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Is Tech M&A Value-Additive?

Ani Deshmukh
Princeton University, ani.deshmukh09@gmail.com

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Abstract

Given rising M&A deal volume across all high-tech subsectors, the ability to measure post-acquisition performance becomes critical. Despite this growth, the relevant academic literature is severely lacking (Kohers and Kohers 2000). Using an event-study approach, I find that acquirers and targets both realize statistically significant day-0 abnormal returns (1.23% [p<0.1] and 8.1% [p<0.01], respectively). As positive stock returns signal positive growth prospects in a semi-strong efficient market, AR regressions found that firms' technological relatedness, deal financing, purchase price premiums, and the relative book to market ratio, explained most variance. Overall, high-tech transactions are value-additive for both targets and acquirers.

Keywords

tech, M&A, acquisition, merger, target, shareholder, wealth, software, event

Cover Page Footnote

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I. Introduction

The deployment of services, compute power, storage, and development platforms through the cloud heralds robust growth prospects for the internet, software, and IT services sectors. With an estimated 20% compounded annual growth rate until 2020 and fast product cycles (Wall Street Journal 2011), cloud computing is driving vendors to acquire firms that aid IT/rack space consolidation, product-cross selling, and patent portfolio development. Total deal value rose by 100 percent across all tech sectors to $107.1 billion in 2010, alongside a 73% increase in deal volume to 165 total transactions (PWC 2011). Within this context, the ability to measure post-acquisition performance becomes critical.

On a general level, mergers and acquisitions can leverage scalable business models through enhancing operational efficiency (e.g. lowering average fixed costs through reductions in administrative overhead, IT/R&D overlap, and facility closures) or reinvent business models by exposure to new customers, markets, or products (Harvard Business Review 2011). Through such synergies, M&A allows the sum of parts to exceed the standalone valuations of both firms, enabling bidders to offer hefty purchase price premiums; in any transaction, these projected differences are accounted for by goodwill and definite-life intangible assets.

Although high-tech M&A has received much attention from the financial press, the academic literature regarding these acquisitions is severely lacking (Kohers and Kohers 2000). By analyzing all domestic, high-tech, publically-announced M&A transactions from November 10, 2002 to November 10, 2011, my study will determine the shareholder wealth implications following announcements of high-technology acquisitions. More specifically, I presume that both targets and acquirers will experience statistically significant and positive abnormal returns (AR). I use a standard event study methodology to ascertain abnormal returns by subtracting actual returns from risk-adjusted expected returns that are benchmarked to a CRSP value-weighted market index. If abnormal returns are significant, I will proceed to develop multiple regression models for targets and acquirers. For acquirers, I will regress abnormal returns against percentage of cash used to finance the deal, percentage of purchase price allocated to goodwill and acquired intangibles (i.e. the purchase price premium), relative market cap, concentration (a measure of technological complementarity), relative book to market value, industry subsector, seasonality, and year of transaction. Because transaction premiums flow directly to the target shareholders, abnormal returns for targets will only be regressed against the percentage of cash used to finance the deal, the logarithm of the purchase price premium, industry subsector, seasonality, and year of transaction. For both firms, cumulative abnormal returns are also analyzed to assess the significance of drifts, reversals, and overall market efficient pricing of firms before and after acquisition announcements.

As the first paper to focus on high-tech merger-related abnormal returns using only a 21st century dataset, I hope to update the 20th century data dominated and industry-agnostic event study literature base. With regards to the second phase of the study, I introduce several improvements to AR and CAR multiple regression models: first, I control for industry subsector; second, I incorporate a purchase price premium regressor that measures the impact of acquired intangible value on acquirer returns; and third, I adapt the technology concentration index (usually reserved for software companies) to encompass acquisitions by *any* high-tech firm.

II. Literature Review

The literature surrounding M&A value creation is extensive and primarily makes use of short-term event studies to assess the significance of observed abnormal returns relative to the expected normal returns of target and acquirer firms during the period of the acquisition (Bruner 2003, Duso et al. 2010). Crucial to this methodology's success is the assumption of semi-strong market efficiency (EMH), whereby stock prices reflect the present discounted value of all future returns and therefore immediately adjust to new public information (Fama 1970, 1976, Jensen 1978, Watts and Zimmerman 1986). Any variation in actual versus expected risk-adjusted returns is thus attributed to the effect of an M&A announcement on the firm's expected returns.

Burton Malkiel (2011) reiterates his support of semi-strong EMH despite the 2008 financial crisis. Although prices immediately reflect all public information, it does not mean the information is accurate. The diversity of research analyst estimates, complicated by the additional sensitivity tables incorporated into their DCF valuations, makes determining a single, true value impossible. What EMH guarantees is that if information is public, then it will be incorporated into stock prices. With an M&A announcement, purchase premiums are clearly delineated, and thus markets are expected to respond in kind.

Robert Bruner (2003) devotes an entire chapter of his book *Applied Mergers and Acquisitions* to consolidating the mass of research surrounding M&A value creation. Of the 120 event study papers analyzed, all suggest that targets receive significantly positive market returns while acquirers receive zero adjusted returns, with 66% of studies reporting acquirers earning slightly positive, though insignificant, abnormal returns (Bruner 2003). This markedly differs from the common view that "corporate marriages only rarely end in bliss." (Suroweicki 2008)

Targets typically experience statistically significant positive returns regardless of time period, if nothing else due to the premium above current share price that acquirers offer (Siougle et al. 2010). In fact, Healy, Palepu, and Ruback (1990) find that unsuccessful/blocked mergers cause targets to return to their pre-merger share price, indirectly showing how the initial premium is the main determinant of post-acquisition abnormal returns. Table 1 summarizes the most highly cited studies on target shareholder returns and finds that a majority of firms experience statistically significant positive returns (Table 1):

