Innovation Worth Buying:

The Fair-Value of Innovation Benchmarks and Proxies

James Potepa The George Washington University jpotepa@gwu.edu

Kyle Welch The George Washington University kylewelch@gwu.edu

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Abstract

Innovation is notoriously hard to measure. Using a novel data set of the appraised value of itemized firm intangibles, we benchmark the validity of the many innovation proxies used in multiple literatures. This approach more accurately validates and calibrates the economic value of existing measures. We find that trademark counts as well as the market response to new patents are both significant and consistent predictors of innovation. However, our results indicate that three other commonly used proxies—patent count, citation-weighted patent count, and research and development expenditure—are not robust measures for the value of innovation but may capture the value of the advances a firm has already developed. Finally, we find that the appraiser valuations of identified brand innovations and in-process technology are consistent with the market's pricing but that this is not true for developed technological assets.

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E-mail addresses: jpotepa@gwu.edu (J. Potepa); kylewelch@gwu.edu (K. Welch)

1. Introduction

Research has primarily relied on patent counts and citation-weighted patent counts to measure firm-level innovation across accounting, finance, and economic literatures. However, firm innovation may not be correlated with patents. Zingales (2000) argued that "technology firms whose main assets are the key employees, is changing the vary nature of the firm." AirBnb, Uber, and Netflix have transformed markets, yet patents don't defend their core innovations. Moreover, many firms opt to retain trade secrets instead of publicly disclosing discoveries in patents, thus patent measures do not necessarily tell the full story of innovation. This problem is especially concerning given that patent measures are themselves hard to validate and prior studies find conflicting results. We aim to solve this problem by examining the value of common proxies for innovation using a more direct benchmark—the appraised fair value of a firm's intangibles assets.

Using the best tools available, the literature has attempted to validate patents and trademark measures with noisy benchmarks or esoteric settings. These measures include optional self-reported valuation surveys (Harhoff, Narin, Scherer, and Vopel 1998; Harhoff, Scherer, and Vopel 2003; Trajenberg 1990), Tobin's Q, or future performance (Hall, Jaffe, and Trajtenberg 2005; Hirschey and Richardson 2003; Hirschey, Richardson, and Sloan 2001; Hall, Thoma, and Torrisi 2007; Pandit, Wasley, and Zach 2010). One recent paper attempts to validate the use of citation count as a measure of quality using the success of patented strains of hybrid corn (Moser, Ohmstedt, and Rhode 2017). This variation is driven by a lack of precise benchmark values to calibrate the economic value of innovation proxies. This is clearly a significant issue given the conflicting findings about the validity of innovation measures across papers (e.g. Alcacer,

Gittelman, and Sampat 2009; Abrams, Akcigit, and Popadak 2013). We believe the post transaction fair value of itemized intangible assets provides the solution.

Using the fair-value estimates provides a well-identified dependent variable (compared to the above alternatives) to test innovation proxies as it links existing measures to their appraised and audited dollar value across a large sample of firms and industries. Statement of Financial Accounting Standards 141 (SFAS 141) requires acquiring firms to identify an acquisition target's intangible assets after a merger or acquisition, including its developed technology, brands, and goodwill. Third-party experts value intangible assets and then external auditors scrutinize these assessments. Access to confidential information combined with significant experience in assessing intangibles would indicate these third party appraisers produce the most accurate valuations. These valuations have even been used in courts to assess damages in patent infringement cases.¹ Moreover, the use of purchase-price allocation fair values as a benchmark has been well established in the literature (e.g., Kimbrough 2007). These identified intangible assets provide a more precise identification to benchmark the value of innovation proxies than relying on self-reported estimates of value or overly broad and noisy performance measures (e.g., Tobin's Q).

The literature proxies innovation with various independent variables from public data, and earlier work attempts to validate these measures using the dependent variables and methods noted above (e.g., Tobin's Q; patented strains of hybrid corn). The most common independent variables that proxy for innovation in the literature include research and development

¹ Courts have found that "valuations created under SFAS 141 are germane and relevant to damage calculations in IP infringement" (Pursel and Annis 2011). For example, the courts ruled against a firm that over-valued the intangible assets in a license agreement and then subsequently revealed a lower value when the fair value was disclosed as a result of a merger (Integra Lifesciences I Ltd. v. Merck KGaA, 331 F.3d860, 871-72, 66 U.S.P.Q.2d 1865, 1873 (Fed. Cir. 2003), vacated and remanded on other grounds, 545 U.S. 193, 74 U.S.P.Q.2d (BNA) 1801 (2005)). In another case, the plaintiff in a patent infringement lawsuit lost after the patent was revealed to have a no fair value when it was sold after the infringing activity (Spectralytics Inc. v. Cordis Corp., 650 F. Supp. 2d 900, 915 (D. Minn. 2003)).

expenditures (Lev and Sougiannis 1996; Kothari, Laguerre, and Leone 2002; Barron, Byard, Kile, and Riedl 2002), patents (Gu and Wang 2005; Kraft et al. 2017; Li 2016; Faurel et al. 2016), trademarks (Li 2016; Faurel et al. 2016), and the market reaction to patent submissions (Kogan et al. 2017). However, it is not clear that these measures are good proxies of capturing invention, which are the advances already developed, or the wider area of possible future developments of interest to researchers—innovation (Maclaurin 1953).² To illustrate, Qualcomm invented assisted GPS technology in 2004, enabling increased precision and integration of cell phones and GPS. Lyft and Uber exploited this invention, transforming black car and taxi services with ride sharing. We run a number of tests to shed light on whether the various measures are useful proxies for the inventions already developed by the firm, and we also validate whether these measures can capture the innovations beyond inventions that are of strong interest to researchers.

With our novel dependent variable measure, we examine each of the innovation proxies (i.e., R&D expense, patent count, patent citation count, trademarks, and Kogan et al.'s (2017) market response measure) and find that some do indeed significantly predict firm innovation but that others are less consistent and subject to variations. Specifically, the new stock market-derived estimated value of patent holdings of Kogan et al. (2017) as well as trademark counts significantly predict innovation-related intangible assets. We find little evidence patent counts, citation-weighted patent counts, or research and development expenditure relate to innovation-related intangible assets. However, patent and citation-weighted patent counts are relevant measures of a firm's existing technology. Overall, our findings indicate that trademark counts

² Schumpeter (1939) said: "It is entirely immaterial whether an innovation implies scientific novelty or not. Although most innovations can be traced to some conquest in the realm of either theoretical or practical knowledge that has occurred in the immediate or the remote past, there are may which cannot. Innovation is possible without anything we should identify as invention." For a more detailed discussion of the difference between invention and innovation, see Maclaurin (1953) or Bertoni and Tykova (2015).

and the Kogan et al. (2017) patent value measures are the most robust and consistent proxies for innovation.

Our second group of tests compares post-transaction appraisal values and the market's pre-acquisition valuation. Valuation experts and auditors are given greater access and detail about value drivers than external market participants pricing based on incomplete information. In many cases, technological and other advances are not disclosed publicly and, if they are, rarely is information provided at the same level of detail granted to the appraisers and auditors. Despite the challenge of valuing these complex intangibles with incomplete information, our findings indicate the market's valuations of a firm's brand innovation and in-process research and development assets are consistent with the purchase price allocation. However, there is a difference between the market's assessment of a firm's developed technology and the valuation expert's conclusion, suggesting purchase price allocations contain additional information not disclosed to the markets. Moreover, the significant proxies for technological and brand innovation predict the market value of the firm before the acquisition, even after controlling for the fair value of the other assets disclosed in the allocation process. This provides additional support that the relevant proxies we find in earlier analyses are significant and robust predictors of innovation based on the market's assessment as well as that of third-party valuation experts.

