, as a fourth method I also use first principal component analysis of the three proxies.

Focusing on technology, marketing, customer and other identifiable intangible assets, I find evidence of significant variation in the intangible asset composition of firms. [6] I use this variation to partition firms with respect to scalability and economic dependence. Specifically, I expect technology and marketing intangible assets to have relatively higher scalability, on average, than customer and other intangible assets. I expect technology intangible assets to have relatively lower economic dependence, on average, than marketing intangible assets and I expect customer and other assets to have a mix of relatively higher and lower economic dependence. As discussed in detail in Section 4, this allows the classification of firms into high, low and indeterminant groups for scalability and economic dependence.

Using an empirical specification expanded from Burgstahler and Dichev (1997), I find cross-sectional differences in firm valuation multiples consistent with my hypotheses. Multiples are increasing in the scalability of intangible assets and decreasing in the economic dependence

[6] This is consistent with ex-ante expectations. For example, a firm like Advanced Micro Devices (Nasdaq AMD) is expected to have a portfolio of intangible assets heavily weighted towards technology assets. A firm like Aramark (NYSE ARMK) is expected to be heavily weighted towards customer assets, and a firm like Tiffany (NYSE TIF) heavily weighted towards marketing intangible assets.

of intangible assets. Results are robust to the inclusion of a variety of controls for industry, risk and expected growth differences. Results for scalability (economic dependence) hold after controlling for the economic dependence (scalability) of a firm's intangible assets. Supplemental tests show that results hold across the distribution of market-to-book ratios, which helps exclude differences in firm's investment opportunity sets as an alternative explanation. Further, tests partitioned based on the expected size of a firm's portfolio of intangible assets show that the magnitude of effect is increasing in the size of a firm's portfolio of intangible assets. Tests partitioned based on tangible asset specialization show that effects exist for firms with different degrees of asset specialization, which helps reinforce that economic dependence is distinct from traditional views of asset specialization. Finally, effects are significant across the spectrum of firm lifecycles and across partitions of different analyst expectations of future growth.

To determine whether the effects of scalability and economic dependence exist independent of the accounting treatment of intangible assets, I run several additional tests. First, I split my sample based on whether a firm has recorded intangible assets on its balance sheet to verify that results are not being driven by differences in internally developed versus externally acquired intangible assets. Second, I run tests using enterprise value-to-gross profit and enterprise value-to-sales multiples to address concerns that the impact on earnings from internally generated versus externally acquired intangible assets could be impacting my empirical tests. Finally, I split my sample to show that results are not impacted by significant changes in accounting guidance for externally acquired intangible assets, effective in 2002.[7] In all three analyses I find results are robust across specifications.[8]

[7] In 2001 the FASB issued SFAS 141 and SFAS 142. SFAS 141 required that all business combinations be accounted for using the purchase method, eliminating the option to use the pooling method. SFAS 142 required firms to perform an annual two-step test for goodwill impairment and eliminated the amortization of goodwill.

[8] Empirical evidence from this study is consistent with investors pricing differences in scalability and economic dependence. However, unexplored in this study is if investors accurately price differences in scalability and economic

This study makes several primary contributions to the literature. First, I show how composition of a firm's intangible assets changes the relation between fundamental accounting measures and the market value of equity (e.g., Feltham and Ohlson 1995, Barth et al. 1998, Hao et al. 2011). Second, by documenting how a firm's intangible asset composition is associated with the real option characteristics of a firm, I provide a novel insight on the valuation impact of intangible assets. This links intangible asset composition to the distribution of a firm's potential future cash flows and creates a potential role for intangible asset composition in a wide variety of topics including return predictability (e.g., Piotroski 2000, Mohanram 2005, Daniel and Titman 2006, Hwang and Sohn 2010), volatility returns relation (e.g., Grullon et al. 2012, Lyle 2018), valuation of skewness in expected future cash flows (Mitton and Vorkink 2007, Barberis and Huang 2008, Zhang 2013), distress risk (e.g., Franzen et al. 2007) and debt capacity/cost of debt (e.g., Loumioti 2012). Third, I contribute to literature that explores the impact of specialization and redeployability (e.g. De Vita et al. 2011) by illustrating the impact of a new construct, economic dependence. Finally, I develop an empirical framework to estimate firms' compositions of intangible assets, which provides future researchers an empirical strategy to explore these and other topics.

dependence and what role accounting recognition and disclosure plays in the pricing of intangible assets. Untabulated asset pricing tests reveal preliminary evidence of significant positive alpha in a Fama French four factor model for hedge portfolios formed based on scalability but limited evidence of positive alpha for portfolios formed based on economic dependence. I look forward to exploring this question in future research.

2. Scalability and Economic Dependence of Intangible Assets

2.1 Intangible Assets

In this study I focus on variation in composition across a firm's identifiable intangible assets.[9] The most common identifiable intangible assets can broadly be described as technology, marketing, or customer related.[10] Technology intangible assets include patented and unpatented technology, computer software, and trade secrets such as secret formulas or recipes. The most common marketing intangible assets are brands, trade names, and trademarks, but this category also includes assets like domain names, franchise rights, and trade dress.[11] Customer intangible assets commonly include customer lists or databases of customer information, and either formal or informal contractual relationships. Remaining identifiable intangible assets that are not technology, marketing or customer related are heavily weighted towards contract based intangible assets including non-compete agreements, licenses, permits and other contracts or agreements. For purposes of this study I label these remaining identifiable intangible assets as "other" intangibles.

Under U.S. GAAP, the accounting treatment of internally generated and externally acquired intangible assets differ. The costs of internally developing or maintaining identifiable intangible assets are generally recognized as an expense when incurred, whereas the costs of identifiable intangible assets acquired externally through an asset purchase or a business

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[9] The FASB defines intangible assets as those assets (excluding financial assets) that lack physical substance and distinguishes identifiable from non-identifiable intangible assets. Per ASC 805-20: An asset is considered identifiable by the FASB if it meets either of the following criteria: (a) It is separable, that is, capable of being separated or divided from the entity and sold, transferred, licensed, rented or exchanged, either individually or together with a related contract, identifiable asset, or liability, regardless of whether the entity intends to do so; or (b) it arises from contractual or other legal rights, regardless of whether those rights are transferable or separable from the entity or other rights and obligations.
[10] For example, based on a global survey completed by E&Y in 2009, the three most common identified intangible assets in financial statements were customer related assets, brands/trademarks, and technology. While that survey focuses on acquired intangible assets, I expect the results generalize to all identifiable intangible assets.
[11] A brand is a general marketing term that commonly refers to a group of complementary intangible assets such as a trade name, trademark, and distinctive packaging or coloring (trade dress).

combination are capitalized at fair value.[12] However, I focus on all of a firm's identifiable intangible assets independent of how they are accounted for under U.S. GAAP and independent of whether they were internally or externally acquired. Accordingly, the theoretical predictions developed below are meant to apply to all of a firm's identifiable intangible assets, regardless of whether they are explicitly recorded on a firm's balance sheet.

2.2 Scalability

I define scalability based on the expected cost to extend an asset's use. An intangible asset with a lower expected cost to extend the asset's use is more scalable. Some intangible assets, such as knowledge assets have no capacity limit preventing use of the asset in additional investment opportunities (Romer 1990). At the other end of the spectrum, some intangible assets more closely resemble tangible assets and have a limited capacity. More broadly, an intangible asset that has high scalability can be used in an additional investment opportunity without having to incur costs to (1) acquire additional units of the intangible asset, (2) develop additional units of the intangible asset and/or (3) discontinue another beneficial use of the intangible asset. Examples of the impact of scalability are illustrated in Figure 1. For scalable assets, the original cost incurred to produce the asset does not have to be incurred again when the asset is used in additional investment opportunities (Jones 2005). This concept generalizes to a setting where managers have to pay some cost to reuse or extend an intangible asset. Scalability is then a function of these reuse or extension costs.

Intangible assets with relatively higher scalability include technology related intangibles (e.g., patents, software or trade secrets), marketing related intangibles (e.g., brands, tradenames,

[12] An exception to expensing when incurred includes the capitalization of software development costs after technological feasibility is established under ASC 985.

franchise rights) and some customer related intangibles (e.g., customer databases or lists). These assets can generally be extended at a lower direct marginal cost than an intangible asset with low scalability.[13] Consider, for example, the file allocation table ("FAT") patents held by Microsoft. FAT was originally designed for floppy disks in the 1970s but has since been extended to numerous other technologies including hard drives, digital cameras and USB drives. In each case, extending the use of the FAT did not impact existing uses or require expenditures to build or acquire additional units of FAT technology. As another example, Apple has developed a valuable trademark. Over time, it has extended the use of that trademark to numerous new products including iPads, iPhones, iPods, iTunes, Apple watches and a large variety of accessories. Using the Apple trademark in each extension does not require discontinuing previous uses nor does it require purchase of additional units of tradename.

Some intangible assets however are expected to have significantly lower scalability. Many assets in the other group are not scalable beyond the terms or scope of the initial contract unless a firm incurs costs to develop new contracts or renegotiate existing contracts. Assets in the other group may also be valuable because there is a scarcity of available similar contracts or because the terms of the existing contract are off market. In both cases, there is a cost to extend the use of the asset. For example, Marriott International recorded numerous lease agreements as contractual intangible assets from the 2016 acquisition of Starwood Hotels and Resorts. These leases cannot be extended beyond the terms already agreed to without a renegotiation process and cannot be duplicated and used for other purposes without discontinuing the current use. As

[13] I use the term "direct marginal cost" to recognize that there may be indirect costs from extending the use of an asset. Such costs can include negative externalities to existing uses of the intangible asset. For example, licensing a technology to a competitor can negatively impact a competitive advantage the technology currently provides a firm. Extending the use of a brand to an unrelated product or inferior product can dilute the brand. Using a customer list or database too extensively can diminish the marginal contribution of additional uses of that data. This study currently does not explicitly address potential cross-sectional differences in the expected magnitude of such indirect costs. This is an area for additional exploration as I work to complete my dissertation.

another example, the bulk of identifiable intangible assets from the 2016 acquisition of Virgin Atlantic by Alaska Airlines related to airport slots, contractual rights to take-off or land at a slot-controlled airport during a specific time period. A slot cannot be used simultaneously or used for an alternative flight without discontinuing the use for the original flight. Both the Starwood lease agreements and the Virgin Atlantic airport slot rights are examples of other assets considered to have relatively lower scalability.

Some customer related intangible assets also have relatively lower scalability including customer relationships and backlog.[14] Customer relationship intangible assets and backlog generally exist through a formal or informal contract. Leveraging existing relationships in future investment opportunities or expanding backlog requires additional investment in developing or expanding those formal or informal contracts. Consider for example the case of Boeing's disclosed backlog intangible asset. At year end 2017 Boeing disclosed $488.1 billion in backlog. Backlog represents orders for products and services where no contingencies remain. Boeing cannot extend the order (essentially a contractual relationship) beyond the terms already agreed to without entering a renegotiation process with the customer. Further, it is counterintuitive to consider extending this backlog asset to multiple uses or to new projects. In each of these examples, the intangible asset has a relatively higher cost to extend its use and has relatively lower scalability.

2.3 Economic Dependence

I define economic dependence as the correlation between cash flows generated from an intangible asset's different uses (both current and potential future uses). Assets with a higher

[14] U.S. public firms are required to disclose material amounts of order backlog in their 10-K filings. However, backlog is not recognized in the financial statements as an asset.

correlation between cash flows for different uses have higher economic dependence. The fair value of an intangible asset can be simplified to the incremental cash flows that can be generated from using the asset as an input in the available set of investment opportunities (Penman 2009).[15] As a current input to production, intangible assets add incremental expected cash flows from either expected cost reductions or expected revenue increases. In a dynamic setting, however, the correlation between the realized outcomes from using an intangible asset and its ex-post fair value should vary with the economic dependence of the asset. The impact of economic dependence on the net present value of a firm's uses of its intangible assets is illustrated in Figure 2 for a 2 period setting with a negative shock to one of the uses of the intangible assets.

My construct of economic dependence is related to an extensive finance and accounting literature studying asset redeployability and the impact of asset specificity or specialization. Asset specificity is defined by Williamson (1985) as "the degree to which an asset can be redeployed to alternative uses by alternative users without sacrifice of productive value."[16] The construct of asset specificity focuses on the existence and number of alternative productive uses of an asset. Asset specificity does not imply high or low economic dependence. An asset with high or low economic dependence could be characterized as highly specialized or not. For example, the Amazon brand and the Abercrombie & Fitch (A&F) brand are both marketing intangible assets that I classify as having high economic dependence. However, the A&F brand is more specialized and less redeployable than the Amazon brand because A&F is associated with apparel targeted at a specific demographic while Amazon is associated with a broad range of products and services.

[15] According to ASC 820-10-20: "Fair value is the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date."

[16] There is an extensive body of literature that builds off / differs from this definition or focuses on one element or another of asset specificity. For a summary see De Vita et al. (2011).

Technology intangible assets are expected to exhibit the lowest economic dependence and marketing intangible assets the highest. If a marketing intangible asset is used in an investment that experiences a significant negative outcome, the value of the marketing intangible asset ex-post is negatively impacted. This is because the value of a marketing intangible asset is in part created and sustained by the quality of the other assets it is jointly used with and by the overall success of the investment opportunity. In contrast, if a technology intangible asset is used in an investment that experiences a significant negative outcome, the value of the technology intangible asset ex-post is not expected to be as negatively impacted.[17] The value attributes of a technology asset are largely created through prior investment in research and development ("R&D"). Once these attributes have been established, the future value of the asset is less dependent on the successful outcomes of projects using the technology as an input than for a marketing asset.

Numerous examples of differences in economic dependence for marketing versus technology intangible assets exist. Consider for example, the negative impact on Volkswagen's brand value from the recent emissions scandal and the decline in value of the Sears or Kodak brands as the respective companies operating results declined.[18] In contrast, Microsoft's FAT technology has been used in a variety of investments that eventually failed, such as floppy disks, Palm Pilots, and Blackberry cellular devices. The value of the technology intangible asset, however, is less correlated with these investment failures. Microsoft continues to receive substantial cash flows from new investments that utilize FAT technology (e.g., USB flash drives, Android phones). Similarly, despite Kodak's brand decline in value, a significant part of the

[17] This prediction would not hold if the bad outcome revealed previously unknown negative information related to the value attributes of the technology.