Table 1: Review of Studies on Post-Acquisition Target Returns*

Study	Sample Period	Sample Size	Event Window	% Positive Returns (Day 0)	Cumulative Abnormal Return (CAR)
Langetieg (1978)	1929-69	149	(-120,0)	71.6%	+10.63%
Bradley, Desai, Kim (1988)	1964-84	236	(-5,5)	95%	+31.77%
Dennis and McConnell (1986)	1962-1980	76	(-1,0)	70%	+8.56%
Bannerjee and Owers (1992)	1978-87	33	(-1,0)	85%	N/A
Kaplan and Weisbach (1992)	1971-82	209	(-5,5)	94.7%	+26.9%
Berkovitch and Narayanan (1993)	1963-88	330	(-5,5)	95.8%	N/A
Maquieira, Megginson, and Nail (1998)	1963-96	55	(-60,60)	83%	+38.08%
Mulherin (2000)	1962-97	202	(-1,0)	76%	+10.14%
DeLong (2001)	1988-95	280	(-10,1)	88.6%	+16.61%

*adapted from Bruner (2003)

All studies (regardless of time period assessed) report significant cumulative abnormal returns within the pre-announcement day event windows, indicating a steady price run-up prior to the day-0 announcement. Dodd (1980) finds a 6.59% appreciation in target shares starting 10 days prior to the event, while Keown and Pinkerton (1981) isolate that nearly half of the total price appreciation occurs starting 25 days before. Dennis and McConnell (1986) and Asquith (1983) also find most cumulative abnormal returns beginning 20 days before the event. Duso et al. (2010) and Andrade et al. (2001) argue for a shorter event window as per 21st century data, finding that most returns accumulate within 5 days of the announcement.

Two traditionally opposing views – the information leakage and market anticipation hypotheses – are best merged to explain pre-announcement cumulative abnormal returns. The former hypothesis argues that as insiders buy shares, brokers either mimic the unusual trading patterns or react to information leaked via word-of-mouth (Sanders and Zdanowicz 1992); the market anticipation model applies leakage to a larger investor base, arguing that gradual release of information (albeit still private) influences share appreciation (Jensen and Ruback 1983). In both cases, the threshold between private and public information is blurred.

In the post-announcement period, Siougle et al. (2010) find that markets generally react efficiently, with short-term reversals occurring only when high-magnitude events cause investor overreaction. Ketcher and Jordan (1994) find that the market quickly corrects for overreaction as almost all of the short-term reversal in stock prices occurs 1 day after the event. Kohers and Kohers (2001) apply the overreaction hypothesis to high-tech acquirers. They argue that complex R&D and tech-related synergies increase investor uncertainty over the true stock price, ultimately resulting in significant “market errors in judgment” that are corrected by longer-term price reversals (Kohers and Kohers 2001). Daniel et al. (1998) confirm that overreaction is more prevalent in cases of uncertain information, even when all financial details regarding a transaction may be disclosed. Though Kohers and Kohers (2001) studied price reversals over 3 years, I expect similar reversals to hold in the post-announcement event window in cases where the percentage of purchase price allocated to goodwill and intangibles is significantly high.

By analyzing 126,386 earnings announcements from 1988-2005, Rusticus et al. (2008) found that larger bid-ask spreads resulted in greater post-announcement drift. And as transaction costs (e.g. bid-ask spread, shorting cost, etc.) vary inversely with firm size

(Stoll and Whaley 1983), it logically follows that firm size impacts the absolute value of drift (Bernard and Thomas 1989).

Besides accounting for post-acquisition drift, firm size determines abnormal returns for acquirers and targets as larger-cap firms need a larger dollar excess to generate the same percentage abnormal return as smaller firms. Asquith, Bruner and Mullins (1983) report that the returns to buyers in mergers with relative partner size (target market cap/acquirer market cap) greater than or equal to 10% was 2.4% greater than those below 10%. However, excessively large targets make integration difficult, exhibiting a curvilinear effect on acquirer abnormal returns (Hitt et al. 2009).

Overall, shareholders of the bidder firm do not experience significant abnormal returns, with most experiencing slightly positive (Dodd and Ruback 1977, Jarell and Poulsen 1989, Malatesta 1983, Kohers and Kohers 2000) or negative surprises (Houston et al. 2001, Eckbo et al. 2000, Morck et al. 1990, Walker 2000, DeLong, 2001, Goergen and Renneboog 2004) depending on firm-specific characteristics. Table 2 provides a brief summary.

Table 2: Review of Studies on Post-Acquisition Acquirer Returns*

Study	Sample Period	Sample Size	Event Window	% Positive Returns (Day 0)	Cumulative Abnormal Return (CAR)
Dodd and Ruback (1977)	1958-78	124	(0,0)	N/A	2.83%
Asquith, Bruner, and Mullins (1983)	1963-79	170	(-20,+1)	N/A	3.48%
Lang, Stulz, and Walkling (1989)	1968-1986	87	(-5,5)	N/A	0%
Kohers and Kohers (2000)	1987-96	1634	(-1,0)	N/A	1.44%
Kohers and Kohers (2001)	1984-95	304	(-1,5)	N/A	1.26%
Fuller, Netter, and Stegemoller (2002)	1990-2000	3135	(-2,2)	N/A	1.77%
Beitel et. al. (2002)	1985-2000	98	(-1,0)	53%	0.06%
Dodd (1980)	1970-77	60	(-1,0)	N/A	-1.09%
Jennings and Mazzeo (1991)	1979-85	352	(-1,0)	37%	-0.8%
Healy, Palepu, Ruback (1992)	1979-84	50	(-5,5)	N/A	-2.2%
Eckbo and Thornburn (2000)	1964-83	390	(-40,0)	N/A	-0.3%
Mitchell and Stafford (2000)	1961-1993	366	(-1,0)	N/A	-0.07%
DeLong (2001)	1988-95	280	(-10,1)	33.6%	-1.68%
Ghosh (2002)	1985-1999	1190	(-5,0)	N/A	-0.96%
Kuipers, Miller, and Patel (2003)	1982-1991	138	(-1,0)	N/A	-0.92%