Interpretation of our results is subject to a number of limitations. First, our sample is limited to firms that are acquired, which may differ from the wider population of companies. However, it does seem likely that innovation would be a key significant factor in an acquirer's purchase decision. Second, the patent measures explored may be problematic, given time-related issues driven by the differences in patent submission dates and skews in patent numbers. For example, our benchmarking sample could bias against measures requiring more time, like

citation-weighted patent counts. We strive to reduce this effect by using a citation-weighed patent measure that controls for time since submission, following Kogan et al. (2017). We also take the natural log of patent and trademark counts to ensure a few large observations do not drive the results. Third, our measure of innovation includes goodwill, which could include assets associated with innovation (e.g. human capital assets) also encompass unidentifiable value unrelated to innovations (e.g. synergies or overpayment). Synergies are unlikely to relate to innovation, as their value is, by definition, specific to the union of two firms. A fourth limitation is that we effectively scale the proxies by firm size, using the weighted least-squares specification, to ensure our findings are not driven by a small number of larger firms. However, we would like to capture whether these proxies can inform us about the value of innovation overall. Thus, we rerun the analysis with an unscaled ordinary least-squares regression. This leads to qualitatively similar results.

Overall, our paper makes three main contributions. First, we provide a cleaner setting in which to identify and benchmark the value of innovation proxies by focusing on the fair values of intangible assets. This approach allows us to find compelling evidence about the suitable proxies for measuring innovation. This topic has become increasingly important across literatures, despite the lack of clear guidance on how to measure innovation. Our results show that the new measure proposed by Kogan et al. (2017) and trademark counts are the only proxies that significantly and consistently predict the value of innovation; the Kogan et al. (2017) measure is the strongest predictor of value across total and itemized asset values, including brand assets. Second, we find no compelling evidence that three commonly used proxies—patent count, patent citation count, and research and development expenditure—relate consistently and significantly to innovation, but they do capture the technological inventions already developed

by a firm. Third, we show evidence that the market generally prices invention and innovation in a manner consistent with third-party valuation experts: there is no significant difference in the respective assessments of brand intangibles and in-process research and development, though there is a significant difference between their assessments of developed technology. This result is not entirely surprising, given the information asymmetry between valuation experts and the market for many technological advances and the complicated nature of valuing these assets

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 articulates our hypotheses and research design. Section 4 explains our sample selection, and section 5 describes the data. Section 6 presents our results, and section 7 provides additional analyses. Section 8 concludes.

2. Literature Review

Understanding and measuring innovation has attracted widespread interest, including from management scientists, economists, lawyers, and managers. In accounting and finance, researchers have focused on whether innovation is properly impounded in prices and forecasts by market participants and information intermediaries as well as whether firms encourage innovation through compensation. Economics, using patent data, has studied how regulatory policy has impacted innovation.

The Search for Innovation Proxies

Simple patent measures, like patent counts or citation-weighted patent counts, have several limitations and research finds conflicting evidence about the use of citations as a measure of value (Alcacer, Gittelman, and Sampat 2009; Abrams, Akcigit, and Popadak 2013). Firms may instead rely on keeping their inventions hidden under the Uniform Trade Secrets Act of

1985. Trademarks represent an innovation measure much less covered in the literature, yet they have potential to capture innovation distinct from patents (Li 2016; Faurel et al. 2016; Sander and Block 2011). If a product or service is unique enough, trademarks enable a firm to protect the innovations deployed in delivering the product or service. Yet trademarks have significant variation in value. For example, the Naked Chicken Chalupa trademark owned by Taco Bell likely is a different type of advancement than the Android trademark that Google provides with its free operating system software. Overall, it is not entirely evident when, or even if, patent and trademark measures are sufficient proxies for the value of a firm's current inventions, much less its innovative ability.

Research in accounting examines whether users of accounting information understand the value of innovation. This is an important concept, as Christensen (1997) notes that managers themselves have difficulty evaluating innovations that will transform their industries. Extending this research, Christensen et al. (2003) document that the most threatening innovations to a firm are frequently overlooked and undervalued by market participants, due to a focus on the traditional measures of performance. Early accounting papers examined research and development expenditures to explore whether the market and information intermediaries correctly value innovations. Lev and Sougiannis (1995) find that a measure of capitalized research and development is value relevant to investors. However, investors do not fully incorporate this information, given that there is a continuing relationship between capitalized research and development costs and future returns. Also, analysts will use more private information when a firm has a relatively high amount of intangible assets, but this still leads to greater analyst forecast errors, compared to low intangible-asset firms (Barron et al. 2002). More recent papers use patent and trademark data to explore whether incentives can drive innovation

and whether information intermediaries properly understand innovation's value. Li (2016) reexamines the role of analysts, showing that they properly account for long-term innovation in stock price but underreact to the influence of short-term brand-related innovation. Compensation committees are shown to support innovation by adjusting risk incentives in CEO compensation (Faurel et al. 2016).

The finance literature has adopted the use of patents as a proxy for innovation as well. He and Tian (2013) claim that analyst coverage hinders innovation. They argue that innovation, proxied by patents and citations, is negatively impacted by short-term pressure from analysts to meet or beat earnings expectations. Another paper examines whether executive compensation can incentivize top management to encourage innovation at their firms (Baranchuk et al. 2014). These authors find that longer-term stock option grants to executives are associated with increased innovation, which they define as future patent counts. Finally, overconfident CEOs lead to greater innovation as proxied by patents but only in certain industries, according to Hirshleifer, Low, and Teoh (2012).

The economics literature has attempted, with mixed results, to prove the value of patents and citations. One group of papers focuses on validating citations as a measure of patent value. Most of these papers rely on a survey asking participants to value their patents, given that no objective third-party valuation of patents was publicly available (Harhoff et al. 1998; Harhoff et al. 2003; Trajenberg 1990). While the owners of patents may be familiar with their intangible assets, it is unclear that they are qualified to value them. The approach is also subject to selfselection biases, as the data is generated from an optional survey. Moser et al. (2017) attempt to examine the performance of patents to understand the role of citations. They argue that the variety of patents for hybrids of corn offer a way to test whether the performance of each type is associated with citations. They find corn-hybrid yields are associated with citations of those hybrids. There are two limitations with their approach. First, it is not necessarily generalizable beyond patents for corn hybrids. Second, the performance of the patent is not necessarily correlated with the value of the patent, given the costs and demands for this product are not discussed. Thus it is not clear how useful that patents, citations, and trademarks are as proxies for innovation. These papers cannot—and do not claim to—validate whether patent counts or citations inform about overall innovation. The most concerning issues is that these methodologies led to findings contradicting the validity of the patent citation measure (Alcacer, Gittelman, and Sampat 2009; Abrams, Akcigit, and Popadak 2013). In addition to issues noted above, Tabakovic and Wollmann (2017) that show patent examiners grant significantly more patents to their future employers.

To deal with the issues of both patent count and citation-weighted patent measures, a new proxy has emerged that values patents using the abnormal stock market reaction to new patent filings. Kogan et al. (2017) use this measure in sample covering multiple decades and find that it is associated with growth, reallocation, and creative destruction to a much greater extent than citation-weighted patent counts.

Validating Innovation Proxies with Benchmarks

In the search for the best proxies for innovation, a major problem also emerges from the lack of well-identified measures of innovation value to use as dependent variables to validate the various measures. Research relies on whether patent data is associated with a general measure future firm performance, most typically future operating performance or Tobin's Q (Hall et al. 2005; Hirschey and Richardson 2003; Hirschey et al. 2001; Hall et al. 2007; Pandit et al. 2010). Tobin's Q is basically a market-to-book ratio. Thus market mispricing, possibly driven by

information asymmetry, may prove problematic as a numerator.³ Also, accounting does not fully value internally generated intangibles, which may lead to the mispricing of book assets and thus limit proper identification. As an alternative to Tobin's Q, accounting-based operating performance measures have also been used. However, this approach is constrained by the number of periods that can be observed. For example, Pandit et al. (2010) can only examine future performance over the next five years. The time restrictions on this methodology mean it is difficult to capture the value of innovation for the long term, which is where most of it likely resides. While all of these papers attempt to control for other factors driving performance, there are many predictors of Tobin's Q and future performance that are difficult to capture and include in these works. Firm age, growth through acquisition, and changes in strategy can all drive the results but may be unrelated to innovation.