[18] See for example, (a) *Volkswagen Sales drop for First Time in 13 Years*, The Wall Street Journal 2016, (b) the 10-K filings for Sears for 2016 which details Sears tradename impairments of $180M in 2015 and $381M in 2016, and (c) *The last Kodak moment?* The Economist 2012.

company's reorganization strategy was to monetize "a war chest of 1,100 digital-imaging patents crucial to cameras, phones, and other devices" and to pursue litigation against companies believed to have infringed on Kodak patents, including Apple and HTC.[19]

3. Hypothesis Development

3.1 Prior Literature

Firm value reflects the present value of expected future cash flows (see Penman 1998 for a summary). However, future cash flows are uncertain at the valuation date and prior research provides evidence that firm value depends on the distribution of potential future cash flows and discount rates.[20] A real options framework models the value of a firm's ability to choose between future alternatives with different cash flow implications. For example, value can be expressed as a non-linear function of a firm's recursion value (RV) and the value of the firm's adaptation (AOV) and growth options (GOV).[21]

$$\text{Value} = f(RV, AOV, GOV) \quad (1)$$

Recursion value refers to the cash flows generated by a firm's assets as currently deployed with the firm's business strategy (Burgstahler and Dichev 1997). Adaptation option value refers to a firm's future option to adapt its assets (sell, abandon, reposition) if the cash flows produced from the recursion value are less than the adaptation value (Burgstahler and Dichev 1997, Berger et al. 1996). A higher adaptation option value reflects the benefit from relatively greater downside

[19] CNET 2012 *Kodak files for Chapter 11 bankruptcy protection.*
[20] This concept is present in recent papers that discuss state dependent stochastic cash flows and discount rates (Hansen and Jagannathan 1997), investor sensitivity to downside risk (Ang et al. 2006) the potential validity of a conditional CAPM model (Petkova and Zhang 2003, Lewellen and Nagel 2003), how uncertainty about future profitability impacts current valuation ratios (Pastor and Veronesi 2003), and how investors value positive skew in the distribution of potential future cash flows (Mitton and Vorkink 2007, Barberis and Huang 2008).
[21] While not perfect substitutes, a concept like the adaptation option has been discussed as the abandonment option (e.g., Berger et al. 1996, Barth et al. 1998, Pinnuck and Lillis 2007) and the option to discontinue operations (Zhang 2000). Similarly, the growth option has been discussed as an option to expand operations (Zhang 2000) .

protection. Growth option value refers to a firm's future option to invest in additional projects or to extend the use of existing assets in current projects (Hao et al. 2011). A higher growth option value reflects the benefit from relatively greater growth potential.

A real options framework is used in several studies examining the pricing of GAAP book value of equity and earnings. Burgstahler and Dichev (1997) provide evidence consistent with market value as a convex function of the value of a firm's net assets and earnings, due to the option to adapt assets to an alternative use. Barth et al. (1998) find that as a firm's financial health declines, the pricing multiple (and incremental explanatory power) for book value increases and the pricing multiple (and incremental explanatory power) for earnings decreases. The authors note this is consistent with investors placing greater weight on proxies for liquidation value as a firm's financial health decreases and attribute their results to declines in the value of unrecognized net assets as financial health decreases.[22] Hao et al. (2011) find that growth increases the association between earnings and market value for firms with higher profitability but not for firms with lower profitability, consistent with the predictions in Zhang (2000). Together, these studies establish that book value and earnings convey complementary information for equity valuation. Book value provides a proxy for the adaptation value of a firm's assets and earnings a proxy for expected future cash flows from a firm's current investments and for a firm's growth options. Pricing multiples on earnings and book value are increasing in the magnitude of unrecognized assets. I extend this real options framework to develop hypotheses and empirical tests analyzing the impact of variation in the scalability and economic dependence of a firm's intangible assets.

[22] Barth et al. (1998) specify unrecognized assets as including "research and development, brand names, technological core competencies, customer loyalty, and growth options."

Another body of research has investigated the challenge of accounting for intangible assets and how intangible assets impact the pricing of book value and earnings. Numerous studies provide evidence that R&D expenditures, advertising expenditures, and the capitalization of investments in internally developed intangible assets, including software development, provide value relevant information to investors (e.g., Hirschey and Weygandt 1985, Lev and Sougiannis 1996, Aboody and Lev 1998). Other studies have used external indications of value to demonstrate the relevance of brands and customer relationships that are not recorded as assets under U.S. GAAP if internally developed (Barth et al. 1998, Bonacchi et al. 2015).

A related series of studies considers the impact of conservative accounting on the pricing of accounting information. Feltham and Olson (1995) highlight that accounting conservatism biases operating assets downwards more than financial assets, because financial assets are recorded at closer to their fair values. Ahmed et al. (2000) provide evidence consistent with this conservative accounting bias, finding a higher multiple for operating assets. Zhang (2000) predicts that conservatism increases the price-to-book multiple for all firms and the price-earnings multiple for firms that are growing. The theory underlying these results is that book value and earnings are biased downward because of conservative accounting and that price multiples increase to compensate for this bias. The immediate expensing of advertising and R&D expenses is one widely studied cause of conservatism, with conservatism increasing in the intensity of such expenditures (e.g., Ahmed et al. 2000).

This literature informs my predictions about how differences between firm growth option and adaptation option values impact valuation multiples. That is, when accounting metrics (earnings or book value of equity for example) fail to incorporate value relevant information, this information is forced into the relation between market measures of value and current accounting metrics (i.e. price-to-earnings or price-to-book multiples). This literature also emphasizes the importance of controlling for a firm's investment lifecycle stage, expected future growth, and magnitude of unrecognized assets in empirical tests.

3.2 The Impact of Scalability

Theories typically assume firms select the optimal set of investments conditional on existing assets and opportunities. Over time, as opportunities change, existing assets can be adapted or extended to capitalize on previously unanticipated opportunities to grow the business. This ability to adapt or extend assets gives rise to growth option value. The lower the marginal cost to extend or scale an asset to an additional opportunity, the higher the growth option value. In other words, for assets with high scalability, the strike price of the real option is lower (Kulatilaka and Perotti 1998). All else equal, the lower the strike price for a growth option, the more valuable the option. Higher option value is expected to have a positive impact on firm value by increasing expected future cash flows. However, differences in the distribution of potential future cash flows are not reflected in the accounting earnings and balance sheet metrics and therefore affect the relation between market measures of value and current accounting metrics (i.e. price-to-earnings or price-to-book multiples). This motivates my first hypothesis (stated in alternative form):

H1: Firm valuation multiples are increasing in the scalability of intangible assets.

3.3 The Impact of Economic Dependence

Variation in the economic dependence of a firm's intangible assets is expected to have a significant impact on the downside distribution of a firm's potential future cash flows. As the correlation between an intangible asset's fair value and cash flows realized from its current use increases, the correlation between the asset's adaptation value and the recursion value of the firm is also expected to increase. In the case of extreme dependence, the value of the firm is entirely due to recursion value, because events that reduce recursion value also reduce the adaptation value, effectively eliminating any downside protection from adaptation. In a real options framework, greater correlation between the recursion value and adaptation value equates to lower option value.[23] Again however, differences in the distribution of potential future cash flows are not reflected in the accounting earnings and balance sheet metrics and therefore should affect the valuation multiple if priced by investors. This motivates my second hypothesis (stated in alternative form):

H2: Firm valuation multiples are decreasing in the economic dependence of intangible assets.

4. Research Design

My research design has the three key components discussed below. First, in Section 4.1 I describe the methodology developed to estimate cross sectional variation in firm's intangible asset composition. Next, in Section 4.2 I discuss how intangible asset composition is used to classify firms into high, low and indeterminant groups for scalability and economic dependence. Finally, in Section 4.3 I describe the empirical specification expanded from Burgstahler and Dichev (1997) that is used to test my hypotheses.

4.1 Cross Sectional Variation in Intangible Asset Composition

I examine variation in the intangible asset composition of firms' across the four groups discussed in Section 2; technology, marketing, customer and other intangible assets. Using these four groups, firm *i*'s total intangible assets at time *t* ($IA_{i,t}$) can be described as:

$$IA_{i,t} \equiv Tech_{i,t} + Mrkt_{i,t} + Cust_{i,t} + Other_{i,t}, \qquad (2)$$

[23] Prior research on option valuation with a stochastic strike price shows the value of a long position in a put option decreases as the correlation between the stochastic strike price and underlying asset value increases (Myers et al. 2001).

where *Tech, Mrkt, Cust, and Other* are the fair values of firm i's technology, marketing, customer and other intangible assets respectively at time *t.* Although firms commonly invest in multiple types of intangible assets, there can be substantial variation in relative composition across firms, where some firm's intangible assets are more heavily weighted towards one or more intangible asset type(s).

H1 and H2 apply to a firm's entire portfolio of identifiable intangible assets and focus on the composition of the portfolio rather than the size of the portfolio.[24] Ideally, the composition of a firm's intangible assets would be reported in the firm's financial statements, allowing for direct observation of inputs to Equation (2). However, U.S. GAAP does not permit recognition of most internally developed intangible assets and I cannot directly measure a firm's intangible asset composition. Accordingly, I introduce three alternative, complementary methods for overcoming this data limitation. These methods are not reliant on a firm having recorded intangible assets on its balance sheet, but instead allow estimation of intangible asset composition across all of a firm's identifiable intangible assets independent of how the assets are accounted for under U.S. GAAP and independent of whether the assets were internally or externally acquired.

4.1.1 Purchase Price Allocation Method

For my first approach, the purchase price allocation ("PPA") method, I use observable fair values for intangible assets from purchase price allocations. Specifically, I use a dataset of 5,208 purchase price allocations from business combinations occurring between 2003 and 2015.[25] This data is collected by Houlihan and Lokey as part of its annual Purchase Price

[24] For H1 and H2 to have a material effect a firm needs to hold a large enough portfolio of intangible assets. The average firm is expected to hold a large enough portfolio for effects to be present in sample wide tests. However, I explore in supplemental analyses the impact of intangible asset portfolio size.
[25] Data provided by Houlihan and Lokey, Inc., an independent, advisory-focused, global investment bank (NYSE HLI).

Allocation Study. For an acquisition to be included in the dataset, the acquirer must be a U.S. publicly traded company, the ownership percentage acquired must be 50% or greater and the acquirer must have disclosed purchase consideration, identifiable intangible asset fair values, and estimated goodwill. Houlihan and Lokey collects details on the allocation of the purchase price to tangible assets, goodwill, and identifiable intangible assets (including in-process R&D, technology, marketing and other). This dataset allows me to observe the composition of the acquired firm's intangible assets. I aggregate acquisition data across Fama French 48 industries to develop industry-based expectations for the composition of intangible assets. The industry measure is then mapped onto each firm in the industry.[26] I summarize the results of this analysis in Appendix B.

As implemented here, the PPA method for developing proxies requires dropping the time and firm subscripts from the original Equation (2) because it uses all observations within an industry across all time periods to estimate the industry composition of intangibles. This approach does not capture heterogeneity in intangible asset composition within industry groups or changes in the composition of an industry's intangible assets over time. Additionally, this approach may work poorly for industries where few acquisitions occur or where the intangible assets of acquired companies in the dataset are not representative of the acquiring firm's intangible asset composition.

[26] Acquisitions occur for a variety of reasons (Lewellen 1971). In many instances, the target and acquiring firms are similar and the composition of intangible assets for the acquired company likely provides a reasonable proxy for the composition of intangible assets of the acquiring firm. For example, this could include acquisitions motivated by consolidation, efficiency or competitive reasons. In other instances, the composition of intangibles for the acquired company may not provide a reasonable proxy for the acquiring firm. For example, this could include acquisitions for diversification, vertical or horizontal integration or for financial reasons (Lewellen 1971). However, each acquisition provides a signal on the intangible assets that are important to a specific type of firm or, at a minimum, the intangible assets that are held by the firm post acquisition. Aggregating enough acquisitions across similar types of firms should provide a less noisy signal of the composition of intangible assets for that type of firm.

4.1.2 Disclosure Method

For my second approach, the disclosure method, I use textual analysis of firms' annual 10-K filings to distinguish between firms where different types of intangible assets are discussed relatively more or less in comparison to other intangible assets. This is based on an analysis of the relative frequency of intangible asset related words in the 10-K fillings. I develop a master word list (see Appendix C) based on a review of FASB accounting standard codifications and intangible asset practice aids from Big Four accounting firms. Relative word frequencies for each intangible asset group from are then used as proxies for the expected composition of a firm's intangible assets.

The disclosure method enables me to consider variation within industry and across time. However, this method assumes that a firm's discussion of intangible assets in its annual filing is representative of the composition of its intangible assets. Prior research has shown that disclosure is impacted by a variety of factors that could affect the accuracy of the disclosure method proxies including firm performance (e.g., Miller 2002, Merkeley 2013), proprietary costs of disclosure (e.g., Ellis et al. 2012, Bernard 2016) and demand for information (e.g., Lang and Lundholm 1996, Chen et al. 2002).

4.1.3 Intensity Method

For my third approach, the Intensity method, I use company expenditures on advertising, R&D and SG&A to estimate the relative intensity of a firm's investments in different types of intangible assets. Relative intensities of investment are then used as proxies for the expected composition of a firm's intangible assets. R&D expenditures proxy for investments in technology, advertising expenditures proxy for investments in marketing, and SG&A expenditures proxy for investments across all four types of intangible assets. My methodology departs from prior studies that evaluate these investments relative to total expenditures (e.g., Lev and Sougiannis 1996, Srivastava 2014). Instead, I use SG&A as the deflator because with this change, the intensity measure shifts to providing information on the relative intensity of a firm's investments in different types of intangible assets. This allows me to distinguish between firms where R&D (technology) or advertising (marketing) compose a relatively greater or lesser proportion of a firm's current investment in intangible assets.

The intensity method enables me to consider variation within industry and across time. However, the intensity method does not account for the firm's external investments in intangible assets. Additionally, it does not account for potential disconnects between a firm's current investments in intangibles and the composition of a firm's intangible assets created through past and current investments. This could be of particular significance for a firm that has changed its pattern of investment, e.g. a firm that is in a mature or declining stage and is no longer actively investing in the creation of new intangible assets. Finally, this method does not allow for separate estimates of customer and other intangible asset composition.

4.2 Scalability and Economic Dependence Proxies

4.2.1 Measure of Scalability

To distinguish between firms with significantly different scalability of intangible assets I create a variable $SCALABILITY_{i,t}$. If the proportion of a firm's technology and marketing related intangible assets is high, I expect that firm to have relatively higher scalability. Operationally, I define high scalability firms as those with a proportion of technology and marketing assets in the top third of the sample in that period. Firms with a proportion of technology and marketing in the lower third of the sample are classified as low scalability firms and the remaining firms are classified in an "indeterminant scalability" group:

$$SCALABILITY_{i,t} = \begin{cases} High\ ("HS")\ if: & \frac{Tech_{i,t} + Mrkt_{i,t}}{IA_{i,t}} \geq P_{67}\left(\frac{Tech_t + Mrkt_t}{IA_t}\right) \\ Low\ ("LS")\ if: & \frac{Tech_{i,t} + Mrkt_{i,t}}{IA_{i,t}} \leq P_{33}\left(\frac{Tech_t + Mrkt_t}{IA_t}\right) \\ indeterminant\ \ otherwise & \end{cases} \quad (3)$$

where subscript *i* denotes a firm and *t* denotes a time period.