*adapted from Bruner (2003)

A major factor in both acquirer and target returns seems to be the method of financing. Huang and Walkling (1987), Travlos (1987), Yook (2000) and Heron and Lie (2002) find that stock-based deals generate negative abnormal returns for acquirers while cash-based deals have no significant impact. Asquith et. al. (1990) find a 2.6% (t=9.25) significant difference in 2-day announcement excess returns between cash (0.2%, t=1.05) and stock mergers (-2.4%, t=-11.60), with mixed cash/stock mergers generating a -1.47%

excess return. Bouwman et al (2004) argue that market timing plays a major role in choice of financing; stock market booms prompt using overvalued stock to buy target shares, while merger waves cause managers to follow the pack for fear that inaction may lead to rival success (hence, late-movers underperform early-movers). For targets, cash deals generate significantly higher abnormal returns than stock deals; Asquith et al (1990) quantify the difference at 13.38% (t=20.86). One possible explanation for this difference may be the immediate taxability of cash, which necessitates higher investor returns (Asquith et al. 1990).

Besides controlling for firm size and method of payment, Kohers and Kohers (2001) also control for market perceptions of poor managerial execution (the book-to-market ratio) using a sample of only high-technology acquisitions. Though bidders experienced statistically significant short-term abnormal returns (2-day event period cumulative abnormal return of 1.44%, i=1634) (Kohers and Kohers 2000), 3-year long event studies (Kohers and Kohers 2001) revised prices downward for firms that had low book-to-market values (known as growth, or glamour firms). This latter finding confirms Rau and Vermaelen's (1998) results that value acquirers (high book-to-market ratios) outperformed growth acquirers over the long term, with the former group experiencing 16% returns compared to the latter's 4%. Lang et al (1989), however, construe a falling book-to-market ratio as a function of the market's rising confidence in a firm's managerial performance in excess of its expected, risk-adjusted return. In the short term, Lang et al. (1989) find that low book-to-market bidders gain the largest abnormal returns when acquiring high book-to market targets, understood as well-managed acquirers buying poorly-managed targets. This confidence in managerial efficiency explains the short-run investor overreaction found in the Kohers and Kohers (2000) study, but as integration may fail to capture projected synergies (such as estimated growth and earnings targets), long-run stock prices decline. I will also incorporate a relative book-to-market ratio (target to acquirer) to account for how seamlessly the market expects post-announcement synergies to be realized; higher relative book to market ratios should therefore have a positive impact on abnormal returns. In the case of tech M&A, however, book to market ratios do not explain the whole story. Because many tech acquisitions depend on revenue-enhancing synergies *across* different subsectors, they imply merging firms' culture, R&D, and strategy, and are much harder to implement than simply managing a firm more efficiently through cost-cutting, employee reduction, or asset divestments (Gaughan 2011).

Interestingly, method of payment was insignificant for short and long-term returns (Kohers and Kohers 2000, 2001), indicating that investors do not differentiate between stock and cash-financed acquisitions. However, because the 90s faced significant tech-related M&A and IPO activity, all without much concern over deal structure or company financials (Chaudhuri and Tabrizia 1999), a large percentage of the Kohers and Kohers (2000, 2001) 1987-1996 sample set is biased towards acquisitions from the mid-90s. In fact, Kohers and Kohers (2000) found that by just being a technology company, bidders experienced significant positive returns (t=2.46). Therefore, I plan to include deal financing as a regressor in my models as investor perception, cash reserves, and technology-sector market value have all changed since the 90s.

Despite the issues outlined above, as this is one of the few studies that observe short-term post-acquisition abnormal returns for high-tech bidders, I predict my observed acquirers will also experience significant positive surprises. Unfortunately, Kohers and Kohers did not devote any attention to deal-specific intangible value (grouped under goodwill and acquired intangibles on the acquirer's balance sheet), which constitutes the largest percentage of any tech acquisition and drives most of the potential synergy (PWC 2011). Hitt et al. (2009) succinctly state, "The acquisition premium has been examined in only a minority of M&A studies," despite its having been identified as a "significant variable."

To remedy this, I will include the percentage of purchase price allocated to goodwill (i.e. the purchase price premium) as a regressor in my multiple regression model for acquirer return. Studies by Jennings et al. (1996) and Lys et al. (2011) confirm that there exists a positive correlation between goodwill and long-term returns due to the former's definition as the present discounted value of all expected synergies. However, both assume a linear relationship between goodwill and returns and do not take as their reference point the M&A announcement date. Although I do not analyze long term returns due to the variety of confounding variables involved, my study does account for goodwill's short-term impacts surrounding an M&A announcement. Because paying excessively high premiums reflects overpayment (especially when bidding competitively for targets) and undue pressure on squeezing out synergy gains, goodwill should have a curvilinear, rather than monotonic impact on acquirer abnormal returns. For targets, using the logarithmic value of goodwill captures the monotonic impact that the additional premium should have on pre-announcement share prices.

Using a deal-specific regressor to assess intangible-driven abnormal returns represents a marked improvement over the more common Tobin's *q* (Chen and Jian

2011). (*Q* is approximately defined as the inverted book-to-market value [Chung and Pruitt 1994]). Though its explanatory power is strong for managerial performance (Lang et. al. 1989), it is *not* a valid measure for intangible value.

Zeff and Durnham (1997) find a negative correlation between market-to-book ratios (Tobin's *q*) and acquired goodwill for US firms with sales revenue over $1 billion and a market to book ratio of at least 5. Unless an acquisition is fully cash financed (in which case crediting cash is matched by debiting goodwill), book value of equity will increase to accommodate goodwill as the latter is an acquired asset. In this manner, the acquirer's book value will more closely resemble its market value (Zeff and Durnham 1997), exerting downwards pressure on *q* even when the acquirer's intangible value rises.