Compared to the literature, our innovative approach allows for the most direct test between the proxies for and the value of innovation. We are the first researchers to test whether the measures used for innovation relate to the overall value of innovations from audited appraisal values. Our setting is the only one that allows for a market transaction and third-party valuation experts to specifically value these intangible assets. Given we know the total value of innovation, we can directly test these proxies.

FASB 141 Purchase Price Allocations

Our approach requires the detailed disclosure of the fair value of assets purchased by an acquirer after a merger or acquisition. SFAS 141 required all acquiring firms to provide in the footnotes of their financial statements the allocation of assets purchased as a result of a business

³ As mentioned earlier, firms may keep certain advances secret to maximize long-term profitability (i.e., proprietary costs are too high). Thus using a market that only has access to incomplete information may bias the results. This is especially concerning given our analysis shows the market does not price the technologies already developed by a firm in the same manner as valuation experts that are given more complete access to information about its advances.

combination. This regulatory change also eliminated the pooling option. Thus there should be no concern about accounting treatment choice leading to self-selection issues. While it is relatively simple to value many tangible assets, it is more challenging for intangibles. Thus patented technologies, trademarks, and other intangibles are all typically valued by third-party consultants. These experts specialize in the valuation of these resources and have significant reputational concerns; thus they have sufficient skill and the right incentives to value intangibles accurately.

Purchase price allocations required by SFAS 141 have been used as benchmarks in prior literature. Kimbrough (2007) uses the allocation data as a benchmark to ascertain whether the market misprices R&D capital. More recently, a paper has examined the market pricing of customer-related intangibles using this data (Liang and Yeung 2016). Its authors find that the market does not fully incorporate the manager's private information about these assets. We build on this literature, using asset allocations as a benchmark, but apply the approach to innovation measures.

3. Hypothesis Development and Research Design

We examine two research questions. First, are proxies used to measure innovation valid? Second, do investors properly impound the value of innovation, given their limited information compared to the fuller disclosure made to the actuary and auditors?

Given mixed results in the literature on innovation proxies discussed earlier, we examine how well existing proxies identify innovation value. Fair value estimates of a firm's intangible assets come from the post-transaction purchase price allocation from a public acquirer's 10-K. We extract fair value estimates of a firm's innovations from the asset allocation provided after the company is purchased by a U.S.-based public acquirer.⁴ An example of a fair value asset allocation from a firm in our sample is provided in Appendix B. Under the Financial Accounting Standards Board's Statement of Financial Accounting Standards 141, the acquirer must disclose the fair market value of all identifiable assets acquired from a target, including intangible assets. The most common types of intangibles are developed technologies, brand, customer relationships, backlogs, noncompete agreements, and goodwill. These act as a benchmark against which we can test various proxies.

Among the intangibles are assets that represent a firm's innovations. We argue that the firm's developed technologies, in-process research and development, brand, and goodwill capture innovation. Developed technologies and in-process research and development are broad categories of any technological advances owned by the firm.⁵ Given there are certain innovations that would not be considered technological but still represent the output of the firm's advances, we also consider the value of the firm's brands. As mentioned earlier, Uber has no patentable assets preventing ride-sharing competition. According to our conversations with valuation experts, Uber's innovation in redefining the taxi industry would be captured by the value of developed technology (which includes unpatented core technology), brand, and goodwill. Given these three types of intangibles encompass the already developed innovations of a firm, to capture those innovations anticipated, we also include the goodwill associated with the transaction because this captures future advances that will not be valued directly by the accounting system but are valuable according to a market transaction.

⁴ Our sample is exclusively comprised of firms that have been purchased. While these firms may have different characteristics from the overall population of firms, they are also likely to have innovations that make them a valuable target. Furthermore, we believe the third-party expert verification of technological and brand innovation value provides a significant benefit that outweighs the cost of the limited sample.

⁵ During the earlier part of our sample, in-process research and development is considered the assets associated with research and development that has no future use. Given these may simply represent noise during certain periods, we rerun the analysis removing in-process research and development from the definition of our dependent variable, innovation intangibles. The results are qualitatively similar.

Innovation thus represents the sum of the advances already developed, which we refer to as inventions, as well as the future value that can be generated by the advances a firm is expected to produce. While our hypotheses will focus on the broader question of innovation, we will perform additional analyses to provide insights into a firm's current inventions as well. Based on prior research, we test whether five common innovation proxies have some relationship with innovation: research and development expense, patent count, citation-weighted patent count, market response to patent filing (Kogan et al. 2017), and trademark count. The literature is unclear about the proper measure to use, and several papers use only one or two proxies. The most recent paper in the literature uses the market reaction to a firm's various patent submissions to value the patent stock of the firm (Kogan et al. 2017), so we consider this measure, too, as it seems to perform well in their paper. These measures may not be valid: few firms have patents, and there may be too much noise since there is significant variation in the value of certain patents. We also consider a proxy used previously, research and development expenditure. Research and development expense clearly shows the input into the creation of innovation, though its relationship with the output is not clear. This leads to our first four hypotheses, stated in the alternative.

H1: Research and development expenditure is positively related to the fair value of innovation.

H2: Patent count is positively related to the fair value of innovation.

H3: Citation weighted patent count is positively related to the fair value of innovation.H4: Market response to patent is positively related to the fair value of innovation.

The above measures above all aim to capture inventions, which may or may not become innovations. Firms can produce other meaningful advances not be captured by these four proxies. Notably, brand innovation not only encompasses the value of creating of a useful name, picture, sound, or other identifying feature, but it also it encapsulates value that is likely not patentable. For example, in the 1980s, software was not well protected or patentable, yet Microsoft created considerable value then. Currently, algorithms that might improve driverless technology (something of interest to multiple companies) are patentable but hard to discover and prosecute, as algorithms are hidden within encrypted software products. Uber does not have patents to protect it from ride-sharing competition, but its brand captures part of the value it has created from innovations that improve its services. Based on prior research, we test whether trademark counts may be associated with innovation (e.g., Faurel et al. 2016). This leads to our fifth hypothesis, stated in the alternative.

H5: Trademarks are positively related to the fair value of innovation.

To test the above hypotheses, we rely on the fair value asset allocation provided after a target is acquired. The fair values are a required disclosure for any material merger or acquisition, and accounting rules mandate an expert third-party appraisal of the acquired assets. After the valuation is performed, it will also be evaluated and audited by specialty groups within accounting firms that focus on appraisal consulting and auditing. Thus the valuations include a qualified estimation and verified assumptions from an objective third party. The disclosure provides the fair value of a target firm's intangibles, potentially including both technological and brand innovations if they are identifiable.

We use the fair value of relevant intangibles from the allocation as the dependent variables in a weighted least-squares regression with the market value of the target 40 days before the acquisition announcement determining the weight. This approach is typical for the literature evaluating allocation data and effectively scales by the size of the target. For more

detail on this methodology, see Easton and Sommers (2003) or Kimbrough (2007). This method ensures that we control for size and that the larger firms do not drive the significance of our coefficients.⁶ The independent variables are the various proxies used in the literature as well as relevant control variables.

For our analyses, we use the monetary value of innovation from the fair-value asset allocation process as the dependent variable. We define innovation-related intangibles (*InnovIntangible*) as the sum of developed technology (*DevTech*), in-process research and development (*IPRD*), the value of brand (*Brand*), and goodwill (*Goodwill*). This comprises all the developed technological and brand-related advances of a target (*DevTech*, *IPRD*, and *Brand*) as well as an estimate of future innovations (*Goodwill*). This is not capturing R&D expenditure but the outputs from investing in the discovery of technology. The independent variables are the various proxies for innovation.