I estimate Equation (3) using intangible asset composition from the PPA, Disclosure and Intensity methods, providing three different measures of *SCALABILITY* for each firm. As discussed in Section 4.1, each of these methods is imperfect. However, the three methods are more likely to misidentify asset composition in different situations. I use principal component analysis to create a fourth measure for *SCALABILITY* that is based on the common correlation across the PPA, Disclosure and Intensity measures (the "PC" Method).[27] To execute a principal component analysis I assign value -1, 0, and 1 to Low, indeterminant and High firms respectively. I find that the first principal component explains 63% of the variation in *SCALABILITY* across the three different methods. I then use the extracted first principal component to divide the sample into terciles of High, indeterminant and Low for each period.

4.2.2 Measure of Economic Dependence

To distinguish between firms with significantly different economic dependence of intangible assets I create a variable $DEPENDENCE_{i,t}$. If the proportion of a firm's technology related intangible assets is low and the proportion of its marketing related intangible assets is high, I expect that firm to have relatively higher economic dependence. Operationally, I define high economic dependence firms as those with a proportion of technology assets in the bottom

[27] Empirical results for tests of H1 are robust to alternative methods of aggregating across the PPA, Disclosure and Intensity proxies including limiting the sample to firms where two of the three methods result in the same classification for *SCALABILITY* and partitioning based on a simple average across the three methods.

third of the sample for a given period and marketing assets in the top third. Similarly, low economic dependence firms have a proportion of technology assets in the top third of the sample for a given period and marketing assets in the bottom third. I classify all other firms into an "indeterminant economic dependence" group:

$$DEPENDENCE_{i,t} = \begin{cases} High\ ("HD")\ if: & \frac{Tech_{i,t}}{IA_{i,t}} \leq P_{33}\left(\frac{Tech_t}{IA_t}\right) \boldsymbol{AND}\ \frac{Mrkt_{i,t}}{IA_{i,t}} \geq P_{67}\left(\frac{Mrkt_t}{IA_t}\right) \\ Low\ ("LD")\ if: & \frac{Tech_{i,t}}{IA_{i,t}} \geq P_{66}\left(\frac{Tech_t}{IA_t}\right) \boldsymbol{AND}\ \frac{Mrkt_{i,t}}{IA_{i,t}} \leq P_{33}\left(\frac{Mrkt_t}{IA_t}\right) \\ Indeterminant\ otherwise & \end{cases} \quad (4)$$

where subscript *i* denotes a firm and *t* denotes a time period.

I estimate Equation (4) using intangible asset composition from the PPA, Disclosure and Intensity methods, providing three different measures of *DEPENDENCE* for each firm. Again, I use principal component analysis to create a fourth measure for *DEPENDENCE* that is based on the common correlation across the PPA, Disclosure and Intensity measures.[28] The first principal component explains 64% of the variation in *DEPENDENCE* across the three different methods.

4.3 Market Value as a Convex Combination of Book Value of Equity and Earnings

To test the impact of scalability and economic dependence on firms' valuation multiples I first focus on earnings and book value and borrow from prior research that shows firm value can be expressed as a convex combination of book value of equity and earnings. I start with the empirical specification used in Burgstahler and Dichev (1997):

$$V_{i,t} = \alpha_0 B_{i,t-1} + \alpha_1 X_{i,t} + \epsilon_{i,t} \quad (5)$$

[28] Empirical results for tests of H2 are also robust to alternative methods of aggregating across the PPA, Disclosure and Intensity proxies including limiting the sample to firms where two of the three methods result in the same classification for *SCALABILITY* and partitioning based on a simple average across the three methods.

Where V_t is a firm's market capitalization, B_{t-1} is the book value of equity at the beginning of the period and X_t is earnings before extraordinary items over the period *t*-1 to *t*. Lagged book value is used to separate the impact of *B* and *X* given current earnings is a component of current book value. To help operationalize the prediction that *V* is a convex combination of *X* and *B,* Burgstahler and Dichev (1997) divide both sides of the equation by B_{t-1}. This allows them to "hold book value constant while testing for the incremental impact of earnings." The equation becomes:

$$V_{i,t}/B_{i,t-1} = \alpha_0 + \alpha_1 X_{i,t}/B_{i,t-1} + \varepsilon_{i,t-1,t} \quad (6)$$

In this transformed equation the intercept (α_0) is the price-book multiple and proxies for the adaptation option value of the firm's assets. Additionally, the coefficient (α_1) is a firm's price-earnings multiple and proxies for a firm's recursion value and also incorporates growth option value. Through simple modifications to this base model as discussed below, I am able to test H1 focusing on the impact of scalability on a proxy for recursion and growth option value and I am able to test H2 focusing on the impact of economic dependence on a proxy for adaptation option value.

5. Sample and Empirical Analysis

5.1 Sample Selection and Descriptive Statistics

I select all firm-years from 1994 to 2016 with data in the Compustat and CRSP databases sufficient to calculate my variables of interest. I require observations to have (1) market value of equity data in CRSP as of three months after the fiscal year end, (2) necessary data to calculate beginning of year tangible book value of equity (*TBV), (3)* positive earnings and positive lagged *TBV*. I remove regulated and financial industries (SIC codes 4900-4999 and 6000-6999) and restrict my focus to firms that trade on the NYSE, AMEX, or NASDAQ exchanges with a CRSP share code of 10 or 11 (common shares) and a price per share greater than $1.00. Collectively, these filters help limit extreme observations and outlier firms and are similar to filters used in prior research (Burgstahler and Dichev 1997 and Hao et al 2011).

My primary tests build off scaled versions of market value and earnings *VB* and *XB* respectively. *VB* is a firm's market capitalization scaled by its beginning of period *TBV*. *XB* is a firm's earnings before extraordinary items scaled by its beginning of period *TBV*. Plots of the raw data for these two variables revealed extreme outliers. Consistent with Burgstahler and Dichev (1997) I trim the most extreme top and bottom 3% of *XB* and the extreme top 3% of *VB*. These steps result in a final sample of 26,862 firm-year observations. Finally, although I limit my main empirical analysis to firms with positive earnings, in robustness tests I relax the restriction that earnings be positive and instead require positive gross profit, which expands the sample size from 26,862 to 34,720 for Enterprise Value based robustness tests.

Table 1 Panel A provides descriptive statistics on the underlying variables used in this study. All variables are defined in Appendix A. The average market-to-book ratio (*VB*) in my sample is 4.47. This high average is a result of excluding loss firms. Similarly, the impact of dropping loss firms is reflected in the heavy concentration of firms in the *GROWTH* (35%) and *MATURE* (52%) lifecycle stage in my sample (Dickinson 2011). As expected, my proxy for size, total assets (*AT*), exhibits significant right skewness so I control for size in my regression analyses using the natural log of this variable (*logAT*). There is significant variation within the sample in the level of intangible assets held by firms as proxied by the proportion of total expenses that are SGA related (*SGA_II*). *SGA_II* does not measure differences in the composition of intangible assets but is included to identify potential correlation between levels of intangible assets at a firm and scalability and economic dependence. Approximately 70% of the sample has some externally acquired intangible assets on the balance sheet (*ACQUIRED_I*).

5.2 Cross Sectional Variation in Intangible Asset Composition

As expected, there exists significant variation across firms in the composition of intangible assets for each of the PPA, Disclosure and Intensity methods. I illustrate this variation in Figures 3-5. Figure 3 summarizes industry average intangible asset compositions from the purchase price allocation dataset and shows significant differences across Fama French 48 industries. For example, the average proportion of technology intangible assets for industries like Electrical Equipment, Pharmaceutical Products and Medical Equipment is significantly higher than for industries like Textiles, Apparel, Beer & Liquor and Tobacco Products where marketing intangible assets dominate. Still other industries like Banking, Coal and Transportation exhibit high proportions of Customer and Other intangible assets and lower proportions of both marketing and technology intangible assets.

Shifting from an industry to a firm-year level, Figures 4 and 5 provide scatter plots summarizing variation in composition across the 26,862 observations in my sample based on the Disclosure and Intensity methods. In these figures, the y-axis represents the estimated proportion of technology intangibles and the x-axis the proportion of intangibles. The proportion of customer and other intangibles can also be inferred from these figures, where those observation closest to the origin represent firms with the highest proportion of customer and other intangible assets. This follows from the identity presented in Equation (2). In Figures 4 and 5 we again see significant variation across the sample in composition of intangible assets.

Table 2 provides correlation analyses across estimated compositions and shows significant positive correlation within intangible asset groups across the three methods.

Specifically, positive correlation in estimated technology composition ranges from 0.60 to 0.64 across the three methods. Positive correlation in marketing composition ranges from 0.33 to 0.48 and in the combined groups of customer and other it ranges from 0.44 to 0.46. This is consistent with each proxy capturing the same construct. However, these analyses also show significant variance across the three methods. Accordingly, to demonstrate the robustness of my findings I report empirical results for the primary tests of H1 and H2 using proxies developed using each of the PPA, Disclosure, Intensity and principal component methods.

5.3 Tests of Scalability and Economic Dependence

Table 1 Panels B & C provide descriptive statistics with the sample split into high, low and indeterminant partitions for scalability in Panel B and economic dependence in Panel C. Panel B of Table 1 provides initial univariate evidence that valuation multiples are increasing in scalability with the average *VB* for the high scalability group (*HS*) significantly larger than for the low scalability group (*LS*) but no significant differences between earnings to book value of equity (*XB*) or total assets (AT) across the *HS* and *LS* firms. However, the majority of the other control variables show *HS* and *LS* firms are significantly different along a number of dimensions making it difficult to draw inferences from a univariate analysis.

Table 1 Panel C provides the first evidence that valuation multiples are decreasing in economic dependence with the average *VB* for the high economic dependence group (*HD*) significantly smaller than for the low group (*LS*). Earnings to book value of equity (*XB*) and total assets (*AT*) are not significantly different across the *HD* and *LD* firms. However, all of the other control variables show *HD* and *LD* firms are significantly different along a number of dimensions again making it difficult to draw inferences from a univariate analysis.

To more formally test H_1, I make several modifications to Equation (6). First, I substitute TBV in place of book value to remove any externally acquired intangible assets from a firm's balance sheet. This changes the dependent variable to the ratio of firm's market capitalization to beginning of period TBV (VB) and the independent variable of interest to the ratio of earnings to beginning of period TBV (XB). Making this change allows for cleaner tests of my hypotheses independent of whether a firm's intangible assets were internally developed or externally acquired.[29] Then, I modify Equation (6) to include indicator variables *HS*, *LS,* and interactions between those variables and *XB*. The primary focus is on the coefficients for these interaction terms which, in this specification, reflect the association of scalability with a proxy for recursion and growth option value. I also add a variety of control variables and fixed effects as discussed below. With these changes, the estimated equation is:

$$VB_{i,t} = \alpha_0 + \alpha_1 XB_{i,t} + \alpha_2(XB_{i,t} * HS_{i,t}) + \alpha_3(XB_{i,t} * LS_{i,t}) + \alpha_4 HS_{i,t} + \alpha_5 LS_{i,t} + Z'\beta + \varepsilon \qquad (7)$$

where *HS* and *LS* are indicator variables that equal one when *SCALABILITY* is equal to "HS" or "LS" respectively and zero otherwise.

I include a variety of control variables that prior research has established impact the relation between market price and accounting information. The controls, represented by Z' in Equation (7), are as follows: PM, ATO and LEV are the DuPont decomposition of return on equity into a profitability, efficiency and leverage component which have been linked to variation in future earnings and firm risk in prior research (e.g., Nissim and Penman 2001, Soliman 2008); *logAT* is the natural log of a firm's total assets and is used as a proxy for size, $BETA$ is a measure of the systematic risk of a security in relation to the market portfolio, *T12RET* is the trailing 12 month return, all of which prior research has shown have a relation

[29] Internally developed versus externally acquired intangible assets and their potential impact on the income statement are explored in greater detail in supplemental tests discussed later in the paper.

with firm risk (e.g., Fama and French 1993). Finally, I include *SGA_II* to control for differences in the amount or level of intangible assets a firm holds. I include time fixed effects to control for unobserved common shocks to valuation multiples to all firms across time. I include industry fixed effects and lifecycle fixed effects to control for time-invariant differences between firms in different industries (Fama and French 1997) and at different lifecycle stages (Dickinson 2011) both of which could impact firm valuation multiples.[30]

Based on H_1, I expect to see higher price-earnings multiples for *HS* firms as compared to *LS* firms, consistent with scalability positively impacting the value of a firm's option to extend the use of existing intangible assets. Accordingly, I predict that $\alpha_2 > \alpha_3$ in Equation (7). I report the results of estimating Equation (7) in Table 3. Panel A summarizes the magnitude of the difference between α_2 and α_3 and tests the significance of the difference using a two tailed F-test. Panel B presents the regression coefficients for the full model specification underlying the information in Panel A. Column (1) presents results using the PPA measure of *SCALABILITY*, Column (2) the Disclosure measure, Column (3) the Intensity measure and Column (4) the PC measure.[31] Across all four specifications, I find that the price-to-earnings multiple for *HS* firms is larger than for *LS* firms. Effects are also economically significant with the difference between α_2 and α_3 ranging from 1.96 to 3.59 which is equivalent to 14% to 26% of the price-to-earnings multiple from estimating Equation (7) without the *HS* and *LS* terms.

[30] In untabulated tests I also estimate models where the time, lifecycle and industry fixed effects are interacted with the *XB* independent variable. Results are qualitatively similar to the models shown in Equations (7) and (8) with valuation multiples increasing in scalability and decreasing in economic dependence.
[31] I exclude Industry fixed effects in the PPA specification as there is no variation within industry in the indicator variables *HS* and *LS* under the PPA Method.

5.4 Tests of Economic Dependence

To test H2 I make similar modifications to Equation (6) but drop all HS and LS terms and instead include indicator variables HD and LD. The coefficients for these indicator variables reflect the association of economic dependence with the intercept term from the model, a proxy for adaptation option value. I also add the same fixed effects discussed above for Equation (7):

$$VB_{i,t} = \alpha_0 + \alpha_1 XB_{i,t} + \alpha_2 HD_{i,t} + \alpha_3 LD_{i,t} + Z'\beta + \varepsilon \qquad (8)$$

where *HD* and *LD* are indicator variables that equal one when *DEPENDENCE* is equal to "HD" or "LD" respectively and zero otherwise and the controls included in Z' are the same as for Equation (7) discussed above.

Based on H_2, I expect to see lower price-book multiples for *HD* firms as compared to *LD* firms consistent with economic dependence negatively impacting the value of a firm's option to adapt its intangible assets to a different use. Accordingly, I predict that $\alpha_2 < \alpha_3$ in Equation (8). I report the results of estimating Equation (8) in Table 4, which is organized the same as Table 3. Panel A summarizes the magnitude of the difference between α_2 and α_3 and tests the significance of the difference using a two tailed F-test. Panel B presents the regression coefficients for the full model specification underlying the information in Panel A. Column (1) presents results using the PPA measure of *DEPENDENCE*, Column (2) the Disclosure measure, Column (3) the Intensity measure and Column (4) the PC measure.[32] Across all four specifications, I find that the price-to-book multiple for *HD* firms is smaller than for *LD* firms. The difference between α_2 and α_3 ranges from -0.47 to -0.86 which is equivalent to 11% to 19% of the sample wide average market-to-book multiple (VB).