Megna and Klock (1993) confirm that *q* is a poor measure of intangible value in most high-tech companies. As a firm's true *q* (q_i') is fundamentally unobservable ($q_i' = MV_i/(K_{1i}+K_{2i})$ where K_{1i} is a firm i's tangible and acquired intangible assets and K_{2i} is a firm's non-acquired intangible assets), Megna and Klock test whether intangible assets accurately reflect a firm's *q* ratio with the following equation: $q_i = MV_i/K_{1i} = q_i' + q_i'(K_{2i}/ K_{1i})$. And as q_i' by definition must equal 1, Tobin's *q* is regressed against the summation of all non-acquired intangibles (capitalized in-process R&D, patent stocks, etc.): $q_i = \beta_0 + \sum \beta_j(K_{2ji}/K_{1i}) + u_i$ (where the summation applies to all j intangibles ranging from 1 to N). Though the model explained 40% of the variation in *q*, the insignificant effect of patent stock (t=0.33) is rather surprising, considering patents comprise around 31% of the total transaction size in high-tech acquisitions (Benoit and Cauthorn 2006). Therefore, assuming tobin's *q* as a valid measure of intangible-driven abnormal returns should be discouraged.

Though *q* breaks down in the case of acquirers, the metric does function as an accurate measure of a target's intangible value. This is because market and book value increase in lockstep to reflect the premium paid on all outstanding shares.

Overall, goodwill reflects the fact that high-tech firms are increasingly situated in innovation networks and thus profits are no longer derived from linearized product chains (Blaxill and Eckardt 2009). IP pure-play companies, such as Qualcomm, add a completely new dimension towards M&A returns analysis by generating revenue solely through licensing knowledge gained through R&D. In this manner, strategic M&A spend can become a powerful predictor of future innovative growth (Liu 2005).

Following this further, judicious spending delivers the greatest return when focused on acquiring complimentary technologies. As per a landmark study by Gao and Iyer (2006), acquisitions of targets that sell products within adjacent technology stacks (e.g. services, applications, middleware, systems, and hardware) experience greater long-term returns than those of targets offering products within the same stack as the acquirer. For example, EMC's (data storage hardware) purchase of VMware (virtualization services) and Oracle's (database management) acquisition of Sun (servers) both led to statistically significant day 0 abnormal returns ($p<0.01$; t-statistic of 13.2 and 12.4, respectively). In both cases, product bundling and cross-selling generated revenue in excess of the usual building of scale through elimination of redundant R&D costs. This process of buying inventions through M&A, rather than developing them in-house, becomes ever more important in an era where high-tech product life-cycles continually decline (Odilon and Banks 2007).

In light of this finding, I modify Gao and Iyer's weighted concentration index to compare the percentage of sales that each acquirer and target generates within the services, software/IP licensing, and hardware/industrials domains. The intellectual property-driven middle layer is filled primary by software, internet (e.g. search, social media, applications), and IP licensing companies (which represent R&D-heavy semiconductor and networking/data communication firms); the bottom layer is laden with industrial companies and products (e.g. data storage systems, servers, networking infrastructure, semiconductor fabs); and the top layer is comprised of nearly all firms. I expect increasing subsector concentration to yield lower abnormal returns.

(1) Concentration = $A_{Serv}*T_{Serv} + A_{SW}*T_{SW} + A_{HW}*T_{HW}$
A = percentage of acquirer sales; T = percentage of target sales

Another problem I hope to remedy is the field's lack of industry focus. With goodwill and synergy-related intangibles comprising the majority of purchase price allocation to any asset category in high-technology M&A (median values of 70% in internet and 63% in software/services) (PWC 2011), studies applying traditional performance drivers such as firm size or method of payment, though statistically significant, do not capture the importance of *industry-specific*, intangible-driven growth (Castedello and Klingbeil 2009). By controlling for industry-fixed effects, I aim to better ascertain post-announcement abnormal returns by industry subsector. My data will only concern the following four major high-tech subsectors: internet, computers, networks/data communication, and semiconductors.

Finally, I will control for time fixed effects (year and seasonality [i.e. quarter of acquisition]). Strong equity markets, a robust economy, and cheap debt financing pushed M&A deal flow and volume to its highest level since 2002 in Q4 of 2007. The $4 trillion in completed M&A easily surpassed the $3.2 trillion mark set in 2000 and 2006. Though the 2008 financial crisis flushed M&A activity until 2009, 2010 and 2011 faced record dealmaking thanks in part to rich cash reserves (estimated at $2 trillion), rebounding market conditions, and low-interest debt financing (Ernst and Young 2011, Wall Street Journal 2011). Similarly, the S&P North American Technology Sector Index has continued to deliver record earnings since 2008 (Ernst and Young 2011), giving firms the flexibility to finance acquisitions through rising equity prices or large cash reserves. Overall, acquirers are finding it cheaper to purchase earnings through acquisitions rather than invest their cash in low-yielding fixed income instruments or riskier internal projects. As a result, 2011 quarterly deal volume and value remain above 80 and $26 billion, respectively, with average transaction size of $320 million (a 19% increase over 2010).

Regardless of annual market trends, seasonality within the tech sector explains the relatively large value and volume seen in Q3 and Q4 (Acquisitions Monthly 2008). Deal execution usually rises from November to January as end-of-year sales push up acquirer stock prices, falls in February, and then holds constant until November (Ernst and Young 2011).