First, we consider research and development cost, *R&DExp*, as the sum of research and development expensed over the prior five years.⁷ We then investigate whether research and development expenditure is associated with innovation as shown in equation (1):

InnovIntangible =
$$\alpha + \beta R \& DExp + \gamma Controls + \varepsilon.$$
 (1)

A positive and significant coefficient on *R&DExp* would indicate this is a valid proxy and provide sufficient reason to reject the null of hypothesis 1. Second, we consider whether the number of patents held by the target, *PatentCount*, is associated with its technological innovation as shown in equation (2):

⁶ In untabulated tests, we rerun the analysis using an ordinary least-squares specification and find qualitatively similar results.

⁷ Given R&D expenditure is not well populated in Compustat, we rerun the analysis with SG&A costs as an alternative proxy. This measure is much noisier, but there are significantly more nonzero observations. In untabulated results, we find qualitatively similar results to R&D expenditure.

PatentCount is defined as the natural log of one plus the number of patents, applied for and granted, held by the target firm according to the U.S. patent office database. The log transformation helps counteract the extreme skew in the raw patent count. A significant coefficient on *PatentCount* would indicate that this is a valid proxy and provide sufficient evidence to reject the null of hypothesis 2. Third, we examine whether innovation is associated with citation-weighted patent counts, *PatentCiteCount*, as shown in equation (3):

$$InnovIntangible = \alpha + \beta PatentCiteCount + \gamma Controls + \varepsilon.$$
(3)

This variable is taken from the Kogan et al. (2017) patent data set and adjusts the citation weights, relative to all the citations in the year of a patent's submission, to control for truncation issues. This would be a valid proxy and allow us to reject the null of hypothesis 3 if the coefficient on *PatentCiteCount* is positive and significant. We consider an alternative measure, the value of patent stock as determined by the stock market reaction from the day before to the day after a patent submission for each of a firm's patents. Kogan et al. provide evidence this may be a useful measure of value creation and destruction. Therefore we test whether innovation is associated with the market's assessment of patent value, *PatentMktResp*, as shown in equation (4):

$$InnovIntangible = \alpha + \beta PatentMktResp + \gamma Controls + \varepsilon.$$
(4)

A positive and significant coefficient on *PatentMktResp* would indicate this is a valid proxy and provide sufficient support to reject the null of hypothesis 4.

To test hypotheses 5, we use a specification similar to one used to test the first four hypotheses but with trademark count as the independent variable. Trademark count, *TrademarkCount*, represents the natural log of one plus the number of trademarks held by the target at the time of the acquisition. As before, we use a weighted least-squares regression with the weight determined by the target firm's market value 40 days prior to the announcement of the acquisition. We then test whether trademark count is associated with brand innovation, as shown in equation 5:

InnovIntangible =
$$\alpha + \beta$$
 TrademarkCount + γ Controls + ε . (5)

A positive and significant coefficient on *Trademarks* would support its use as proxy for innovation and provide sufficient evidence to reject the null of hypothesis 5.

We take several steps to ensure our results are robust. We include additional controls in our main analysis to mitigate any concern that omitted correlated variables drive our results. As an additional control for size, we include the value of tangible assets, *TangibleAssets*. Innovation is unlikely to be found in the firm's tangible assets, so this acts as a useful measure of firm size. We also include industry fixed effects based on GICS sector codes and year fixed effects based on the acquisition effective date in certain specifications.⁸ From interviews with valuation experts at both major intangible-asset appraisal firms and three of the four main audit firms, we learned that including IPRD, developed technology, brand, and goodwill would capture innovation. However, we also consider the total appraised value of intangibles to remove

⁸ Alternative industry definitions lead to qualitatively similar results for our significant proxies. Both trademark count and the estimated value of patents are robust and consistent measures of innovation.

uncertainty by replicating the entire analysis with total intangibles, *Intangibles*, as the dependent variable.⁹

We also consider whether the measures are capable of predicting the inventions already developed by the firm and more generally if they are realistic by examining which proxies can predict a given type of intangibles. Specifically, we investigate whether the appropriate proxies can predict the current inventions measured by the firm's already developed technologies and brand value. We expect certain patent-related measures or possible research and development expenditure to predict technology-related intangibles but only trademarks to predict brand related inventions. We also expect that these measures are not be associated with in-process research and development costs, given that these assets are written off as valueless. Finally, we anticipate the strongest proxies for innovation overall should also significantly predict goodwill, which represents only future inventions.

For our final analysis, we examine whether the market prices innovation with limited information by examining the target's market value prior to the acquisition. Innovation is likely associated with significant profits, so stock market participants should be interested in factoring this into their analyses. However, innovation is a challenging to measure, which should be clear from the numerous conflicting papers about its proxies. Also, the market has less access to information than an acquirer. Valuation experts are provided full access to information about the company's innovations and motivations about the acquisitions. The literature finds that innovations are not properly incorporated into prices or forecasts (e.g., Li 2016; He and Tian 2013). Thus it is not clear whether investors can properly infer innovation value with limited

⁹ While firms may encourage the misclassification of certain intangible assets, it would impossible to claim an intangible asset is tangible given its lack of physical substance.

disclosure. Our setting allows us to test whether the market's assessment of the firm displays any bias, compared to the asset allocation. This leads to our final hypothesis, stated in the alternative.

H6: Market prices do not reflect the private information used to value of technological and brand assets.

To test the hypothesis above, we compare the market value of the target firm four weeks before the announcement of the acquisition to the fair value asset allocation. We use a similar approach to the prior analysis with a weighted least-squares regression with the dependent variable defined as the market value of the firm 40 days before the announcement of the acquisition, *TgtMktValue*. The weight is determined by the dependent variable, the market value of the target. This methodology controls for scaling and is consistent with prior research (Easton and Sommers 2003; Kimbrough 2007; Liang and Yeung 2016). The independent variables are the various assets of the target firm, as provided in the allocation disclosure. The exact specification is shown in equation 6 below.

$$TgtMktValue = \alpha + \beta_1 DevTech + \beta_2 IPRD + \beta_3 Brand + \beta_4 CR + \beta_5 NonCompete + \beta_6 OtherIntangibles + \beta_7 TangibleAssets + \beta_8 Goodwill + (6)$$

$$\gamma FixedEffects + \varepsilon.$$

The independent variables represent a disaggregation of all the assets acquired in the transaction. Developed technologies, *DevTech*, is the value of any acquired technologies. In-process research and development, *IPRD*, represents research and development assets and expenses. *Brand* refers to the value of the brand-related intangibles. Customer-related intangibles, *CR*, represents the firm's customer relationships and customer lists. *OtherIntangibles* is a catchall category for nonphysical assets that cannot be grouped with other types of intangibles (e.g., noncompete agreements). *TangibleAssets* is the value of any physical assets purchased. Finally, *Goodwill* represents the purchase price less any tangible and identifiable intangible assets. We also include industry and year fixed effects. If the coefficient on *DevTech* or *Brand* is significantly different from 1, this would indicate mispricing of innovation and would be sufficient evidence to reject the null of hypothesis 6.

4. Sample Selection

The initial sample is based on all transactions reported by the Securities Database Corporation (SDC) mergers and acquisition database from July 1, 2001, to Dec. 31, 2010. The beginning of the sample is limited by the introduction of SFAS 141, which required firms to disclose the fair value estimates of various types of acquired assets. The research design also requires publicly traded U.S. acquirers as well as targets. This ensures there is a mandatory disclosure of this information on the part of all acquirers and that there will be a market value for the target company. Finally, the acquirer is required to purchase 100 percent of the target's equity, and the time between the announcement and effective date of the merger must be within one year.