[32] I exclude Industry fixed effects in the PPA specification as there is no variation within industry in the indicator variables HS and LS under the PPA Method.

5.5 Simultaneous Tests of Scalability and Economic Dependence

In the last of my primary tests I estimate a model to show that scalability and economic dependence are distinct effects and that H_1 holds after controlling for differences in the economic dependence of a firm's intangible assets and that H_2 holds after controlling for differences in the scalability of a firm's intangible assets. In this specification, Equation (6) is modified to:

$$\begin{aligned} VB_{i,t} = \alpha_0 &+ \alpha_1 XB_{i,t} + \alpha_2(XB_{i,t} * HS_{i,t}) + \alpha_3(XB_{i,t} * HS_{i,t} * LD_{i,t}) + \alpha_4(XB_{i,t} * HS_{i,t} * HD_{i,t}) \\ &+ \alpha_5(XB_{i,t} * LS_{i,t}) + \alpha_6(XB_{i,t} * LS_{i,t} * LD_{i,t}) + \alpha_7(XB_{i,t} * LS_{i,t} * HD_{i,t}) \\ &+ \alpha_8(XB_{i,t} * LD_{i,t}) + \alpha_9(XB_{i,t} * HD_{i,t}) + \alpha_{10} HS_{i,t} + \alpha_{11}(HS_{i,t} * LD_{i,t}) \\ &+ \alpha_{12}(HS_{i,t} * HD_{i,t}) + \alpha_{13} LS_{i,t} + \alpha_{14}(LS_{i,t} * LD_{i,t}) + \alpha_{15}(LS_{i,t} * HD_{i,t}) \\ &+ \alpha_{16} LD_{i,t} + \alpha_{17} HD_{i,t} + Z'\beta + \varepsilon \end{aligned} \qquad (9)$$

If H_1 holds after controlling for differences in economic dependence, I expect the coefficient on *XB* to be larger for *HS* firms compared to *LS* firms given *DEPENDENCE = HD* ($\alpha_2+\alpha_3 > \alpha_5+\alpha_6$), *ID* ($\alpha_2 > \alpha_5$) and *LD* ($\alpha_2+\alpha_4 > \alpha_5+\alpha_7$). If H_2 holds after controlling for differences in scalability, I expect the intercept term in Equation (9) to be smaller for *HD* firms compared to *LD* firms given *SCALABILITY = HS* ($\alpha_{12}+\alpha_{17} < \alpha_{11}+\alpha_{16}$), *IS* ($\alpha_{17} < \alpha_{16}$) and *LS* ($\alpha_{15}+\alpha_{17} < \alpha_{14}+\alpha_{16}$). I report the results of F-tests on the significance of the differences for each of the above predictions in Table 5. Several specifications are omitted where the intersection of LS and LD is essentially an empty set for all four approaches and the intersection of *LS* and *HD* is an empty set for the PPA measures. Column (1) presents results using the PPA measures of *SCALABILITY* and *DEPENDENCE*, Column (2) the Disclosure measures, Column (3) the Intensity measures and Column (4) the PC measures. I find that the price-to-earnings multiple for *HS* firms is larger than for *LS* firms given economic dependence across 6/7 specifications tested with effect sizes ranging from 2.28 to 4.78. Further, I find that the price-to-book multiple for *HD* firms is significantly smaller than for *LD* firms given scalability across 7/8 specifications tested with effect sizes ranging from -0.52 to -1.33.

5.6 Variation in Market-to-Book

A potential alternative explanation for my results is that *SCALABILITY* and *DEPENDENCE* sort firms on other characteristics that are correlated with market-to-book. This could include differences in a firm's investment opportunity set, accounting conservatism, the size of a firm's portfolio of intangible assets, delayed recognition of economic gains and losses or one of the other constructs market-to-book has been associated with.[33] In each case, the concern is that empirical results exist not because of the effects of variation in scalability and economic dependence, but rather because these proxies essentially sort firms on market-to-book.

In my primary tests, I address this concern by including a range of control variables and fixed effects. As a supplemental analysis, I use quantile regressions to examine the extent to which results for scalability and economic dependence are contingent on the magnitude of market-to-book (*VB*). Quantile regressions model the relation between the specified independent variables and different percentiles (quantiles) of the dependent variable. Estimating quantile regressions allow me to determine whether the scalability effect documented in Table 3 and the economic dependence effect documented in Table 4 vary across the conditional expectation of *VB*. If scalability and economic dependence effects result from sorting firms based on *VB*, I would expect effects to not hold across the distribution of *VB*. In contrast, based on H1 and H2, I expect an effect to exist across the distribution of *VB* and that the magnitude of the effect is increasing in the size of a firm's portfolio of intangible assets.

Table 6 and Table 7 present results from estimating Equation (7) and Equation (8) using quantile regressions with bootstrapped standard errors and the PC measures for *SCALABILITY* and *DEPENDENCE*. In Table 6, significant differences are present across the distribution of *VB*

[33] See for example Roychowdhury and Watts (2007) and Beaver and Ryan (2000).

between *HS* and *LS* firms ($p < 0.01$ in all quantiles). In Table 7, significant differences are present across the distribution of *VB* between *HD* and *LD* firms ($p < 0.01$ in all quantiles). In both tables the magnitude of the effect is increasing in the size of *VB*. These results are not consistent with the alternative explanation that empirical results exist because of sorting on different levels of market-to-book.

5.7 Variation in Effect with Size of Intangible Asset Portfolio

For scalability or economic dependence of a firm's intangible assets to have a significant effect on valuation multiples, a firm needs to hold a material amount of intangible assets. The effect of scalability and economic dependence should be increasing in the relative importance of intangible assets to a firm. Table 8 presents estimations of Equations (7) and (8) partitioned by terciles of *SGA_II*, a proxy for the relative importance of intangibles to a firm. Panel A of Table 8 summarizes difference in coefficients and F-tests of significance for each tercile of *SGA_II*. Panel B presents the regression coefficients for the full specification that the information in Panel A is based on. The results in Table 8 are consistent with ex-ante expectations based on H1 and H2. The magnitude of effect increases monotonically across *SGA_II* terciles for both scalability and economic dependence and the lowest level of significance is for the firms where intangible assets are expected to be of the least importance (i.e. the first tercile of *SGA_II*).

5.8 Variation in Asset Specialization

My construct of economic dependence is related to an extensive literature studying asset redeployability and asset specificity or specialization (for a summary see De Vita et al. 2011). As discussed previously. asset specialization does not imply high or low economic dependence. An asset with high or low economic dependence could be characterized as highly specialized or not. Accordingly, valuation multiples should be decreasing in the economic dependence of intangible assets independent of a firm's asset specialization.

To present empirical evidence supporting this assertion, I re-estimate Equation (8) on a sample partitioned by asset specialization. Specifically, I start with the 15 most and least specialized industries as reported by Kim and Kung (2016). This list is developed using data from the Bureau of Economic Analysis capital flow table on tangible asset investment by industry. The Kim and Kung list is based on a concentration measure designed to capture the specialization and liquidity of capital across different industries. I classify Fama French industry groups that contain one or more of the most (least) specialized BEA industries from Kim and Kung (2016) as High (Low) specialization and classify firms from all other industries as Medium specialization. The results of re-estimating Equation (8) on this partitioned sample are shown in Table 9 and are consistent with valuation multiples decreasing in economic dependence across firms in all three partitions of asset specialization.

5.9 Additional Robustness Tests

In Table 10, Panel A I switch to using an enterprise value perspective and show results are robust in models using enterprise value-to-sales and enterprise value-to-gross profit multiples for both my primary sample and for a sample that relaxes the restriction that earnings are positive, which demonstrates empirically how results generalize to a broader set of firms than included in my base sample. Also in Table 10, I show that results are robust to re-estimating Equations (7) and (8) across a variety of additional tests designed to help eliminate alternative explanations. Specifically, in (Panel B) I show that results are robust across different accounting treatment of intangible assets by partitioning the sample before and after the effective dates of FAS 141 and 142 and partitioning based on whether a firm has externally acquired intangible assets recorded on its balance sheet. In (Panel C) I show that results exist across firms at different stages of development by partitioning the sample using firm lifecycle stage. In (Panel D) I show that results are not concentrated in high expected growth firms by partitioning the sample using IBES long term growth estimates.

6. Conclusion

In this study, I examine two sources of heterogeneity in the valuation of intangible assets: scalability and economic dependence. I develop a novel approach to measuring these constructs and find that valuation multiples exhibit associations with proxies for each. Scalability positively impacts the value of a firm's option to extend the use of existing intangible assets and is associated with higher valuation multiples. Economic dependence negatively impacts the value of a firm's option to adapt its intangible assets to a different use and is associated with lower valuation multiples. These results highlight the importance of considering different properties of intangible assets when examining the relation between market prices and accounting information. This study also links intangible asset composition to variation in the distribution of a firm's potential future cash flows, which has potential implications in a wide variety of research topics. Finally, beyond these insights, I hope that the empirical framework for estimating intangible asset composition developed in this study provides researchers a methodology that will prove useful in future intangible asset research.

Looking forward, this study creates a base that can be used to explore the impact of different accounting treatments, disclosure choices, and information environments on the pricing of intangible asset composition. I show that, on average, investors price differences in scalability and economic dependence of a firm's intangible assets. Exploring the factors that impact the efficient pricing of intangible asset composition could provide useful insights to the role of accounting in providing investors value relevant information and could help inform the challenging question of how intangible assets should be accounted for.

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Appendix A: Variable Definitions

ACQUIRED_I	=	Indicator variable set equal to 1 when Compustat variables INTANO or GDWL are <0
AT	=	Compustat variable AT
ATO	=	Compustat variable SALE divided by beginning of period *TBA*
BETA	=	1-year historical beta calculated using daily prices. If 1 year of data is not available, the longest available data stream is used subject to a minimum requirement of 60 historical price observations. Beta's are matched with financial statement datadates using a three month lag convention.
DECLINE	=	Indicator variable set equal to 1 when a firm has either (a) positive cash flows from investing and financing activities but negative cash flows from operating activities, or (b) positive cash flows investing activities but negative cash flows from operating and financing activities. Otherwise the variable equals 0. (Dickinson 2011)
DEPENDENCE	=	See section 4.1 for a detailed discussion of this variable. The base formula is included below, but the calculation of *DEPENDENCE* varies across the three different proxies described in section 4.1; the Intensity, Disclosure and PPA proxies. $HD\ if\!: \frac{Tech_{i,t}}{IA_{i,t}} \leq P_{33}\left(\frac{Tech_{j,t}}{IA_{j,t}}\right)\ \boldsymbol{AND}\ \frac{Mrkt_{i,t}}{IA_{i,t}} \geq P_{67}\left(\frac{Mrkt_{j,t}}{IA_{j,t}}\right)$ $LD\ if\!: \frac{Tech_{i,t}}{IA_{i,t}} \geq P_{66}\left(\frac{Tech_{j,t}}{IA_{j,t}}\right)\ \boldsymbol{AND}\ \frac{Mrkt_{i,t}}{IA_{i,t}} \leq P_{33}\left(\frac{Mrkt_{j,t}}{IA_{j,t}}\right)$ $OD\ otherwise$
GROWTH	=	Indicator variable set equal to 1 when a firm has positive cash flows from operating activities and financing activities but negative cash flows from investing activities. Otherwise the variable equals 0. (Dickinson 2011)
HD	=	Indicator variable for firms with relatively high economic dependence of intangible assets. Set equal to 1 when *DEPENDENCE = "HD"* and 0 otherwise.
HS	=	Indicator variable for firms with relatively high scalability of intangible assets. Set equal to 1 when *SCALABILITY = "HS"* and 0 otherwise.
ID	=	Indicator variable for firms not categorized as either HD or LD. Set equal to 1 when *DEPENDENCE = "indeterminate"* and 0 otherwise.
INTRO	=	Indicator variable set equal to 1 when a firm has negative cash flows from operating activities and investing activities but positive cash flows from financing activities. Otherwise the variable equals 0. (Dickinson 2011)
IS	=	Indicator variable for firms not categorized as either HS or LS. Set equal to 1 when *SCALABILITY = "indeterminate"* and 0 otherwise.
LD	=	Indicator variable for firms with relatively low economic dependence of intangible assets. Set equal to 1 when *DEPENDENCE = "LD"* and 0 otherwise.
LEV	=	Beginning of period *TBA* divided by beginning of period *TBV*
logAT	=	Natural log of Compustat variable AT
LS	=	Indicator variable for firms with relatively low scalability of intangible assets. Set equal to 1 when *SCALABILITY = "LS"* and 0 otherwise.

MATURE = Indicator variable set equal to 1 when a firm has positive cash flows from operating activities but negative cash flows from investing activities and financing activities. Otherwise the variable equals 0. (Dickinson 2011)

PM = Compustat variables IB divided by SALE

SCALABILITY = See section 4.1 for a detailed discussion of this variable. The base formula is included below, but the calculation of *SCALABILITY* varies across the three different proxies described in section 4.1; the Intensity, Disclosure and PPA proxies.

$$HS\ if: \quad \frac{Tech_{i,t} + Mrkt_{i,t}}{IA_{i,t}} \geq P_{67}\left(\frac{Tech_{j,t} + Mrkt_{j,t}}{IA_{j,t}}\right)$$

$$LS\ if: \quad \frac{Tech_{i,t} + Mrkt_{i,t}}{IA_{i,t}} \leq P_{33}\left(\frac{Tech_{j,t} + Mrkt_{j,t}}{IA_{j,t}}\right)$$

$OS\ otherwise$

SHAKEOUT = Indicator variable set equal to 1 when a firm has either (a) positive cash flows from operating, investing and financing activities (b) negative cash flows from operating, investing and financing activities, or (c) positive cash flows from operating and investing activities but negative cash flows from financing activities. Otherwise the variable equals 0. (Dickinson 2011)

SGA_II = Compustat Variables XSGA divided by SALE less IB

TBA = Compustat variables AT less INTANO less GDWL

TBV = Compustat variables CEQ less INTANO less GDWL

T12RET = Aggregation of monthly RET from CRSP msf file: $(1+RET_t)$* $(1+RET_{t-1})$*…* $(1+RET_{t-11}) - 1$. CRSP data is matched with financial statement datadates using a three month lag convention.

VB = CRSP variables (SHROUT*PRC)/1000 divided by beginning of period *TBV*. CRSP data is matched with financial statement datadates using a three month lag convention.

VB_EV = CRSP variables (SHROUT*PRC) /1000 plus Compustat variables DLC and DLTT all divided by beginning of period *TBA*. CRSP data is matched with financial statement datadates using a three month lag convention.