III. Methodology

Test 1 – Abnormal Return Significance

M&A announcement dates are searched for using LexisNexis, an electronic database for legal, business, high-tech, and governmental-related information. The first day where rumors about the acquisition appear in the press is chosen as the M&A announcement date (day 0). As the first news leak regarding a potential acquisition oftentimes precedes the official press release by a week (Andrade et al. 2001), I will consider cumulative abnormal returns over a longer 21-day event window. This is a marked improvement over most other M&A event studies, which only study a (-1, 0) event window (Table 1, 2) due to the 1-day lag between coverage in the Wall Street Journal and the official announcement (Sanders and Zdanowicz 1992). Though this 2-day window captures most of the abnormal returns (CAR=21.361% [t=6.414]), it leaves out statistically significant pre-announcement returns (CAR(-10,0)=7.352% [t=4.101]) that are most likely the result of the week's earlier news leaks.

With regards to non-public information, although the due diligence process begins well before any news leak, the impact from insider trading is never well-specified and will always be reflected in the estimation window. If significant day-0 ARs or CARs are still realized, then the effect of such illegal activity is minimal. As later seen in the results section, day 0 ARs are significant for both acquirers and targets.

My sample set consists of 313 acquisitions with average value of $497 million. All daily stock return data will be sourced from CRSP while all information from financial statements will be taken from Compustat. Market returns will be taken from the value-weighted CRSP market index.

All 313 acquisitions are high-tech M&A transactions involving *public* US companies from November 10, 2002 to November 10, 2011. I exclude any transactions that involve the following: 1) entities announcing splits, dividends, or earnings within the event window, 2) firms that report missing daily stock returns in the event period, and 3) firms which share overlapping event windows. The first exclusion is meant to isolate merger-specific returns, while the second is a practical construct. The third exclusion is meant to control for cross-sectional AR correlations and will be discussed later in this section.

The first phase of testing uses short-term event studies to gauge the abnormal return to targets and acquirers around the M&A announcement date. Most studies calculate normal returns by benchmarking daily stock returns (calculated as the change in share price divided by the prior day's closing share price) against an industry or large-market index (Bruner 2003), ultimately creating market model-derived OLS regression models:

(2) $R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + AR_{it}$

(3) $AR_{it} = R_{it} - E(R_{it})$

In my model, R_{ft} is the risk-free interest rate on 6-month treasuries, α_i is a time-fixed, firm-specific return in excess of the risk-adjusted return, β_i is the stock's beta or volatility of returns in relation to the market return in excess of the risk free rate ($R_{mt} - R_{ft}$), and AR_{it} is the normally distributed error term, with mean equal to 0, that changes with firm and time. Beta and alpha are both determined from the daily returns data of the estimation window.

Regressing past stock returns against a large-market index is the most common event study methodology used to derive normal returns and will be replicated in this study

(Bruner 2003, Binder 1998). For short-run event studies, Brown and Warner's (1980) conclusion is widely held as true: "Beyond a simple, one-factor market model, there is no evidence that more complicated methodologies convey any benefits."

Beyond just a theoretical defense of using a market risk-adjusted beta, in today's digital economy high tech stock returns heavily rely on market returns (see literature review). Enterprise-wide demand for cloud computing services (e.g. ERP, BI, BPO, CRM) and networking solutions, coupled with consumer-driven demand for mobile chipsets, have made the market model increasingly relevant (Gaughan 2011). Replacing the market model by regressing firm returns against returns from either the firm's respective industry or a contemporary set of firms is not advised as both are affected by a related firms' M&A decision-making (Duso 2010). Furthermore, as SaaS/IaaS services now cater to all industry verticals, software firms' revenue becomes dependent on the health of the overall market. Coupled with horizontal integration *across* industry subsectors (e.g. HP [hardware] purchasing Autonomy [software]), the confluence of mobile, wireless, and the cloud is making M&A decisions more reflective of macroeconomic, rather than industry-specific, conditions (Gaughan 2011). Gaughan explicitly states, "M&A volume tends to follow the level of economic activity."

Because this study assumes that abnormal returns are jointly multivariate normal and identically and independently distributed (a reasonable assumption as per MacKinlay 1997), excluding acquisitions that share overlapping event windows reduces the risk of cross-sectional correlation as any M&A related market or industry impact will now be reflected in the estimation rather than event window used to predict another firm's expected return. Similarly, using a large estimation window of 170 days drives sampling error of beta and alpha to zero, which reduces the likelihood of pre-event serial correlation and thus justifies using unconditional abnormal return variance.

The variance of the cross-sectional average of announcement date abnormal returns is estimated as follows:

(4) $$\sigma^2(\overline{AR}_0) = \sigma^2(\sum_{i=1}^{N} AR_{i0} / N) = (1/N^2)\sum_{i=1}^{N} \sigma^2(AR_{i0})$$

The standard deviation of each firm's abnormal return is derived from the variance within its estimation window:

(5) $$S(AR_i) = \sqrt{\frac{\sum_{t=1}^{T}\left(AR_{it} - \frac{\sum_t AR_{it}}{T}\right)^2}{T-d}}$$

The estimation window ranges from t= -180 to t = -11 (T=170) and the standard deviations are summed across all firms (i=1 to i=313) to generate S($\overline{AR}$). T-d is the degree of freedom (d=2 due to estimated alpha and beta in equation 1). To calculate the significance of any day t abnormal return within the event window, a standard t-test is used, where $t = \overline{AR}_t / S(\overline{AR}_t)$.

As a 21-day event window will also be used, CAR variance must be estimated. Due to the OLS assumption of independent and identical distributions, the variance of CAR is simply the summation of each day's cross-sectional abnormal return variances.