We then examine an acquiring firm's annual and quarterly reports to hand-collect the asset allocation information required as a result of the business combination. We use the first disclosure of the allocation following the effective date.¹⁰ This leads to a sample of 708 firms. We then merge the data with Compustat and CRSP. Finally, we match the target firms with patent and trademark data. Patent data used is from Kogan et al. (2017). Their publicly available data set ends in 2010, thus limiting the end date for our sample period. The trademarks are hand-

¹⁰ For 90% of the data, this is the first post-acquisition quarterly filing.

collected from the U.S. Patent and Trademark Office's Trademark Electronic Search System (TESS) online database.

Purchase Price Allocation Valuation Process

Our approach relies on the allocation of asset values post-acquisition completed by third party experts. Note that in our conversations with the two largest intangible asset appraisers (Duff & Phelps and Houlihan Lokey) as well as the valuation consulting groups of three of the four biggest audit firms, no one indicated the proxies used in the literature motivate their valuation process. In other words, appraisers do not incorporate weighted patent-citation counts, the most common innovation proxy in research, in any part of their valuations. Each right or claim is examined and valued individually along with other nonpublic innovations.

These consultants use many methodologies, including the income, market, and cost approaches. Each approach is determined uniquely by the characteristics of a target firm and valuation situations. The experts meet with the employees of the target and acquirer, at multiple levels, to discuss the relevant intangibles and value drivers. Appraisers use the income approach in valuing patented technology in what is called the relief-from-royalty method. This method is a hybrid of income and market approaches. If comparable intellectual property transactions have happened, a relative valuation would be used in what is called a market approach. An income approach might be used after an analysis of firm profits and excess earnings that is tied to the intellectual property. Finally, appraisers might simply use the cost approach to value intellectual property. The cost approach is very rarely used to estimate the value of patented technology and is most frequently used as a lower bound of valuation estimations (Benoit and Cauthorn 2006). Regulatory bodies, such as the Internal Revenue Service (IRS), the FASB and the SEC, have

identified these valuation methodologies. These definitions of value have been used in court cases measuring patent damages, IRS revenue rulings, and FASB statements. Thus they represent a consistent, objective approach to valuing the innovations across firms.

5. Descriptive Statistics

Detailed descriptive statistics for our sample are provided in Table 1. The sample is comprised of firms that are targets in an acquisition with a purchase price, *PurchasePrice*, which has a mean of \$1.7 billion and a median of \$329 million. Based on the allocation provided by the acquirer, the targets have mostly tangible assets. *TangibleAssets* is \$1.3 billion on average and \$260 million at the median. *Goodwill* is also substantial at \$898 million on average and \$155 million at the median. *Innovation-related intangibles, <i>InnovIntangible*, are \$1.355 billion on average at \$211 million at the median. Developed technologies, *DevTech*, are also significant at \$55 million, but the median firm reports \$0. Similarly, in-process research and development, *IPRD*, averages \$40 million but has a median of \$0. Finally, brand-related intangibles, *Brand*, averages \$25 million, but the median firm reports \$0. Overall, intangibles represent a significant portion of the assets of the average firm, but many targets appear to have no specific intangible assets. However, well over 80% of targets own at least one type of intangible asset.

Most firms in the sample hold trademarks, but patents are relatively uncommon. About 30 percent of the companies in the sample have patents, leading to a mean of 4.2 and median of $0.^{11}$ After the log transformation, this leads to an average patent count measure of 0.55. Similarly, the mean number of average citations is 10.15, but the median is 0. Trademarks are much more common with about 80 percent of firms holding at least one. Trademarks have a

¹¹ "Patent trolls" hold portfolios of patents and are notorious for litigating aggressively to protect them. Patent trolls have outsized reputations and are rare in general. We confirm that none of the targets in our sample would be considered patent trolls, and thus trolls would not impact our results.

mean of 20 and median of 7. After the log transformation, this leads to an average trademark count measure of 2.05. Finally, most firms in the sample do not have research and development expenses, leading to a mean of \$8.5 million and median of \$0.

The correlations reveal a significant association between many of the proxies for innovation and the value of intangibles provided in the asset allocation disclosure (Table 2). All the patent measures are significantly and positively associated with developed technologies, *DevTech*, and in-process research and development, *IPRD*, according to both the Spearman and Pearson correlations. Similarly, trademarks are significantly and positively associated with brand innovation, *Brand*, according to both types of correlations. There is also no significant relationship between research and development expenditure and either type of innovation, according to the Pearson correlations.¹²

6. Results

We find that each of the proxies used in prior research is valid to measures at least certain types of advances already developed by firms but that just two measures can consistently and significantly proxy for innovation. Only the estimated value of patents of Kogan et al. (2017) and trademark count represent significant and robust predictors of innovation across all specifications. Patent count and citation-weighted patent count have some predictive ability, but it is not robust to the inclusion of any controls or fixed effects. The second column of Table 3, Panel A, shows that research and development expenditure also has some explanatory power after all the controls are included, however, it is not significant across all specifications. Patent counts are positively but not significantly related to the innovation, as shown in column 4 (coef=23.59 and p-

¹² The significant correlations among some of the dependent variables may lead to econometric issues. Therefore we test for multicollinearity issues, but the variance inflation factors (VIF) for all the relevant variables are below 5.

value=0.258). Citation-weighted patent counts also do not consistently predict innovation, as shown by the positive but insignificant coefficient in column 6 (coef=0.85 and p-value=0.136). Citation weighting may simply not be sufficient to reduce the noise created by the significant differences in the value of various patents. The only robust patent-based measure is based on the value of patent stocks determined by the stock market, as used by Kogan et al. (2017). As shown in column 8, this measure is a positive and significant predictor of innovation (coef=0.99 and p-value=0.000). In addition, its R-squared of 10.9% for the univariate regression means it alone explains a substantial amount of the variation in innovation values, five times more than the R-squared of the next best measures. Finally, column 10 shows trademarks are positively and significantly associated with innovation (coef=18.08 and p-value=0.015).

We then rerun the tests using total intangibles, *Intangibles*, as the dependent variable in the unlikely event there is shifting between different categories and report the findings in Table 3, Panel B. The results are qualitatively similar to the findings for the full sample, except there is a barely significant coefficient on citation-weighted patent count in column 6. We would interpret this finding with caution, given this significance is not robust to alternative industry fixed effect definitions or specifications. Overall, there is significant reason to reject the null of H4 and H5, and thus we can affirm that the estimated value of a firm's patent stock as well as a count of its trademarks are valid proxies for innovation. There is not sufficient support to reject the null of H1, H2, or H3, given R&D expenditure, patent count, and citation-weighted patent count are not consistently significant measures.

We repeat our analysis on the various types intangibles, which should check that our findings as realistic and allow us to ascertain which proxies can predict inventions already developed as opposed to future innovations. To ensure our results make sense, we examine

whether the measures explain the anticipated types of intangibles. First, we examine which measures predict the technology a firm has already developed, DevTech. We expect patent- and research and development-based measures to be most closely tied to developed technology, and thus we anticipate they will be relevant. The results displayed in Table 4, Panel A, indicate all three patent based measures as well as research and development expenditure are good predictors of technological value. These results indicate that these various patent measures are useful in valuing the technology already invented by the firm but not necessarily future innovations (which would be valued in goodwill). Trademarks cannot predict developed technologies, as shown in column 5. We then examine whether these proxies can predict in-process research and development. This should represent the inventions of the firm that have no value, and thus valid proxies should not relate to this type of intangible. The results shown in Table 4, Panel B, are consistent with our expectation. Patent count is marginally significant, indicating IPR&D is noisy measure and may pick up valueless patents. Finally, we rerun the analysis using the intangible asset *Brand* as the dependent variable. The results shown in Table 5 indicate that trademark count is a robust proxy for brand innovations but research and development expenditure is not. Interestingly, the market response to patent value is a significant predictor, indicating that brand and technology assets may be tied together capturing innovation. Overall, this indicates that most of the measures can capture the value of advances the firm has already made and that our data leads to sensible results.