XB = Compustat variable IB divided by beginning of period *TBV*

XB_GP = Compustat variables IB less COGS all divided by beginning of period *TBA*

XB_S = Compustat variable IB divided by beginning of period *TBA*

Appendix B: Intangible Asset Composition by Industry from Purchase Price Allocation Data

FamaFrench48 Industry	#Deals	Technology		Marketing		Customer		Other Contract	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median
Agriculture	19	5%	0%	11%	0%	59%	79%	24%	2%
Food Products	65	1%	0%	40%	34%	39%	36%	20%	2%
Candy & Soda	6	17%	0%	40%	27%	18%	0%	26%	8%
Beer & Liquor	7	0%	0%	68%	91%	2%	0%	30%	9%
Tobacco Products	8	0%	0%	96%	100%	0%	0%	4%	0%
Recreation	19	15%	4%	32%	17%	34%	20%	18%	0%
Entertainment	30	10%	0%	19%	0%	22%	0%	49%	42%
Printing and Publishing	49	9%	0%	21%	8%	46%	46%	23%	3%
Consumer Goods	53	35%	13%	25%	12%	29%	24%	10%	0%
Apparel	67	2%	0%	68%	84%	21%	7%	9%	1%
Healthcare	86	7%	0%	11%	0%	47%	54%	35%	12%
Medical Equipment	203	58%	70%	10%	1%	24%	9%	8%	0%
Pharmaceutical Products	221	59%	81%	8%	0%	19%	0%	15%	0%
Chemicals	90	25%	13%	18%	8%	40%	42%	18%	0%
Rubber and Plastic Products	33	39%	8%	5%	0%	42%	45%	13%	0%
Textiles	8	4%	0%	53%	55%	27%	19%	16%	3%
Construction Materials	63	12%	0%	20%	13%	55%	63%	14%	0%
Construction	38	6%	0%	25%	9%	44%	55%	25%	3%
Steel Works Etc	57	13%	0%	16%	13%	49%	56%	21%	0%
Fabricated Products	5	8%	0%	33%	7%	58%	59%	0%	0%
Machinery	160	17%	4%	23%	14%	48%	51%	12%	0%
Electrical Equipment	101	32%	16%	15%	4%	44%	50%	8%	0%
Automobiles and Trucks	35	8%	0%	25%	19%	48%	57%	19%	2%
Aircraft	24	12%	0%	15%	5%	52%	67%	21%	1%
Shipbuilding, Railroad Equipment	12	17%	0%	24%	23%	46%	47%	13%	3%
Defense	5	45%	16%	16%	0%	39%	27%	0%	0%
Precious Metals	4	0%	0%	5%	0%	83%	100%	13%	0%
Non-Metallic and Industrial Metal Mining	12	1%	0%	7%	0%	22%	0%	69%	96%
Coal	9	0%	0%	3%	0%	49%	72%	48%	18%
Petroleum and Natural Gas	60	5%	0%	6%	0%	64%	93%	25%	1%
Utilities	37	0%	0%	14%	0%	64%	87%	21%	0%
Communication	149	11%	0%	4%	0%	54%	68%	31%	2%
Personal Services	40	4%	0%	24%	11%	37%	21%	36%	21%
Business Services	1,209	32%	22%	8%	2%	46%	45%	13%	0%
Computers	352	48%	48%	6%	0%	39%	35%	7%	0%
Electronic Equipment	402	54%	61%	5%	0%	34%	24%	7%	0%
Measuring and Control Equipment	112	48%	49%	6%	1%	29%	20%	17%	0%
Business Supplies	37	8%	0%	26%	16%	45%	48%	21%	2%
Shipping Containers	23	6%	0%	10%	0%	71%	91%	13%	0%
Transportation	69	1%	0%	9%	0%	64%	86%	26%	4%
Wholesale	161	11%	0%	20%	5%	52%	57%	18%	0%
Retail	144	7%	0%	30%	8%	37%	21%	27%	5%
Restaraunts, Hotels, Motels	47	2%	0%	33%	0%	9%	0%	56%	60%
Banking	356	1%	0%	1%	0%	17%	0%	81%	100%
Insurance	106	4%	0%	6%	0%	41%	34%	49%	38%
Real Estate	21	4%	0%	22%	0%	43%	42%	31%	12%
Trading	349	9%	0%	4%	0%	26%	0%	61%	100%
Other	45	9%	0%	15%	3%	49%	64%	28%	8%
Average		**15%**		**21%**		**40%**		**24%**	

Notes:

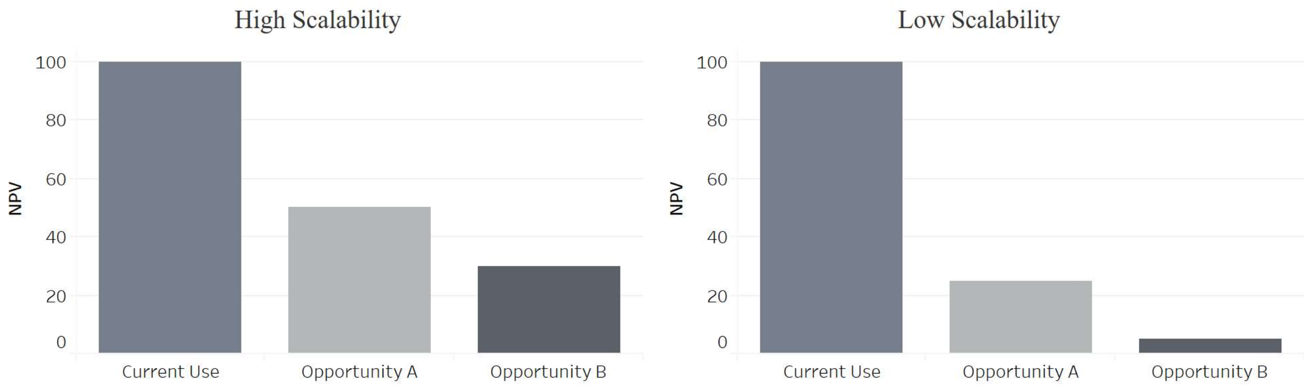
Industries are based on Fama and French (1997). Intanigble asset compositions are calculated using a dataset of 5,208 purchase price allocations from business combinations occurring between 2003 and 2015. This data is collected by Houlihan and Lokey as part of its annual Purchase Price Allocation Study. For an acquisition to be included in the dataset the acquirer must be a U.S. publicly traded company, the ownership percentage acquired needs to be 50% or greater and the acquirer must have disclosed purchase consideration, identifiable intangible asset fair values, and estimated goodwill.

Appendix C: Word List for Disclosure Method

Technology	Marketing	Customer	Other
database	advertising	backlog	advertising contract
mask work	brand	customer	air right
patent	collective mark	customer contract	artistic
r&d	domain name	customer list	ballet
research and	marketing	customer relationship	books
development	service mark	order backlog	broadcast right
secret formula	trade dress	production backlog	compositions
secret process	trade mark		construction contract
secret recipe	trade name		construction permit
software	trademark		contract
technology	tradename		copyright
title plant			drilling right
trade secret			employment contract
unpatented technology			franchise agreement
			lease agreement
			licensing
			literary work
			management contract
			mineral right
			motion picture
			music video
			musical work
			noncompete
			non-compete
			noncompetition
			opera
			operating right
			plays
			route authorities
			royalty
			service contract
			servicing contract
			song lyrics
			standstill agreement
			supply contract
			television program
			timber cutting right
			timber right
			water right

Figure 1:
Impact of Scalability on the NPV of a Firm's Investment Opportunities

Panel A: Scalability impacts the cost of using an asset in an additional investment opportunity



Panel B: Scalability impacts the existing use of the asset when the asset is used in additional investment opportunities

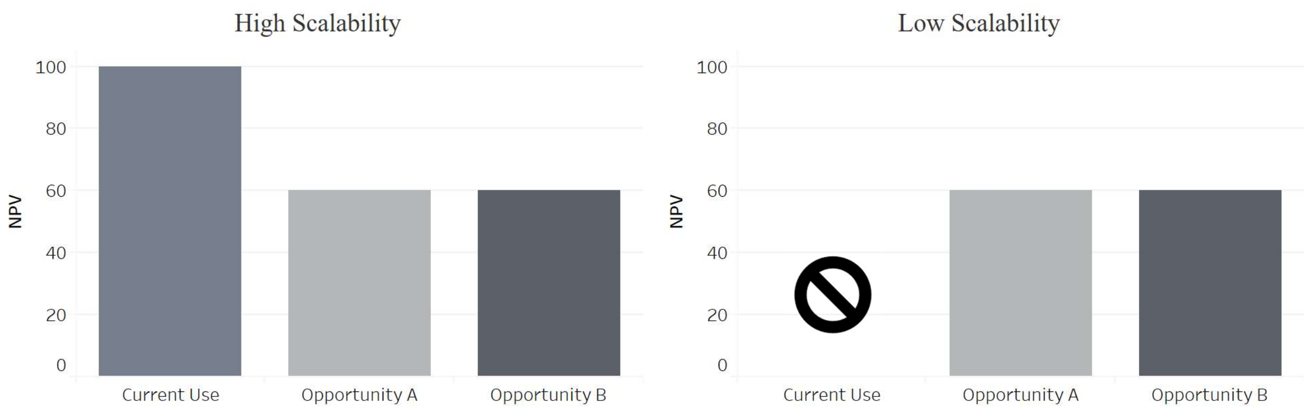
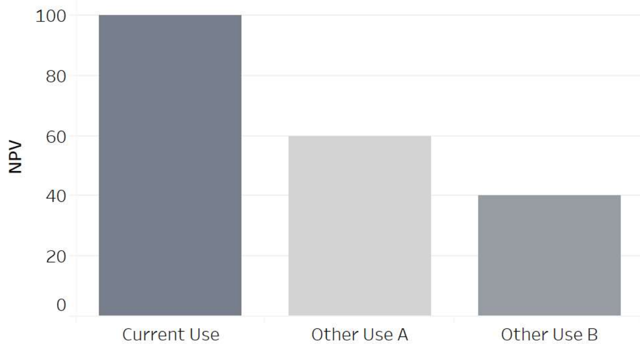


Figure 1 shows two examples of how scalability can impact the net present value ("NPV") of a firm's investment opportunity set. Panel A shows how an intangible asset that has high scalability can be used in additional investment opportunities without having to incur costs to acquire or develop additional units of the intangible asset. For a given opportunity set, this has a positive impact on the NPV of the opportunities for high scalable assets vs. low scalable assets where such additional costs are incurred. Panel B shows how an intangible asset that has high scalability can be used in additional investment opportunities without having to discontinue another beneficial use of the intangible asset whereas an intangible with low scalability requires discontinuation of the current use. For a given opportunity set, this also has a positive impact on the NPV of the opportunities for high scalable assets vs. low scalable assets.

Figure 2:
Impact of Economic Dependence on the NPV of a Firm's Uses of Intangible Assets

Panel A: ***t* = 1** NPV of a firm's uses of intangible asset



Panel B: ***t* = 2** NPV of a firm's uses of intangible asset following a negative shock to a current use

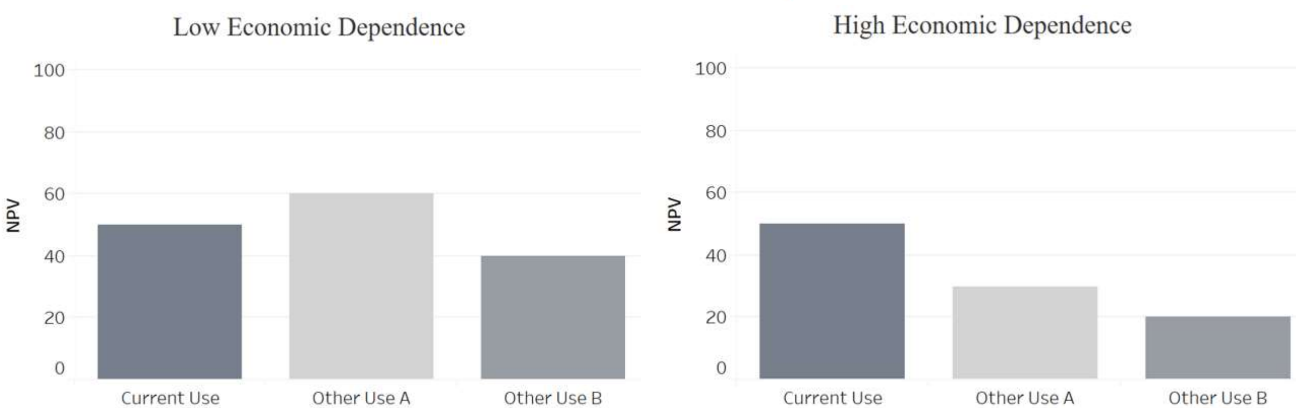


Figure 2 shows a two period example of how economic dependence impacts the NPV of a firm's uses of intangible assets following a negative shock to the *Current Use*. *Other Uses* can include both current and potential future uses. **Panel A** shows the NPV of the firm's uses on an intangible asset. **Panel B** shows the differential impact on NPV that a negative shock to *Current Use* has to *Other Use* for low vs. high economic dependence assets. An intangible asset that has high economic dependence has a higher correlation in NPV between the assets uses. A negative shock to one use of the asset impacts the NPV of other uses more for intangible assets with high economic dependence. In the more extreme cases of high economic dependence (shown in the right figure of Panel B), the NPV of uses is highly correlated and a negative shock to one use impacts the NPV of all uses. In the extreme case of low economic dependence (shown in the left figure of Panel B), the fair value of other uses will be uncorrelated and a negative shock to one use does not impact the NPV of other uses.