Test 2 – Abnormal Return Regressions

The second phase of the study develops multiple regression models that attempt to explain the observed abnormal returns. These models estimate cumulative abnormal returns as well, as all variables are balance sheet items that do not change on a daily basis. The multiple regression models and selected variables for acquirers (equation 6) and targets (equation 7) are listed below:

Relative Size= target market cap/acquirer market cap

Relative Book to Market Value = target book to market value/acquirer book to market value

Computer = binary variable for software, hardware, and IT services subsector

Semiconductor = binary variable for semiconductor subsector

Network = binary variable for networks and data communication subsector

Q2 = binary variable for second quarter

Q3 = binary variable for third quarter

Q4 = binary variable for fourth quarter

2003 = year 2003 binary variable

2004 = year 2004 binary variable

2005 = year 2005 binary variable

2006 = year 2006 binary variable

2007 = year 2007 binary variable

2008 = year 2008 binary variable

2009 = year 2009 binary variable

2010 = year 2010 binary variable

2011= year 2011 binary variable

(6) $AR_{it,acquirer} = B_0 + B_1(\text{Cash/Purchase Price})_{it} + B_2(\text{Goodwill/Purchase Price})_{it} + B_3(\text{Goodwill/Purchase Price})^2_{it} + B_4(\text{Relative Size})_{it} + B_5(\text{Relative Size})^2_{it} + B_6(\text{Concentration})_{it} + B_7(\text{Relative Book to Market Value})_{it} + \delta_2\text{Computer}_i + \delta_3\text{Semiconductor}_i + \delta_4\text{Network}_i + \gamma_2 Q2_t + \gamma_3 Q3_t + \gamma_4 Q4_t + \varsigma_2 2003_t + \varsigma_3 2004_t + \varsigma_4 2005_t + \varsigma_5 2006_t + \varsigma_6 2007_t + \varsigma_7 2008_t + \varsigma_8 2009_t + \varsigma_9 2010_t + \varsigma_{10} 2011_t + \varepsilon_{it}$

(7) $AR_{it,target} = B_0 + B_1(\text{Cash/Purchase Price})_{it} + B_2(\ln(\text{Goodwill}_{it})) + \delta_2\text{Computer}_i + \delta_3\text{Semiconductor}_i + \delta_4\text{Network}_i + \gamma_2 Q2_t + \gamma_3 Q3_t + \gamma_4 Q4_t + \varsigma_2 2003_t + \varsigma_3 2004_t + \varsigma_4 2005_t + \varsigma_5 2006_t + \varsigma_6 2007_t + \varsigma_7 2008_t + \varsigma_8 2009_t + \varsigma_9 2010_t + \varsigma_{10} 2011_t + \varepsilon_{it}$

IV. Results & Discussion

As per Table 3 and Graph 2, day 0 abnormal returns were highly significant at the 5% significance level for acquirers (AR=1.23, *t*=1.97) and 1% level for targets (AR=8.10, *t*=12.65). Acquirer returns mirror those of Kohers and Kohers (2000, 2001), who found CARs of 1.26% (-1,5) and 1.44% (-1,0) compared to CARs of 1.36% and 1.45% for the same periods (Graph 1 and 2). Thus, the data from 1984-1996 seems to correspond well with that from 2002 to 2011. The similarity of my and the Kohers and Kohers results suggests that high-tech acquirers experience significant returns, while those of other industries tend to have insignificantly positive or negative returns (Table 2).

Table 3: Abnormal returns (i=313) for acquirers and targets; bottom values reference two-sided t-statistic

	Day within Event Window																				
	-10	**-9**	**-8**	**-7**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Acquirer	0 0.000	0 0.000	0 0.000	0.45 0.721	-0.14 -0.224	0.01 0.016	0.14 0.224	0.13 0.208	-0.23 -0.368	0.22 0.352	1.23** 1.970	0.11 0.176	-0.02 -0.032	-0.13 -0.208	-0.02 -0.032	-0.03 -0.048	0 0.000	0.04 0.064	0.15 0.240	-0.02 -0.032	-0.02 -0.032
Target	0.01 0.01562	-0.02 - 0.0312	0.09 0.14056	0.11 0.17179	0.13 0.20303	0.23 0.3592	0.32 0.49976	0.87 1.35871	1.25** 1.95217	1.45** 2.26452	8.10* 12.6501	1.62** 2.53001	0.92 1.4368	0.47 0.73402	-0.07 - 0.1093	0.11 0.17179	0.05 0.07809	0.16 0.24988	0.07 0.10932	0.02 0.03123	0 0

* p<0.01, ** p<0.05, ***p<0.1

Graph 1: Abnormal returns (i=313) during event window (t=-10,10); blue=target, red=acquirer

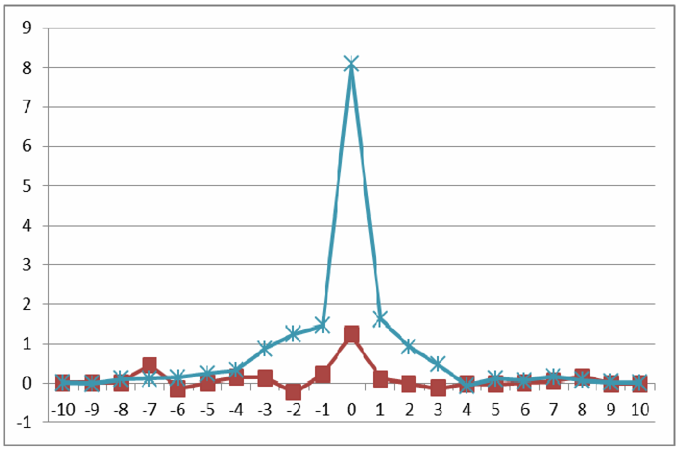
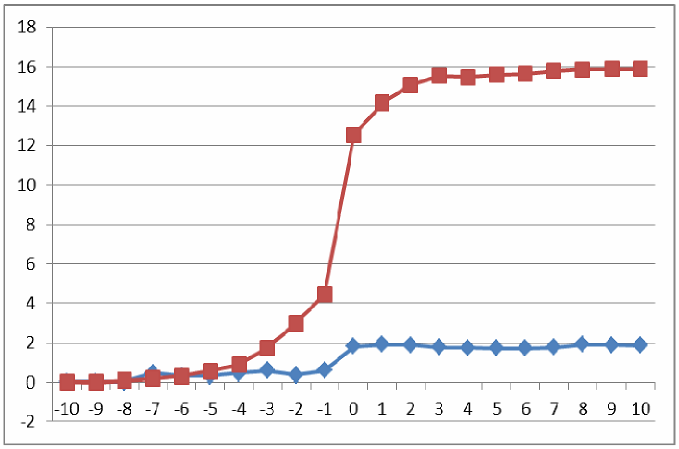