Next we compare whether the proxies can predict innovations, which is represented by the amount of goodwill associated with a transaction. Goodwill measures the amount over the market value of identifiable assets recognized by the accounting system an acquirer is willing to pay for a target. Not all assets that matter to innovations are explicitly identified (e.g., human

capital assets), but they all are grouped into goodwill. Thus goodwill represents the value of synergies and the potential future innovations that a target will develop.¹³ We expect robust proxies should be able to predict the level of goodwill. The results shown in Table 6 are consistent with earlier findings. The coefficients on *PatentMktResp* and *TrademarkCount* are significant and positive, but the remaining patent-based measures are not. There is also some evidence that research and development expenditure is a useful proxy, though it is not robust to other specifications, unlike the other regression measures.

To address our final hypothesis, we examine whether there are differences in the pricing of either technological or brand innovation between the market and valuation experts. Specifically, we compare the market value of the target four weeks prior to the acquisition to the fair value of assets disclosed by the acquirer. As shown in column 1 of Table 7, acquired technology, *DevTech*, is positive and significant (coef=0.74 and p-value=0.000). However, the coefficient is significantly different from one, which indicates that valuation experts do not agree with the market's assessment (F test p-value=0.018). Brand innovation, *Brand*, is positively and significantly associated with the market value of the firm (coef=0.72 and p-value=0.000).¹⁴ Critically, the coefficient is not significantly different from one (F test p-value=0.141). Note, too, that the in-process research and development written off as part of the acquisition has no value, according to the market (coef=0.07 and p-value=0.390). Overall, coefficients that are significantly different from one provide sufficient support to reject the null of hypothesis 6 that the market valuation of brand includes similar access to information used in appraisals.

¹³ Given synergies are specific to the acquirer-target pair, the inclusion of the values created by the joining of two firms should not bias our results, as the noise should not be correlated with innovation.

¹⁴ While the coefficients on *Brand* and *DevTech* are similar in magnitude, the standard error for *DevTech* is significantly higher. Statistically, this higher standard error leads to the significant difference between the coefficient of 0.74 and 1.

We then consider whether our proxies predict the way the market values innovation. We replace the assets related to innovation (*DevTech, IPRD, Brand,* and *Goodwill*) with the patent and trademark proxies but control for the fair value of all other assets. We find that patent count (coef=1.96 and p-value=0.056) and citation-weighted patent count (coef=0.77 and p-value=0.044) both positively predict market value but are not as strong as the estimated value of the patent (coef=0.64 and p-value=0.000). This is even more clear when the measures are included together, which eliminates the significance of all but the estimated patent value and trademark measures, as shown in column 7. Trademarks are also a significant predictor of the market's value of innovation (coef=0.69 and p-value=0.020). Overall, the proxies that we cannot consistently validate using the allocation values are similarly insignificant predictors of the market valuation of such innovation-related intangibles. This indicates that market and fair value allocation assessment both support the use of the market reaction-based value of patent holdings and trademark count as proxies for innovation.

7. Additional Analysis

To ensure our results are robust, we perform a number of additional analyses. Some of the measures we examine have zeros for a significant number of observations; this is especially true of research and development costs. Therefore we rerun the research and development proxy using a three-year as opposed to five-year lagged window. We also consider selling, general, and administrative expense as another potential, but noisy, measure of research and development costs because it is better populated by Compustat. When we rerun the analyses with any of these changes, the untabulated results are qualitatively similar to the main analysis. We consider potential econometric issues associated with our specification as well. The main concern is multicollinearity. This may be an issue given significant correlations among the independent variables. To ensure this does not drive our results, we examine the variance inflation factors (VIF) for each of the coefficients. The lack of VIFs over 5 indicates that multicollinearity is not a concern.

8. Conclusion

Scholars in numerous fields have expressed a desire for valid proxies for innovation. Using a novel and more direct approach, we use accounting disclosures to provide compelling evidence that some, but not all, existing proxies consistently measure a firm's innovation value. Our results indicate the value of patent stocks and trademark counts consistently predict a firm's innovation value. However, other popular proxies, notably patent count or citation-weighted patent count as well as research and development expenditure, are useful but only to measure the advances a firm has already made.

Our analysis also reveals that the market seems to be fully informed about some intangible assets but about others. Brand-related intangibles, along with certain other intangibles, seem to directly match the market's valuation. This result is surprising given the challenge of valuing such a complex construct. However, the market seems to underprice developed technology relative to valuation experts, which may be driven by information asymmetry. We then provide evidence that significant proxies from the earlier analysis can predict the market valuation of the technological and brand innovation but insignificant proxies cannot.

We believe that our validation tests extend the growing academic literature on innovation, which already spans accounting, economics, finance, law, and many other fields. Innovation leads to significant value creation, and possibly destruction, making it a critical topic not just for academics but the world. From Apple's redemption, because of the now ubiquitous iPhone, to Uber's rapid rise at the expense of traditional taxis, innovation makes a significant impact all around us. We want to ensure academics have the right tools to explore this topic and believe our findings represent a critical validation of innovation proxies.

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Appendix A: Variable Definitions

Variable Name	Definition
Patent & Trademarks	
PatentCount	Natural log of 1 plus the number of patents submitted prior to acquisition by target firm and granted, from Kogan et al. (2017).
PatentCiteCount	Citation-weighted patent count from Kogan et al. (2017). Weight of citations varies depending on number of citations for patents granted the same year.
PatentMktResp	Market value of patent derived from three-day abnormal return around patent filing from Kogan et al. (2017).
TrademarkCount	Natural log of 1 plus the number of trademarks registered by the target firm at the time of acquisition.
R&DExp	Natural log of 1 plus the sum of research and development expense of the target firm over the past five years.
Purchase Allocation	
PurchasePrice	Consideration paid to target shareholders (in millions of \$).
TangibleAssets	Sum of the acquirer's fair value estimates of the target's net tangible assets (in millions of \$).
DevTech	Sum of the acquirer's fair value estimates of the target's developed technology-related intangibles (in millions of \$).
IPRD	Sum of the acquirer's fair value estimates of the target's in-process research and development (in millions of \$).
Brand	Sum of the acquirer's fair value estimates of the target's brand related intangibles (in millions of \$).
CR	Sum of the acquirer's fair value estimates of the target's customer- related intangibles (in millions of \$).
OtherIntangibles	Sum of the acquirer's fair value estimates of the target's intangibles that are not categorized as <i>DevTech</i> , <i>IPRD</i> , <i>Brand</i> , or <i>CR</i> (in millions of \$).
Goodwill	Purchase price above the fair value of the net tangible and intangible assets (in millions of \$).
%Goodwill	Goodwill ÷ PurchasePrice
Intangibles	Sum of DevTech, IPRD, Brand, CR, NonCompete, OtherIntangibles, and Goodwill (in millions of \$).
InnovIntangibles	Sum of <i>DevTech</i> , <i>IPRD</i> , <i>Brand</i> , and <i>Goodwill</i> (in millions of \$).
Other	
TgtMktValue	Market value of the target four weeks prior to the announcement of the business combination.

Appendix B: Examples of Asset Allocations

Deluxe Corporation's Purchase of NEBS Inc.

The preliminary purchase price allocation resulted in goodwill of \$445.5 million. We believe that the NEBS acquisition resulted in the recognition of goodwill primarily because of its industry position, the potential to introduce products across multiple channels, and the ability to realize cost synergies. The following illustrates our preliminary allocation of the purchase price to the assets acquired and liabilities assumed (dollars in thousands).