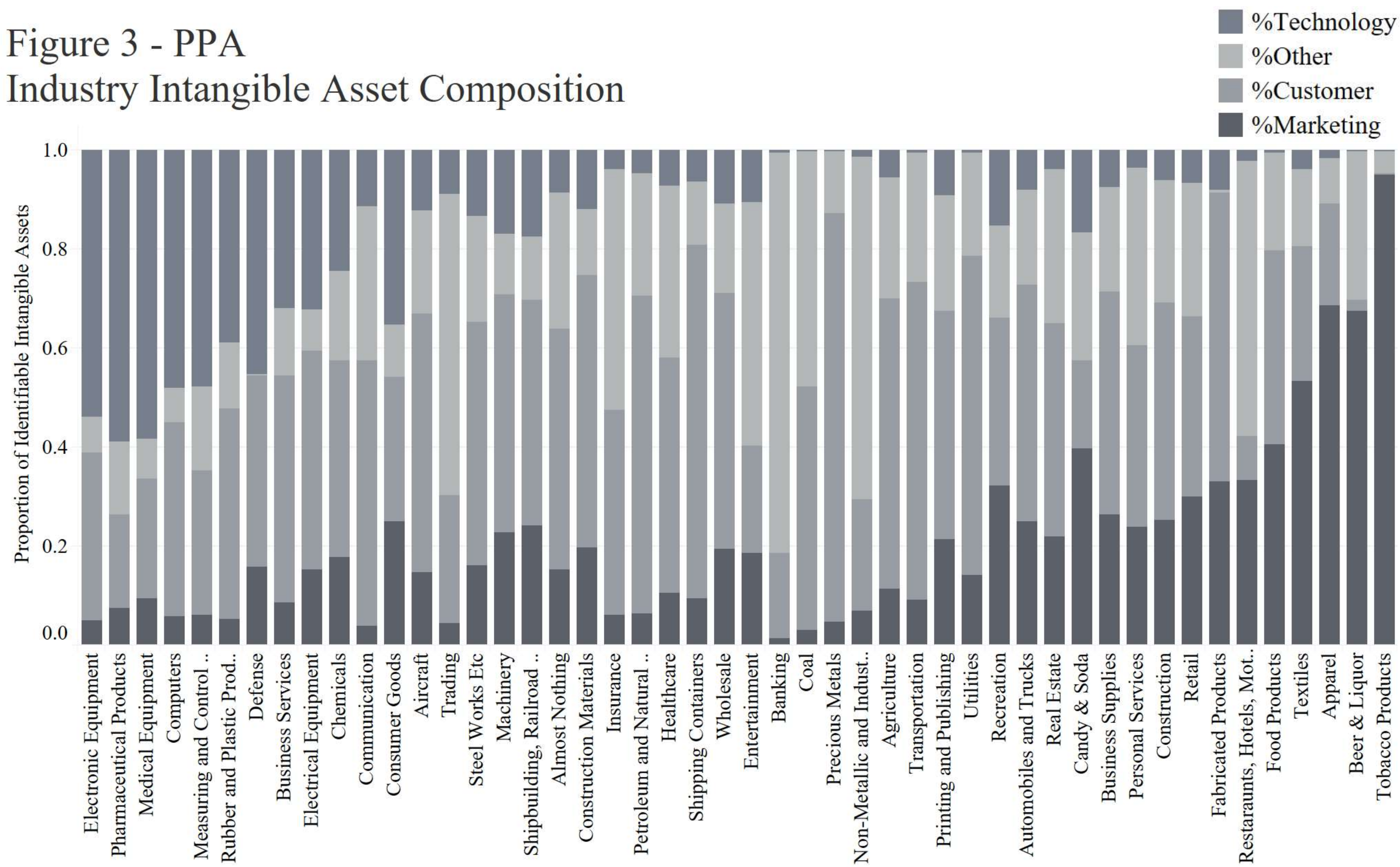


Figure 3 summarizes average intangible asset compositions by industry. Industries are based on Fama and French (1997). Intangible asset compositions are calculated using a dataset of 5,208 purchase price allocations from business combinations occurring between 2003 and 2015. This data is collected by Houlihan and Lokey as part of its annual Purchase Price Allocation study. For an acquisition to be included in the dataset the acquirer must be a U.S. publicly traded company, the ownership percentage acquired needs to be 50% or greater and the acquirer must have disclosed purchase consideration, identifiable intangible asset fair values, and estimate goodwill. A more detailed summary of the Houlihan and Lokey data can be found in Appendix B.

Figure 4 - Disclosure
Frequency of Discussion for Technology vs. Marketing

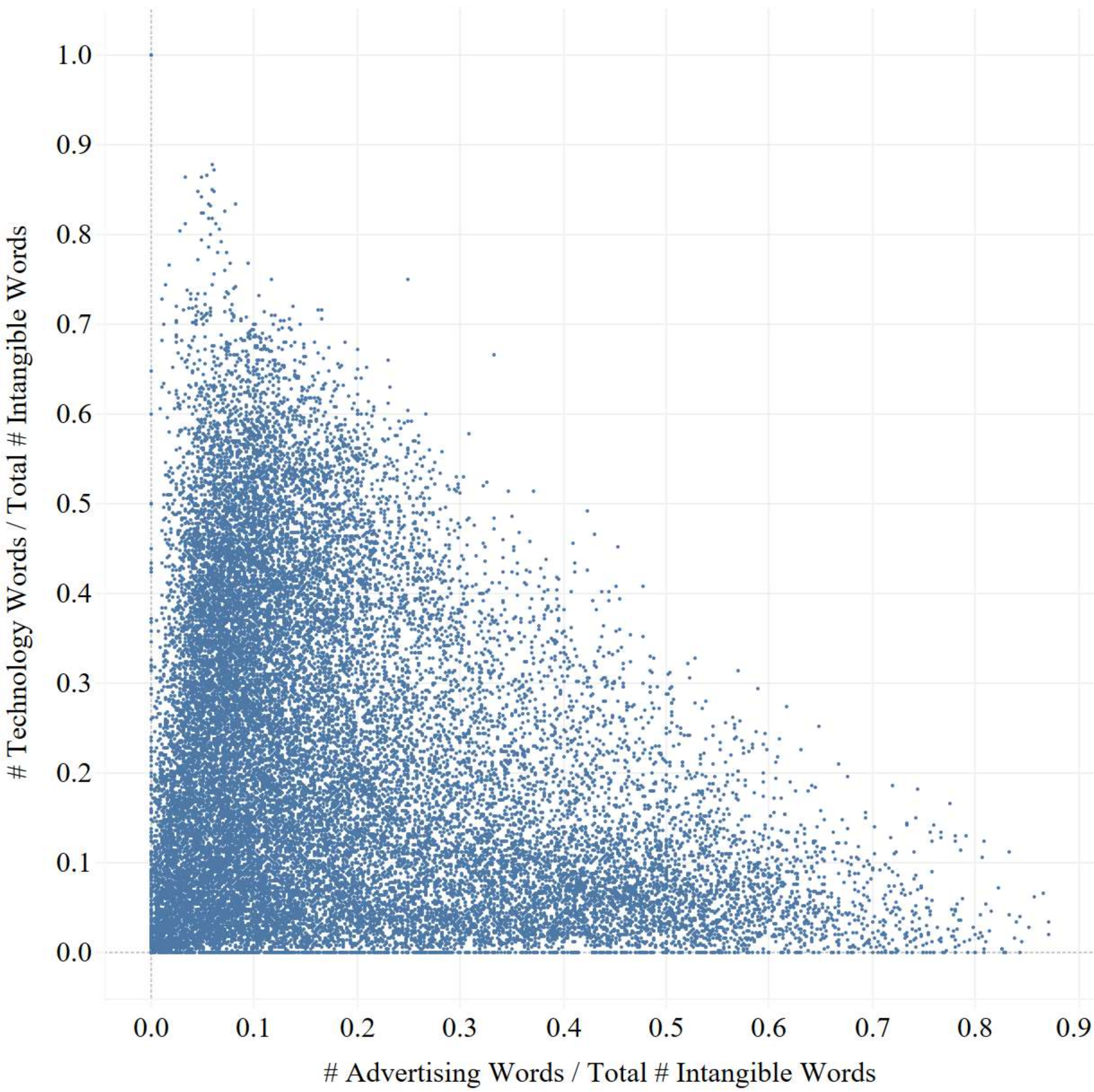


Figure 4 shows a scatter plot summarizing the distribution of technology versus marketing discussion frequency from firms' annual 10-k filings for my sample. The relative frequency of customer and other intangible asset discussion can also be inferred from this figure, where those observation closest to the origin represent firms with the highest proportion of customer and other related discussion. This follows from the identity presented in Equation (2). Discussion frequencies are developed using the master word list summarized in Appendix B.

Figure 5 - Intensity
Proportion of Spending on R&D vs. Advertising

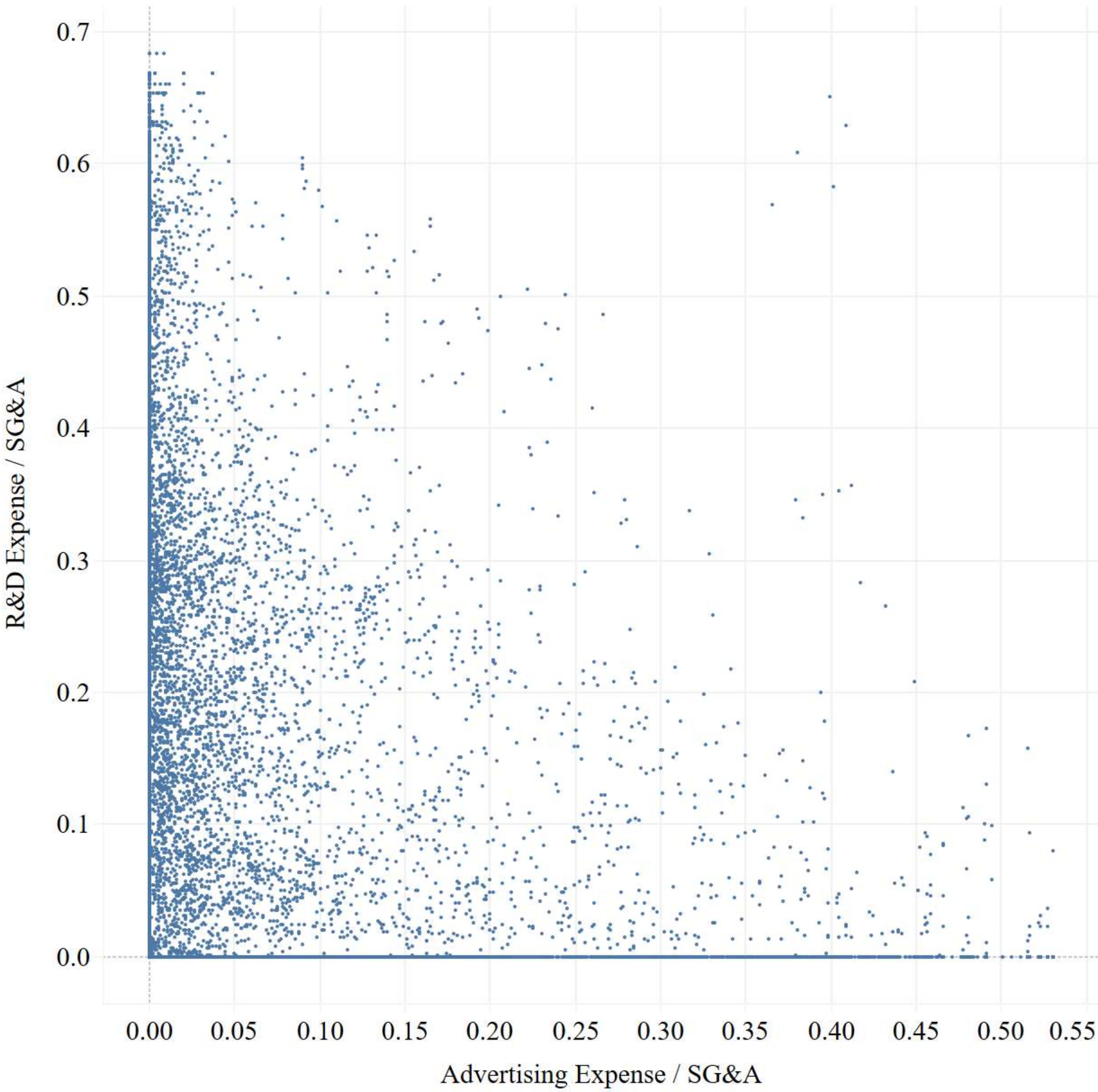


Figure 5 shows a scatter plot summarizing the distribution of R&D versus advertising intensity of investment as a proportion of SG&A. The relative intensity of other SG&A investment can also be inferred from this figure, where those observation closest to the origin represent firms with the highest proportion of non-R&D or advertising investment. This follows from the identity presented in Equation (2). Compustat variables XRD and XAD are used to estimate a firm's investments in R&D and Advertising respectively. Missing observations of XRD and XAD are assumed to equal 0. SG&A expense is estimated using Compustat variable XSGA.

Table 1
Descriptive Statistics

Panel A: Full Sample Descriptive Statistics

	N	Mean	StDev	10%	Median	90%
VB	26,862	4.47	4.14	1.11	3.15	9.59
XB	26,862	0.21	0.17	0.04	0.17	0.43
AT	26,862	2,820	8,781	54	468	5,553
PM	26,862	0.08	0.07	0.01	0.06	0.17
ATO	26,862	1.59	1.00	0.58	1.39	2.84
LEV	26,862	2.52	1.75	1.23	1.96	4.37
BETA	26,862	0.96	0.56	0.23	0.94	1.69
T12RET	26,862	0.20	0.56	(0.35)	0.11	0.80
SGA_II	26,862	0.30	0.22	0.07	0.24	0.63
INTRO	26,862	0.04	0.20	0.00	0.00	0.00
GROWTH	26,862	0.35	0.48	0.00	0.00	1.00
MATURE	26,862	0.52	0.50	0.00	1.00	1.00
SHAKEOUT	26,862	0.08	0.28	0.00	0.00	0.00
DECLINE	26,862	0.01	0.11	0.00	0.00	0.00
ACQUIRED_I	26,862	0.70	0.46	0.00	1.00	1.00

Panel B: Subsample Means Partitioned by SCALABILITY

	HS	LS	IS	Test of diff HS vs. LS
VB	5.39	3.75	4.38	***
XB	0.21	0.20	0.22	
AT	2,882	3,371	2,123	
PM	0.10	0.07	0.06	***
ATO	1.28	1.70	1.78	***
LEV	2.00	2.89	2.60	***
BETA	1.04	0.93	0.90	***
T12RET	0.21	0.20	0.19	
SGA_II	0.42	0.22	0.27	***
INTRO	0.04	0.05	0.04	*
GROWTH	0.38	0.36	0.30	
MATURE	0.46	0.51	0.57	***
SHAKEOUT	0.11	0.07	0.08	***
DECLINE	0.02	0.01	0.01	
ACQUIRED_I	0.72	0.67	0.72	***
Observations	8,433	9,872	8,557	

Table 1 (continued)
Panel C: Subsample Means Partitioned by DEPENDENCE

	HD	LD	ID	Test of diff HD vs. LD
VB	3.84	5.25	3.94	***
XB	0.20	0.21	0.21	
AT	3,004	2,582	2,982	
PM	0.06	0.09	0.07	***
ATO	1.94	1.36	1.63	***
LEV	2.61	2.21	2.84	***
BETA	0.86	1.03	0.94	***
T12RET	0.19	0.21	0.19	**
SGA_II	0.26	0.37	0.23	***
INTRO	0.04	0.04	0.04	
GROWTH	0.29	0.39	0.34	***
MATURE	0.59	0.45	0.54	***
SHAKEOUT	0.07	0.11	0.07	***
DECLINE	0.01	0.02	0.01	
ACQUIRED_I	0.67	0.73	0.69	***
Observations	6,915	11,275	8,672	

Sample include firm-years from 1994 to 2016 with sufficient data in the Compustat and CRSP databases to calculate the variables included in Table 1. Further, I require observations to have positive tangible book value of equity and positive earnings. I require existence of market value of equity data in CRSP as of three months after the fiscal year end. I require that firm-years have the necessary data to calculate beginning of year TBV. I drop financial and utility firms (SIC codes 4900-4999 and 6000-6999) and restrict my focus to firms that trade on the NYSE, AMEX, or NASDAQ exchanges with a CRSP share code of 10 or 11 (common shares) and a price per share greater than $1. Plots of the raw data for these VB and XB revealed extreme outliers. Consistent with Burgstahler and Dichev (1997) I trim the most extreme top and bottom 3% of XB and the extreme top 3% of VB. All variables are defined in Appendix A. Panel A contains descriptive statistics for the entire sample. Panel B presents means for sub samples partitioned by SCALABILITY and Panel C by DEPENDENCE. Panel B and Panel C are based on the Principal Component sample which creates a single proxy capturing the joint correlation across the 3 Proxy Methods (PPA, Disclosure and Intensity). I test whether the High and Low groups of firms have statistically different mean characteristics. ***, **, and * denote significance levels of 1%, 5%, and 10% respectively based on a two tailed t-test for continuous variables and a chi-squared test for indicator variables. Standard errors are clustered by GVKEY.