Table 4: Cumulative abnormal returns (i=313) for acquirers and targets; parenthetical values reference two-sided t-statistic

	Event Window						
	(-10,10)	(-10,-1)	(-5,-1)	(-5,5)	(-1,1)	(1,5)	(1,10)
Acquirer	1.87 (0.65)	0.58 (0.29)	0.27 (0.19)	1.41 (0.68)	1.56 (1.44)	-0.09 (-0.06)	0.06 (0.03)
Target	15.89* (5.42)	4.44** (2.19)	4.12* (2.88)	15.27* (7.19)	11.17* (10.07)	3.05** (2.13)	3.35*** (1.65)

* p<0.01, ** p<0.05, ***p<0.1

Graph 2: Cumulative abnormal returns (i=313) during event window (t=-10,10); blue=acquirer, red=target



The day 0 pop of 1.23% is the only significant abnormal return (at 5% level). As no other acquirer CARs were significant at even 10%, it seems the market efficiently reacts to the first public information regarding the M&A transaction. Due to acquirer CAR insignificance, only the day 0 AR will be used in the acquirer multiple regression models.

In line with much of the event-study literature base, targets possess statistically significant CARs for every selected window (Table 4), yet most surprising are the significant abnormal returns of 1.25%, 1.45%, and 1.62% on days -2,-1, and 1. The significant 2.70% run-up starting two days before the event date casts uncertainty over the day when information regarding the deal first becomes public. But as 99.04% of sampled firms experienced their largest abnormal return on their respective announcement date, the event date seems correctly specified. The day-0 AR peak in graph 1 comprises 75% of the (-2,0) CAR.

In relation to firms in other industries, the tech targets shared similar returns. Relative to a (-5,-1) CAR ranging from 16.9-20.8% (Bruner 2003), my sample set experienced a 15.27% CAR (Table 4). 2 day CARs (-1,0) were 9.55%, fitting comfortably within the 8.56-10.14% range found in prior studies (Table 1).

Because most event studies rely on markets immediately adjusting to all *public* information, the target firms' significant pre-announcement CARs in the (-10,-1), (-5,-1), and (-2,-1) windows – which hint at information leakage and/or insider trading – erode the true day-0 return. Andrade et al. (2001), Dodd (1980), and Duso et al. (2010) confirm that individuals with access to private information are usually responsible for significant pre-announcement CARs up to 10 days prior to the event due to the increased likelihood of deal closure**.**

More disturbing is the positive post-announcement drift. With significant CARs of 3.05% and 3.35% for the (1,5) and (1,10) event windows, respectively, insider trading is no longer an explanation. Rather, because so few understand the intricacies of enterprise and consumer IT, investors may overreact following M&A announcements (Daniel et al. 1998, Kohers and Kohers 2001). With public companies such as Pandora, Yelp, and Zynga all running negative EBIDTA values, deriving a DCF-based enterprise value or a comparables-based EV/EBIDTA multiple is meaningless. If traditional Wall Street valuation methods do not work, then it is no surprise that investors defer to whatever technology receives the most hype. Interestingly, because behavioral finance and EMH are not mutually exclusive (Malkiel 2011), overreaction does not entail market inefficiency.

As many public tech targets are small-cap firms with few outstanding shares (Kohers and Kohers 2001), bid-ask spreads and commissions are large (Stoll and Whaley

1983, Bernard and Thomas 1989). As a result, transaction costs and short selling limitations (due to scarcity of shares) may delay correcting investor overreaction.

It is possible that drift may continue for months after the public announcement (Bernard and Thomas 1989), but as the goal of this paper is to explain abnormal returns within short-term event windows, analysis of long-term CARs is left as a future exercise.

Although most target CARs are significant at 1%, adjusting for serial correlation could have adjusted the return volatility upwards as the returns may have been affected by hidden, intra-window drift. But even with such adjustments, Reinganum (1982) and Brown and Warner (1985) find minimal impact on the significance of abnormal returns, with the latter study concluding that "autocorrelation in the residuals is…small[sic] and appears to pose little problem for event studies." (1985) Table 5 shows the 1st, 2nd, and 3rd-order lag autocorrelations for acquirers and targets; all residual autocorrelations are insignificant, falling within 95% of 0. As a result, an event study method based on OLS regression and standard parametric tests remains well-specified.

Table 5: Autocorrelation plot; parenthetical values reference two-sided t-statistic

	Acquirer	Target
1st order lag	0.063 (0.014)	0.285 (0.062)
2nd order lag	-0.289 (-0.063)	0.154 (0.033)
3rd order lag	-0.085 (-0.019)	0.021 (0.005)

Finally, as daily stock returns may have non gaussian distributions, it is worrisome that so many event studies assume normality due to large sample size selection (Bruner 2003). Given that a stock has unlimited upside but is constrained to a -100% loss, a right-skewed distribution could be likely. With tech stocks, the probability of disruptive inventions (Google Search) or resignation to legacy systems (Sun servers) creates fat-tailed distributions that may render AR normality assumptions incorrect.