Cash and cash equivalents	\$	14.681
Trade accounts receivable	•	71,563
Inventories and supplies		41,729
Deferred income taxes		21,370
Other current assets		14,732
Long-term investments		2,974
Property, plant, and equipment		54,816
Assets held for sale		2,208
Intangibles		333,883
Goodwill		445,450
Other noncurrent assets		8,420
Accounts payable		(34,729)
Accrued liabilities		(81,963)
Long-term debt due within one year		(10,417)
Long-term debt		(155,203)
Deferred income taxes		(86,902)
Other noncurrent liabilities		(3,012)
Total purchase price	\$	639,600

Our preliminary allocation of the purchase price to the assets acquired and liabilities assumed resulted in the recognition of the following intangible assets (dollars in thousands):

	A	Amount	Weighted-average Amortization period
Indefinite lives:			•
Trade names	\$	151,200	
Amortizable intangibles:			
Customer lists		103,900	6.3 years
Distributor contracts		30,900	9.0 years
Internal-use software		25,483	3.6 years
Trade names		16,100	5.0 years
Bank referral agreements		6,300	11.0 years
Total amortizable intangibles		182,683	6.5 years
Total intangible assets acquired	\$	333,883	

Appendix C: Comparison of a Traditional Validation Approach (Pre-Acquisition) and the Use of Fair Value Asset Allocations (Post-Acquisition)



Table 1: Descriptive Statistics

	N	Mean	25 th Pct	Median	75 th Pct	Std Dev
Proxies						
R&DExp	708	8.54	0	0	0	49.11
PatentCount	708	0.55	0	0	0.70	0.93
PatentCiteCount	708	10.15	0	0	3.64	70.57
PatentMktResp	708	70.68	0	0	2.90	576.29
TrademarkCount	708	2.05	1.10	2.07	3.00	1.37
Purchase Allocation						
PurchasePrice	708	1,727.26	106.98	329.40	1,276.29	4,622.48
TangibleAssets	708	1,326.41	80.80	260.28	1,003.00	3,527.54
DevTech	708	54.60	0	0	18.25	208.22
IPRD	708	40.44	0	0	50	189.15
Brand	708	25.46	0	0	1.47	96.47
CR	708	115.55	0	7.79	42.09	354.21
OtherIntangibles	708	215.35	0	0	1.73	855.73
Goodwill	708	898.35	39.12	154.56	633.12	2,314.44
Intangibles	708	1,355.13	63.14	210.86	989.97	3,047.19
InnovIntangibles	708	1,134.00	52.97	193.33	827.42	3,124.79
_						
Other						
TgtMktValue	708	1,210.33	60.55	208.43	824.82	3,616.56

The descriptive statistics apply to the full sample of firms with asset allocations. *PatentCount*, *PatentCiteCount*, and *TrademarkCount* are counts. All other variables are in millions of dollars. All variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

Table 2: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1) PatentCount	-	0.98***	0.96***	0.17***	0.41***	0.23***	0.26***	0.26***	0.48^{***}	0.47^{***}	0.23***	0.18^{***}	0.18***
2) PatentCiteCount	0.89***	-	0.96***	0.18***	0.41***	0.23***	0.26***	0.27***	0.52***	0.48^{***}	0.25***	0.19***	0.19***
3) PatentMktResp	0.49***	0.42***	-	0.17***	0.41***	0.31***	0.34***	0.35***	0.50^{***}	0.49***	0.25***	0.27^{***}	0.27^{***}
4) R&D Exp	0.05	0.04	-0.00	-	0.15***	0.01	0.02	0.02	0.14***	0.02	0.13***	0.01	-0.03
5) TrademarkCount	0.18***	0.16***	0.24***	0.06	-	0.29***	0.34***	0.31***	0.27^{***}	0.16***	0.25***	0.87^{***}	0.96***
6) PurchasePrice	0.26***	0.21***	0.52***	0.01	0.37***	-	0.93***	0.91***	0.18***	0.16***	0.25***	0.87^{***}	0.97^{***}
7) Intangible	0.25***	0.20^{***}	0.57^{***}	0.01	0.41***	0.94***	-	0.98***	0.26***	0.22***	0.31***	0.94***	0.88^{***}
8) InnovIntangibles	0.26***	0.20^{***}	0.56***	0.01	0.32***	0.95***	0.97^{***}	-	0.27^{***}	0.24***	0.29***	0.96***	0.86***
9) DevTech	0.41***	0.38***	0.58^{***}	0.10***	0.22***	0.43***	0.50^{***}	0.51***	-	0.54***	0.42***	0.19***	0.13***
10) IPRD	0.17***	0.13***	0.33***	-0.02	0.13***	0.27***	0.30***	0.33***	0.42***	-	0.09^{*}	0.11**	0.15***
11) Brand	0.26***	0.21***	0.47^{***}	0.06^*	0.30***	0.39***	0.45***	0.44***	0.40^{***}	0.15***	-	0.26***	0.20^{***}
12) Goodwill	0.22***	0.17***	0.48***	0.01	0.28***	0.91***	0.92***	0.93***	0.35***	0.22***	0.34***	-	0.84***
13) TangibleAssets	0.23***	0.18***	0.42***	-0.00	0.28***	0.97***	0.88***	0.92***	0.34***	0.34***	0.32***	0.89***	-

The correlation table is for all firms in the sample. The correlation coefficients above the diagonal are Spearman correlations, and the coefficients below the diagonal are Pearson correlations. All variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. Significance levels of 1%, 5%, and 10% are represented by ***, **, and *, respectively.

Table 3: Proxies for Innovation

Panel A

		Dependent Variable: Innovation Related Intangibles (InnovIntangible)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R&DExp	0.69 (0.128)	0.40 (0.216)								
PatentCount			83.75 ^{***} (0.000)	23.59 (0.258)						
PatentCiteCount					4.43 ^{***} (0.000)	0.85 (0.136)				
PatentMktResp							2.45 ^{***} (0.000)	0.99^{***} (0.000)		
TrademarkCount									48.27 ^{***} (0.000)	18.08 ^{**} (0.015)
TangibleAssets		0.70^{***} (0.000)		0.69^{***} (0.000)		0.69^{***} (0.000)		0.66^{***} (0.000)		0.71 ^{***} (0.000)
Constant	202.68 ^{***} (0.000)	23.53 (0.910)	172.86 ^{***} (0.000)	1.41 (0.955)	$184.87^{***} \\ (0.000)$	7.87 (0.970)	216.21 ^{***} (0.000)	40.67 (0.842)	94.14 *** (0.000)	-36.98 (0.846)
Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Ν	708	708	708	708	708	708	708	708	708	708
Adj R-Squared	0.02%	67.81%	1.68%	68.02%	3.16%	67.76%	10.85%	69.90%	2.35%	67.78%

The analysis above is based on the full sample of firms. The weighted least-squares regression is run with innovation-related intangibles, *InnovIntangible*, as the dependent variable. All variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. Significance levels of 1%, 5%, and 10% are represented by ***, **, and *, respectively.

Table 3: Proxies for Innovation

Panel B

			D	ependent V	ariable: Tota	1 Intangibles	s (Intangible	s)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R&DExp	0.79 (0.150)	0.49 (0.204)								
PatentCount			109.93 ^{***} (0.000)	28.52 (0.239)						
PatentCiteCount					5.54 ^{***} (0.000)	1.29 [*] (0.096)				
PatentMktResp							3.45 ^{***} (0.000)	1.65^{***} (0.000)		
TrademarkCount									65.57 ^{***} (0.000)	26.67^{**} (0.075)
TangibleAssets		0.87^{***} (0.000)		0.84^{***} (0.000)		0.84^{***} (0.000)		0.80^{***} (0.000)		0.85 ^{***} (0.000)
Constant	239.01 ^{***} (0.000)	-10.87 (0.936)	197.61 ^{***} (0.000)	-42.40 (0.864)	$ \begin{array}{c} 184.87^{***} \\ (0.000) \end{array} $	-36.11 (0.878)	251.72 ^{***} (0.000)	5.33 (0.981)	$107.21^{***} \\ (0.001)$	-92.79 (0.379)
Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Ν	708	708	708	708	708	708	708	708	708	708
Adj R-Squared	0.02%	63.67%	2.00%	67.34%	2.96%	63.70%	12.64%	66.42%	2.72%	63.89%

The analysis above is based on the full sample of firms. The weighted least-squares regression is run with total intangibles, *Intangible*, as the dependent variable. All variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. Significance levels of 1%, 5%, and 10% are represented by ***, **, and *, respectively.