Table 2

Correlation Across Methods for Estimating Intangible Asset Composition

		Tech			***Mrkt***			***Cust&Other***		
		PPA	Disclosure	Intensity	PPA	Disclosure	Intensity	PPA	Disclosure	Intensity
Tech	*PPA*	1								
	Disclosure	0.63	1							
	Intensity	0.6	0.64	1						
Mrkt	*PPA*	-0.57	-0.4	-0.35	1					
	Disclosure	-0.24	-0.3	-0.28	0.48	1				
	Intensity	-0.16	-0.16	-0.14	0.33	0.48	1			
Cust&Othe	*PPA*	-0.75	-0.44	-0.44	-0.13	-0.1	-0.07	1		
	Disclosure	-0.36	-0.63	-0.34	-0.04	-0.55	-0.25	0.46	1	
	Intensity	-0.47	-0.51	-0.85	0.15	0.01	-0.39	0.45	0.44	1

This table provides correlations across the three different methods used to estimate a firm's intangible asset composition. The three different methods are discussed in detail in Section 4 and are used to estimate composition across the groups of intangible assets identified in Equation 2, specifically, technology (*"Tech"*), marketing (*"Mrkt"*) and Customer + Other (*"Cust&Other"*). The purchase price allocation ("PPA") method uses observable compositions of intangible assets from a large sample of purchase price allocations. The Disclosure method uses textual analysis of firms' annual 10-k filings to identify the relative frequency of intangible asset related words. The Intensity method uses company expenditures on advertising, R&D and other SG&A to estimate the relative intensity of a firm's investments in different types of intangible assets.

Table 3
Primary Tests of Scalability

Panel A: F-Tests of Scalability

	Method			
	PPA	Disclosure	Intensity	PC
Null: $XB_{i,t}*HS_{i,t} = XB_{i,t}*LS_{i,t}$	(1)	(2)	(3)	(4)
Effect Size	3.24***	3.59***	1.96***	3.41***
F-stat	(21.63)	(40.89)	(11.60)	(37.45)

Panel B: Full regression analysis

DV: $VB_{i,t}$		Method			
		PPA	Disclosure	Intensity	PC
IVs:	(0)	(1)	(2)	(3)	(4)
$XB_{i,t}$	13.58***	13.69***	13.12***	13.71***	13.38***
	(39.08)	*(34.34)*	*(29.28)*	*(30.82)*	*(31.19)*
$XB_{i,t}*HS_{i,t}$		0.85	2.13***	0.58	1.88***
		(1.64)	*(4.40)*	*(1.20)*	*(3.71)*
$XB_{i,t}*LS_{i,t}$		-2.39***	-1.46**	-1.38**	-1.53***
		(-3.65)	*(-2.57)*	*(-2.37)*	*(-2.76)*
$HS_{i,t}$		0.01	0.15	0.52***	0.37***
		(0.07)	*(1.51)*	*(4.74)*	*(3.01)*
$LS_{i,t}$		-0.06	-0.07	0.02	-0.31***
		(-0.46)	*(-0.67)*	*(0.18)*	*(-2.73)*
$PM_{i,t}$	-2.55***	-0.96	-2.75***	-2.62***	-2.91***
	(-3.42)	*(-1.30)*	*(-3.83)*	*(-3.60)*	*(-4.03)*
$ATO_{i,t}$	0.07	0.03	0.07	0.12**	0.10**
	(1.38)	*(0.60)*	*(1.36)*	*(2.29)*	*(2.00)*
$LEV_{i,t}$	0.14***	0.15***	0.18***	0.16***	0.17***
	(4.73)	*(4.78)*	*(6.00)*	*(5.31)*	*(5.94)*
$LogAT_{i,t}$	0.09***	0.03	0.08***	0.07***	0.07***
	(4.04)	*(1.26)*	*(3.34)*	*(2.90)*	*(3.07)*
$BETA_{i,t}$	0.99***	0.96***	1.00***	0.94***	0.96***
	(18.05)	*(17.07)*	*(18.55)*	*(17.35)*	*(17.74)*
$T12RET_{i,t}$	1.88***	1.87***	1.88***	1.88***	1.88***
	(28.86)	*(28.23)*	*(29.11)*	*(29.01)*	*(29.02)*
$SGA\_II_{i,t}$	2.28***	3.25***	1.85***	1.96***	1.80***
	(11.08)	*(15.56)*	*(9.11)*	*(9.78)*	*(8.94)*
Observations	26,862	26,862	26,862	26,862	26,862
R^2	0.530	0.504	0.540	0.536	0.540
Industry F.E.	Yes	No	Yes	Yes	Yes
Life Cycle F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes

This table presents results from estimating Equation (7) and provides evidence that a firm's valuation multiples are increasing in the scalability of its intangible assets. Panel A summarizes the magnitude of the difference in coefficients between high and low scalability firms and tests the significance of the difference using a two tailed F-test. Panel B presents the regression coefficients for the full specification that the information in Panel A is based on. F- and t-statistics presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by GVKEY. All variables are defined in Appendix A.

Table 4
Primary Tests of Economic Dependence

Panel A: F-Tests of Economic Dependence

	Method			
	PPA	Disclosure	Intensity	PC
Null: $HD_{i,t} = LD_{i,t}$	(1)	(2)	(3)	(4)
Effect Size	-0.86***	-0.47***	-0.63***	-0.73***
F-stat	*(40.29)*	*(13.31)*	*(23.33)*	*(31.34)*

Panel B: Full Regression Analysis

DV: $VB_{i,t}$

		Method			
		PPA	Disclosure	Intensity	PC
IVs:	(0)	(1)	(2)	(3)	(4)
$XB_{i,t}$	13.58***	13.68***	13.60***	13.60***	13.58***
	(39.08)	*(40.80)*	*(39.14)*	*(39.29)*	*(39.40)*
$HD_{i,t}$		0.44***	-0.30***	-0.37***	-0.50***
		(3.49)	*(-3.37)*	*(-3.67)*	*(-5.15)*
$LD_{i,t}$		1.30***	0.17*	0.26***	0.23**
		(16.03)	*(1.78)*	*(3.02)*	*(2.22)*
$PM_{i,t}$	-2.55***	-2.08***	-2.63***	-2.66***	-2.65***
	(-3.42)	*(-2.99)*	*(-3.54)*	*(-3.58)*	*(-3.60)*
$ATO_{i,t}$	0.07	0.07*	0.07	0.08	0.08
	(1.38)	*(1.72)*	*(1.50)*	*(1.54)*	*(1.58)*
$LEV_{i,t}$	0.14***	0.15***	0.14***	0.14***	0.14***
	(4.73)	*(5.05)*	*(4.77)*	*(4.74)*	*(4.82)*
$LogAT_{i,t}$	0.09***	0.08***	0.09***	0.09***	0.10***
	(4.04)	*(3.45)*	*(4.04)*	*(4.03)*	*(4.14)*
$BETA_{i,t}$	0.99***	0.87***	0.98***	0.98***	0.98***
	(18.05)	*(15.70)*	*(17.78)*	*(17.73)*	*(17.85)*
$T12RET_{i,t}$	1.88***	1.86***	1.88***	1.88***	1.88***
	(28.86)	*(28.50)*	*(28.90)*	*(28.86)*	*(28.94)*
$SGA\_II_{i,t}$	2.28***	2.64***	2.27***	2.29***	2.28***
	(11.08)	*(13.36)*	*(11.05)*	*(11.14)*	*(11.12)*
Observations	26,862	26,862	26,862	26,862	26,862
R^2	0.530	0.516	0.531	0.531	0.532
Industry F.E.	Yes	No	Yes	Yes	Yes
Life Cycle F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes

This table presents results from estimating Equation (8) and provides evidence that a firm's valuation multiples are decreasing in the economic dependence of its intangible assets. Panel A summarizes the magnitude of the difference in coefficients between high and low economic dependence firms and tests the significance of the difference using a two tailed F-test. Panel B presents the regression coefficients for the full specification that the information in Panel A is based on. F- and t-statistics presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by GVKEY. All variables are defined in Appendix A.

Table 5
Simultaneous Tests of Scalability and Economic Dependence

Panel A: F-Tests of Scalability Given Economic Dependence

	Method			
	PPA	Disclosure	Intensity	PC
Null:	(1)	(2)	(3)	(4)
$XB_{i,t}*HS_{i,t} = XB_{i,t}*LS_{i,t}$ | *DEPENDENCE= HD*		4.08**	1.83	4.78***
		(4.35)	(0.14)	(16.03)
$XB_{i,t}*HS_{i,t} = XB_{i,t}*LS_{i,t}$ | *DEPENDENCE= ID*	2.36**	3.44***	2.28***	3.69***
	(4.72)	(32.01)	(10.69)	(7.48)
$XB_{i,t}*HS_{i,t} = XB_{i,t}*LS_{i,t}$ | *DEPENDENCE= LD*				

Panel B: F-Tests of Economic Dependence Given Scalability

	Method			
	PPA	Disclosure	Intensity	PC
Null:	(1)	(2)	(3)	(4)
$HD_{i,t} = LD_{i,t}$ | *SCALABILITY= HS*	-1.33***	-0.52**	-1.03***	-1.25***
	(41.25)	(5.03)	(21.43)	(29.43)
$HD_{i,t} = LD_{i,t}$ | *SCALABILITY= IS*	-0.67***	-0.22	-0.58**	-0.94***
	(9.52)	(1.26)	(6.25)	(23.01)
$HD_{i,t} = LD_{i,t}$ | *SCALABILITY= LS*				

This table presents the effect sizes from a regression including Scalability and Economic Dependence indicator variables to simultaneously test H_1 and H_2. Asterix indicate the significance of a two tailed F-test of the difference between high and low groups as indicated below. F-statistics presented in parentheses.*, **, and *** denote significance levels of 1%, 5%, and 10% respectively.

$$VB_{i,t} = \alpha_0 + \alpha_1 XB_{i,t} + \alpha_2(XB_{i,t} * HS_{i,t}) + \alpha_3(XB_{i,t} * HS_{i,t} * LD_{i,t}) + \alpha_4(XB_{i,t} * HS_{i,t} * HD_{i,t}) + \alpha_5(XB_{i,t} * LS_{i,t}) + \alpha_6(XB_{i,t} * LS_{i,t} * LD_{i,t}) + \alpha_7(XB_{i,t} * LS_{i,t} * HD_{i,t}) + \alpha_8(XB_{i,t} * LD_{i,t}) + \alpha_9(XB_{i,t} * HD_{i,t}) + \alpha_{10} HS_{i,t} + \alpha_{11}(HS_{i,t} * LD_{i,t}) + \alpha_{12}(HS_{i,t} * HD_{i,t}) + \alpha_{13} LS_{i,t} + \alpha_{14}(LS_{i,t} * LD_{i,t}) + \alpha_{15}(LS_{i,t} * HD_{i,t}) + \alpha_{16} LD_{i,t} + \alpha_{17} HD_{i,t} + Z'\beta + \varepsilon$$

If H_1 holds after controlling for differences in economic dependence, I expect the coefficient on *XB* to be significantly larger for *HS* firms compared to *LS* firms. Specifically:

- $(\alpha_2+\alpha_3 > \alpha_5+\alpha_6)$ to test $XB_{i,t}*HS_{i,t} > XB_{i,t}*LS_{i,t}$ | *DEPENDENCE = HD*
- $(\alpha_2 > \alpha_5)$ to test $XB_{i,t}*HS_{i,t} > XB_{i,t}*LS_{i,t}$ | *DEPENDENCE = ID*
- $(\alpha_2+\alpha_4 > \alpha_5+\alpha_7)$ to test $XB_{i,t}*HS_{i,t} > XB_{i,t}*LS_{i,t}$ | *DEPENDENCE = LD*

If H_2 holds after controlling for differences in scalability, I expect the intercept term in to be significantly smaller for *HD* firms compared to *LD* firms. Specifically:

- $(\alpha_{12}+\alpha_{17} < \alpha_{11}+\alpha_{16})$ to test $HD_{i,t} < LD_{i,t}$ | *SCALABILITY = HS*
- $(\alpha_{17} < \alpha_{16})$ to test $HD_{i,t} < LD_{i,t}$ | *SCALABILITY = IS*
- $(\alpha_{15}+\alpha_{17} < \alpha_{14}+\alpha_{16})$ to test $HD_{i,t} < LD_{i,t}$ | *SCALABILITY = LS*

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by GVKEY. All variables are defined in Appendix A.

Table 6
Scalability across the Distribution of Market-to-Book

Panel A: Quantile Regression F-Tests of Scalability

	Market-to-Book Quantile				
	.10	.25	.50	.75	.90
Null: $XB_{i,t}*HS_{i,t}=XB_{i,t}*LS_{i,t}$	(1)	(2)	(3)	(4)	(5)
Effect Size	2.52***	3.87***	3.93***	4.09***	4.64***
F-stat	*(83.00)*	*(163.20)*	*(84.24)*	*(52.54)*	*(28.85)*

Panel B: Full Quantile Regression

DV: $VB_{i,t}$	Market-to-Book Quantile				
	.10	.25	.50	.75	.90
	(1)	(2)	(3)	(4)	(5)
$XB_{i,t}$	7.44***	10.14***	13.70***	16.22***	17.62***
	(22.67)	*(42.40)*	*(54.73)*	*(61.30)*	*(43.41)*
$XB_{i,t}*HS_{i,t}$	0.78**	1.49***	1.57***	2.35***	3.40***
	(2.28)	*(4.54)*	*(4.15)*	*(9.16)*	*(5.17)*
$XB_{i,t}*LS_{i,t}$	-1.74***	-2.38***	-2.36***	-1.74***	-1.24*
	(-4.70)	*(-9.28)*	*(-7.87)*	*(-4.01)*	*(-1.72)*
$HS_{i,t}$	0.16***	0.13**	0.18***	0.28***	0.34***
	(2.84)	*(2.27)*	*(2.91)*	*(3.70)*	*(2.64)*
$LS_{i,t}$	0.06	0.03	-0.05	-0.17***	-0.26**
	(1.33)	*(1.02)*	*(-1.06)*	*(-2.87)*	*(-2.36)*
$PM_{i,t}$	-2.42***	-2.26***	-2.87***	-3.21***	-4.05***
	(-12.39)	*(-8.72)*	*(-9.07)*	*(-9.33)*	*(-5.73)*
$ATO_{i,t}$	-0.02*	-0.02*	-0.01	0.08***	0.20***
	(-1.76)	*(-1.80)*	*(-0.40)*	*(3.70)*	*(4.34)*
$LEV_{i,t}$	-0.03***	0.01	0.07***	0.22***	0.47***
	(-4.45)	*(0.60)*	*(4.06)*	*(9.54)*	*(11.30)*
$LogAT_{i,t}$	0.10***	0.08***	0.07***	0.00	-0.07***
	(17.51)	*(16.30)*	*(7.58)*	*(0.03)*	*(-3.35)*
$BETA_{i,t}$	0.28***	0.39***	0.56***	0.92***	1.32***
	(14.07)	*(18.66)*	*(28.97)*	*(25.65)*	*(21.22)*
$T12RET_{i,t}$	0.60***	0.86***	1.29***	2.02***	2.88***
	(22.98)	*(27.97)*	*(36.04)*	*(39.15)*	*(28.54)*
$SGA\_II_{i,t}$	0.49***	0.68***	1.11***	1.95***	3.57***
	(12.10)	*(16.55)*	*(12.64)*	*(12.85)*	*(9.77)*
Observations	26,862	26,862	26,862	26,862	26,862

This table presents regression coefficients from estimating Equation (7) using quantile regressions with bootstrapped standard errors and presents evidence that the effect of scalability exists across the distribution of Market-to-Book. The t-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by GVKEY. This table uses proxies for scalability based on the principal component method. All variables are defined in Appendix A.

Table 7
Economic Dependence across the Distribution of Market-to-Book

Panel A: Quantile Regression F-Tests of Economic Dependence

	Market-to-Book Quantile				
	.10	.25	.50	.75	.90
Null: $HD_{i,t} = LD_{i,t}$	(1)	(2)	(3)	(4)	(5)
Effect Size	-0.25***	-0.39***	-0.43***	-0.54***	-0.56***
F-stat	*(37.24)*	*(104.20)*	*(77.62)*	*(43.60)*	*(16.32)*

Panel B: Full Quantile Regression
DV: $VB_{i,t}$

	Market-to-Book Quantile				
	.10	.25	.50	.75	.90
	(1)	(2)	(3)	(4)	(5)
$XB_{i,t}$	6.85***	9.76***	13.56***	16.36***	18.20***
	(54.87)	*(53.60)*	*(97.27)*	*(68.29)*	*(45.44)*
$HD_{i,t}$	-0.13***	-0.21***	-0.29***	-0.33***	-0.46***
	(-4.76)	(-7.93)	(-9.18)	(-6.60)	(-3.96)
$LD_{i,t}$	0.12***	0.18***	0.14***	0.21***	0.10
	(2.83)	*(5.08)*	*(3.39)*	*(2.77)*	*(0.80)*
$PM_{i,t}$	-2.08***	-2.25***	-2.89***	-2.88***	-3.49***
	(-10.17)	*(-8.60)*	*(-8.24)*	*(-6.36)*	*(-5.44)*
$ATO_{i,t}$	-0.04**	-0.03	-0.02	0.06***	0.19***
	(-2.48)	*(-1.58)*	*(-1.35)*	*(2.88)*	*(4.34)*
$LEV_{i,t}$	-0.04***	-0.01	0.04***	0.21***	0.43***
	(-4.06)	*(-0.87)*	*(3.14)*	*(8.31)*	*(8.82)*
$LogAT_{i,t}$	0.10***	0.10***	0.09***	0.02*	-0.03*
	(17.54)	*(16.44)*	*(12.40)*	*(1.85)*	*(-1.74)*
$BETA_{i,t}$	0.29***	0.38***	0.56***	0.94***	1.34***
	(14.91)	*(23.96)*	*(24.36)*	*(25.95)*	*(21.88)*
$T12RET_{i,t}$	0.60***	0.84***	1.28***	2.02***	2.88***
	(26.51)	*(28.72)*	*(35.09)*	*(33.69)*	*(31.06)*
$SGA\_II_{i,t}$	0.61***	0.90***	1.42***	2.52***	4.58***
	(11.14)	*(16.51)*	*(24.72)*	*(13.90)*	*(13.37)*
Observations	26,862	26,862	26,862	26,862	26,862

This table presents regression coefficients from estimating Equation (8) using quantile regressions with bootstrapped standard errors and presents evidence that the effect of economic dependence exists across the distribution of Market-to-Book. The t-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by GVKEY. This table uses proxies for economic dependence based on the principal component method. All variables are defined in Appendix A.

Table 8
Intangible Asset Intensity Analysis

Panel A: Intangible Intensity Partitioned Sample Effect Sizes and F-Tests

	Intangible Intensity Tercile		
Null:	Low	Medium	High
	(1)	(2)	(3)
$XB_{i,t}*HS_{i,t} = XB_{i,t}*LS_{i,t}$	1.58	2.07**	2.81***
	(2.33)	*(4.82)*	*(7.14)*
$HD_{i,t} = LD_{i,t}$	-0.48***	-0.92***	-1.06***
	(8.67)	*(22.51)*	*(9.14)*

Panel B: Intangible Intensity Partitioned Sample Full Regressions

DV: $VB_{i,t}$	Intangible Intensity Tercile					
	Low		Medium		High	
IVs:	(1)	(2)	(3)	(4)	(5)	(6)
$XB_{i,t}$	10.04***	10.36***	14.05***	14.41***	14.14***	14.61***
	(16.39)	*(21.67)*	*(22.76)*	*(25.52)*	*(14.87)*	*(20.91)*
$XB_{i,t}*HS_{i,t}$	1.82*		1.70**		0.55	
	(1.86)		*(2.36)*		*(0.61)*	
$XB_{i,t}*LS_{i,t}$	0.24		-0.38		-2.27*	
	(0.33)		*(-0.42)*		*(-1.91)*	
$HD_{i,t}$		-0.48***		-0.60***		-0.46**
		(-4.09)		*(-3.39)*		*(-2.23)*
$LD_{i,t}$		0.01		0.32**		0.59**
		(0.05)		*(2.18)*		*(2.01)*
$HS_{i,t}$	-0.37*		0.19		0.40*	
	(-1.90)		*(1.03)*		*(1.76)*	
$LS_{i,t}$	-0.12		-0.13		-1.00***	
	(-0.86)		*(-0.78)*		*(-3.57)*	
$PM_{i,t}$	-1.73	-1.95*	-2.45**	-2.24*	-3.73***	-4.29***
	(-1.62)	*(-1.87)*	*(-2.01)*	*(-1.79)*	*(-3.03)*	*(-3.41)*
$ATO_{i,t}$	0.22***	0.23***	0.31***	0.31***	0.33**	0.26*
	(3.14)	*(3.24)*	*(3.74)*	*(3.74)*	*(2.53)*	*(1.92)*
$LEV_{i,t}$	0.19***	0.19***	0.18***	0.17***	0.32***	0.26***
	(4.79)	*(4.75)*	*(4.25)*	*(4.06)*	*(4.25)*	*(3.46)*
$LogAT_{i,t}$	0.10***	0.11***	0.12***	0.14***	0.12***	0.12***
	(2.79)	*(3.01)*	*(3.20)*	*(3.74)*	*(3.14)*	*(2.91)*
$BETA_{i,t}$	0.47***	0.45***	0.90***	0.91***	1.35***	1.45***
	(5.73)	*(5.56)*	*(11.15)*	*(11.28)*	*(13.12)*	*(13.97)*
$T12RET_{i,t}$	1.33***	1.33***	1.75***	1.76***	2.40***	2.40***
	(18.01)	*(18.08)*	*(16.14)*	*(16.28)*	*(20.63)*	*(20.51)*
$SGA\_II_{i,t}$	6.34***	6.43***	4.01***	4.99***	0.42	0.24
	(5.03)	*(5.33)*	*(4.39)*	*(5.42)*	*(0.97)*	*(0.53)*
Observations	8,962	8,962	8,953	8,953	8,947	8,947
R^2	0.514	0.516	0.608	0.607	0.537	0.530
Industry, Yr, LC, F.E.	Yes	Yes	Yes	Yes	Yes	Yes

This table presents estimations of Equations (7) and (8) on a sample partitioned by terciles of Intangible Asset Intensity (a proxy for size of a firm's intangible assets). Panel A summarizes difference in coefficients and F-tests of significance for each tercile. Panel B presents the regression coefficients for the full specification that the information in Panel A is based on. F and t-statistics presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by GVKEY. This table uses proxies for scalability and economic dependence based on the principal component method. All variables are defined in Appendix A.

Table 9

Robustness of Effects across Industries with Varying Specialization of Tangible Assets

Panel A: Specialization Partitioned Sample Effect Sizes and F-Tests

	Tangible Asset Specialization		
Null:	Low	Medium	High
	(1)	(2)	(3)
$HD_{i,t} = LD_{i,t}$	-0.67**	-0.59***	-1.09***
	(4.845)	*(12.29)*	*(18.09)*

Panel B: Specialization Partitioned Sample Full Regressions

DV: $VB_{i,t}$	Tangible Asset Specialization		
	Low	Medium	High
IVs:	(1)	(2)	(3)
$XB_{i,t}$	15.62***	13.29***	10.79***
	(19.47)	*(31.43)*	*(14.20)*
$HD_{i,t}$	-0.10	-0.47***	-0.51***
	(-0.54)	*(-3.36)*	*(-2.84)*
$LD_{i,t}$	0.57*	0.12	0.58***
	(1.74)	*(1.02)*	*(2.63)*
$PM_{i,t}$	-7.37***	-1.57	-0.05
	(-4.02)	*(-1.45)*	*(-0.04)*
$ATO_{i,t}$	0.06	0.08	0.21*
	(0.71)	*(1.25)*	*(1.80)*
$LEV_{i,t}$	-0.01	0.18***	0.28***
	(-0.21)	*(4.70)*	*(4.28)*
$LogAT_{i,t}$	0.11*	0.16***	0.02
	(1.89)	*(5.38)*	*(0.41)*
$BETA_{i,t}$	1.34***	0.83***	1.00***
	(9.94)	*(12.06)*	*(9.66)*
$T12RET_{i,t}$	2.27***	1.68***	1.97***
	(13.46)	*(23.14)*	*(14.32)*
$SGA\_II_{i,t}$	3.15***	2.12***	1.64***
	(6.93)	*(7.21)*	*(4.59)*
Observations	5,446	15,855	5,561
R^2	0.514	0.566	0.518
Industry, Yr, LC, F.E.	Yes	Yes	Yes

This table presents estimations of Equation (8) on a sample partitioned based on tangible asset specialization. Specifically, Fama French industry groups that contain one or more of the most (least) specialized BEA industries from Kim and Kung (2016) are classified as High (Low) specialization. Panel A summarizes differences in coefficients and F-tests of significance. Panel B presents the full regression specification that Panel A is based on. F and t-statistics presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by GVKEY. This table uses proxies for scalability and economic dependence based on the principal component method. All variables are defined in Appendix A.

Table 10
Additional Robustness Analyses

Panel A: Alternative Samples and Valuation Multiples

	Base Sample		Sample including Loss Firms	
	EV to Sales	EV to Gross Profit	EV to Sales	EV to Gross Profit
Null:	(1)	(2)	(3)	(4)
$XB\_ALT_{i,t}*HS_{i,t} = XB\_ALT_{i,t}*LS_{i,t}$	0.39***	0.71***	0.36***	0.73***
	(24.74)	*(6.82)*	*(18.95)*	*(8.60)*
$HD_{i,t} = LD_{i,t}$	-0.27***	-0.26***	-0.32***	-0.30***
	(12.66)	*(15.78)*	*(19.51)*	*(21.08)*

Panel B: Across Accounting Regimes and for Internally Developed vs. Externally Acquired

	Pre FAS 141 & 142	Post FAS 141 & 142	No Externally Acquired	Externally Acquired
Null:	(1)	(2)	(3)	(4)
$XB_{i,t}*HS_{i,t} = XB_{i,t}*LS_{i,t}$	3.22***	3.11***	6.36***	2.79***
	(9.95)	*(25.89)*	*(35.99)*	*(19.80)*
$HD_{i,t} = LD_{i,t}$	-0.43**	-0.84***	-0.42**	-0.84***
	(6.25)	*(24.63)*	*(4.93)*	*(27.88)*

Panel C: Across Firm Lifecycle Stages

	Intro & Growth	Mature	Shake Out & Decline
Null:	(1)	(2)	(3)
$XB_{i,t}*HS_{i,t} = XB_{i,t}*LS_{i,t}$	3.90***	3.24***	3.00**
	(22.84)	*(21.33)*	*(5.75)*
$HD_{i,t} = LD_{i,t}$	-0.74***	-0.61***	-0.82***
	(14.68)	*(18.00)*	*(8.17)*

Panel D: Across Terciles of IBES LTG Estimates

	Low LTG	Middle LTG	High LTG
Null:	(1)	(2)	(3)
$XB_{i,t}*HS_{i,t} = XB_{i,t}*LS_{i,t}$	4.02***	2.56**	1.60
	(28.70)	*(5.072)*	*(2.501)*
$HD_{i,t} = LD_{i,t}$	-0.40**	-0.82***	-0.63*
	(6.215)	*(18.28)*	*(3.466)*

This table presents differences in coefficients and F-tests of statistical significance for tests designed to improve generalizability of results and show robustness across a variety of potential alternative explanations. **Panel A** presents results using a model based on enterprise value, sales or gross profit and tangible book value of debt plus equity. Columns (1)&(2) in **Panel A** use the base sample and Columns (3)&(4) relax the restriction that earnings be positive and instead requires positive gross profit, which expands the sample size from 26,862 to 34,720. **Panel B** Columns (1)&(2) show robustness across different accounting regimes for intangible assets (pre/post effective date of FAS 141 and FAS 142) and in Columns (3)&(4) robustness regardless of whether a firm's intangible assets were internally or externally acquired. **Panel C** partitions the sample based on firm lifecycle stages using Dickinson 2011 proxies. **Panel D** partitions the sample using annual terciles of IBES long term growth ("LTG") estimates. **Panel D** also drops observations where LTG estimates are unavailable reducing the sample from 26,862 to 18,915 observations. This table uses proxies for scalability and economic dependence based on the PC method. F statistics are presented in parentheses. *, **, and *** denote significance levels of 1%, 5%, and 10% respectively. Standard errors are clustered by *GVKEY*. All variables are defined in Appendix A.