 Table 4: Core Technology Measures

		Depend	ent Variable: I	DevTech	
	(1)	(2)	(3)	(4)	(5)
R&DExp	0.14 [*] (0.057)				
PatentCount		$27.30^{***} \\ (0.000)$			
PatentCiteCount			0.79^{***} (0.000)		
PatentMktResp				$0.24^{**} \\ (0.000)$	
TrademarkCount					2.53 (0.394)
TangibleAssets	0.03 ^{***} (0.000)	0.03^{***} (0.000)	0.02^{***} (0.000)	0.02^{***} (0.000)	$\begin{array}{c} 0.02^{***} \\ 0.000) \end{array}$
Constant	0.59 (0.991)	-29.06 (0.577)	-13.96 (0.771)	8.89 ^{**} (0.871)	-7.25 (0.885)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Ν	708	708	708	708	708
Adj R-Squared	10.68%	14.38%	15.50%	27.21%	10.32%

Panel A:

The Panel A analysis above is based on the full sample of firms. The weighted least-squares regression is run with developed RD, *DevTech*, as the dependent variable. All variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. Significance levels of 1%, 5%, and 10% are represented by ***, **, and *, respectively.

Table 4: Core Technology Measures

		Dependent Variable: IPRD								
	(1)	(2)	(3)	(4)	(5)					
P&DEvn	-0.02									
KæDExp	(0.803)									
PatentCount		12.28^{*}								
1 dioneoount		(0.062)								
PatentCiteCount			0.14							
1 utente tie e ount			(0.301)							
PatentMktResp				0.04						
r atoma interesp				(0.212)						
TrademarkCount					-0.03					
	0.02***	0.00***	0.02***	0.00***	(0.994)					
TangibleAssets	0.03	0.02	0.03	0.02	0.03					
C	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)					
Constant	-22.36	-35.26	-25.12	-20.00	-22.30					
	(0.740)	(0.786)	(0.712)	(0.779)	(0.743)					
Voor FE	Vac	Vac	Vac	Vac	Vac					
I cal FE	T es Vos	Tes Vos	Tes Vas	Tes Vas	Tes Vos					
N	708	708	708	708	708					
Adi R-Squared	15 37%	15 97%	15 56%	16.05%	15 36%					

Panel B:

The Panel B analysis above is based on the full sample of firms. The weighted least-squares regression is run with in-process R&D, *IPRD*, as the dependent variable. All variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. Significance levels of 1%, 5%, and 10% are represented by ***, **, and *, respectively.

Table 5: Brand Innovations

		Deper	ndent Variable:	Brand	
	(1)	(2)	(3)	(4)	(5)
R&DExp	0.06 (0.135)				
PatentCount		-0.25 (0.928)			
PatentCiteCount			0.04 (0.645)		
PatentMktResp				0.03^{**} (0.018)	
TrademarkCount					4.89^{***} (0.004)
TangibleAssets	0.01 ^{***} (0.000)	0.01 ^{***} (0.00)	0.01^{***} (0.000)	0.03^{***} (0.000)	$\begin{array}{c} (0.0001) \\ 0.01^{***} \\ (0.000) \end{array}$
Constant	57.18^{*} (0.054)	60.87^{**} (0.039)	56.96 ^{**} (0.036)	30.71^{**} (0.045)	43.13 (0.989)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Ν	708	708	708	708	708
Adj R-Squared	12.99%	12.36%	12.17%	12.73%	16.40%

The analysis for is based on the full sample of firms. A weighted least-squares regression is run with in brand value, *Brand*, as the dependent variable. All variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. Significance levels of 1%, 5%, and 10% are represented by ***, **, and *, respectively.

Table 6: Goodwill

		Depend	ent Variable: G	oodwill	
	(1)	(2)	(3)	(4)	(5)
R&DExp	0.19 (0.518)				
PatentCount		-8.26 (0.659)			
PatentCiteCount			-0.26 (0.593)		
PatentMktResp				0.51^{***} (0.000)	÷
TrademarkCount					20.55^{*} (0.080)
TangibleAssets	0.66*** (0.000)	0.67*** (0.000)	0.67^{***} (0.000)	0.65^{***} (0.000)	0.66 ^{***} (0.000)
Constant	-23.31 (0.347)	-14.04 (0.941)	-18.35 (0.923)	-14.29 (0.939)	-90.02 (0.640)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Ν	708	708	708	708	708
Adj R-Squared	72.23%	72.22%	72.24%	72.91%	72.34%

The analysis for is based on the full sample of firms. The weighted least-squares regression is run with in goodwill, *Goodwill*, as the dependent variable. All variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. Significance levels of 1%, 5%, and 10% are represented by ***, **, and *, respectively.

	Dependent Variable: TotMktValue								
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	
R&DExp PatentCount		(1)	0.26 (0.154)	1.96*		(5)		$\begin{array}{c} (1) \\ 0.23 \\ (0.242) \\ -4.25 \\ (0.166) \end{array}$	
PatentCiteCount				(0.056)	0.77^{**} (0.044)	0.64***		$(0.166) \\ 1.00 \\ (0.378) \\ 0.71^{***}$	
PatentMktResp TrademarkCount						(0.000)	0.69 ^{**} (0.020)	$(0.000) \\ 0.66^{**} \\ (0.020)$	
DevTech		0.74^{***} (0.000)							
IPRD		0.07 (0.359)							
Brand		0.72^{***} (0.000)							
Goodwill		0.21 ^{***} (0.000)							
CR		0.70 ^{***} (0.000)	0.80^{***} (0.000)	0.82^{***} (0.000)	0.82^{***} (0.000)	0.79 ^{***} (0.000)	0.83 ^{***} (0.000)	0.83 ^{***} (0.000)	
OtherIntangibles		0.57 ^{***} (0.000)	0.62 ^{***} (0.000)	0.60 ^{***} (0.000)	0.59 ^{***} (0.000)	0.54 ^{***} (0.000)	0.69 ^{***} (0.000)	0.64 ^{***} (0.000)	
TangibleAssets		0.53 ^{***} (0.000)	0.53 ^{***} (0.000)	0.53 ^{***} (0.000)	0.53 ^{***} (0.000)	0.53 ^{***} (0.000)	0.55 ^{***} (0.000)	0.55 ^{***} (0.000)	
F Test: DevTech-1 F Test: Brand -1 F Test: Goodwill-1		$\begin{array}{c} 0.26^{**} \\ (0.018) \\ 0.28 \\ (0.141) \\ 0.79^{***} \\ (0.000) \end{array}$							
Year FE Industry FE N Adj R-Squared		Yes Yes 708 87.45%	Yes Yes 708 86.71%	Yes Yes 708 85.98%	Yes Yes 708 85.99%	Yes Yes 708 87.25%	Yes Yes 708 86.83%	Yes Yes 708 87.51%	

Table 7: Market ValuesPanel A: Dependent Variable is TgtMktValue

The analysis above is based on the full sample of firms. The weighted least-squares regression is run with the market value of the firm four weeks prior to the announcement of the acquisition, *TgtMktValue*, as the dependent variable. The weight is determined by the dependent variables, *TgtMkltValue*. All variable definitions are provided in Appendix A. All variables are winsorized at the 1st and 99th percentiles. Significance levels of 1%, 5%, and 10% are represented by ***, **, and *, respectively.