Residual non-normality could arise from a multitude of non-merger (albeit financial) announcements during the estimation window that are difficult to discover. For example, Jackson et al. (2006) modified a normally distributed 250-element AR vector by adding an “event blip” to the first 6 periods, and then adding the modified vector to a 250-element S&P 500 daily returns vector. When these returns were regressed against a well-specified model that accounted for the modification, the distribution was almost normal (average skewness=0, average kurtosis=3), but when regressed against the market model, the Jarque-Bera test rejected the hypothesis that the residuals are normally distributed in 96% of the cases; in the well-specified model, only 6.5% of the residuals were rejected (Jackson et al. 2006).

Though alarming, adjusting for non-normality would most likely require reclassifying most non-day 0 ARs and CARs as slightly less significant. Brown and Warner (1985) concur, stating that “the nonnormality of individual-security daily-return residuals has little effect on the inferences drawn from the use of the t-test."

The significance of target CARs and day 0 abnormal returns for targets and acquirers allows further analysis by regressing the returns against various regressors. Two regressors, relative size and relative book to market value, are derived from the data represented in table 6. Because no target had a book to market value greater than 100%, no transactions were undertaken to acquire firms nearing bankruptcy.

Table 6: Mean Equity Values (millions of dollars)

	Acquirer	Target
Market Value (mean, millions)	41878	2,567
Book Value (mean, millions)	6979	713

Table 7: Subsector Distribution (percentage)

Subsector Distribution	Acquirer	Target
Semiconductor	8%	7%
Computer	46%	39%
Internet	36%	47%
Networking	10%	7%

Table 7 highlights that most acquirers belonged to the computer subsector and most targets to the internet subsector. This relationship is logical, as web 2.0 (i.e. the social internet) prompts closer interaction between application developers and larger software and hardware vendors. Alternately, the internet subsector is younger than the computer subsector, thus a fewer number and a higher concentration of earlier stage firms dominate the former.

The sampling data in table 8 closely resemble the data for all high-technology transactions during the 2002-2011 period. 2007 had the strongest year in 21st century tech M&A deal flow and volume, followed by 2011, 2002, 2006, and then 2010. The sampling data follows a similar trend, with 2007 leading with 63 acquisitions (average transaction size of $645 million and total deal volume of $40.6 billion), 2011 following with 47 ($532 million, $25 billion), 2002 with 41 ($660 million, $27 billion), 2006 with 33 ($387 million, $12.8 billion), and 2010 with 29 ($435 million, $12.6 billion).

On a side note, assuming that the subsector dummies correlate with the goodwill/purchase price regressors (as per the 2011 PWC study) may not be true.

Average goodwill percentage per transaction during 2006 and 2010 was 45% and 47%, respectively, even though most of the sampled deals in 2010 involved semiconductor companies.

2010 also had the second highest percentage of purchase price paid out in cash (72%), while 2006 had the least (37%). Because the 2008 financial crash was preceded by a robust US economy, firms most likely used overpriced securities to fund transactions. This seems logical, as average cash percentage in 2008 was 67%.

Table 8: Summary Statistics

					Goodwill	
Year	**Frequency**	**Average Transaction Value (millions of dollars)**	**Total Deal Volume (millions of dollars)**	**Cash/PP**	**Goodwill (millions of dollars)**	**Goodwill/PP**
2002	41	660	27060	46%	277.2	46%
2003	28	432	12096	43%	185.76	42%
2004	26	389	10114	45%	159.49	36%
2005	27	354	9558	43%	120.36	33%
2006	33	387	12771	37%	178.02	45%
2007	63	645	40635	45%	341.85	57%
2008	8	240	1920	67%	50.4	19%
2009	11	354	3894	66%	109.74	33%
2010	29	435	12615	72%	195.75	47%
2011	47	532	25004	74%	287.28	53%
Total	**313**	**497**	**15567**	**54%**	**190.59**	**41%**

Table 9: Multiple regression models for acquirer day 0 abnormal returns

	A1		A2		A3		A4		A5	
	β	Significance	B	Significance	β	Significance	B	Significance	B	Significance
Constant	1.95	1%	1.73	1%	1.56	1%	1.08	1%	0.96	1%
Cash/Purchase Price	x	x	x	x	0.28	5%	0.25	5%	0.24	5%
Goodwill/Purchase Price	x	x	0.21	1%	0.21	1%	0.20	1%	0.20	1%
Goodwill/Purchase Price^2	x	x	-0.003	1%	-0.003	1%	-0.003	1%	-0.003	1%
Relative Size	x	x	x	x	x	x	x	x	0.05	NS
Relative Size^2	x	x	x	x	x	x	x	x	-0.001	NS
Concentration	-1.74	1%	-1.65	1%	-1.65	1%	-1.64	1%	-1.64	1%
Relative Book to Market Value	x	x	x	x	x	x	0.36	1%	0.36	1%
Computer	0.27	5%	0.21	5%	0.21	5%	0.22	5%	0.22	5%
Semiconductor	-0.14	5%	-0.15	5%	-0.13	5%	-0.13	5%	-0.12	5%
Network	-0.12	5%	-0.15	5%	-0.15	5%	-0.14	5%	-0.14	5%
Q2	0.04	NS	0.03	NS	0.03	NS	0.03	NS	0.03	NS
Q3	0.12	NS	0.15	NS	0.13	NS	0.13	NS	0.11	NS
Q4	0.36	5%	0.25	10%	0.24	10%	0.22	10%	0.21	10%
2003	0.03	NS	0.02	NS	0.04	NS	0.05	NS	0.05	NS
2004	0.07	NS	0.04	NS	0.05	NS	0.05	NS	0.04	NS
2005	0.14	NS	0.12	NS	0.12	NS	0.11	NS	0.11	NS
2006	0.15	NS	0.13	NS	0.11	NS	0.11	NS	0.12	NS
2007	0.28	5%	0.22	10%	0.18	10%	0.18	10%	0.17	10%
2008	0.08	NS	0.13	NS	0.04	NS	0.04	NS	0.04	NS
2009	0.22	10%	0.21	10%	0.13	10%	0.11	10%	0.13	10%
2010	0.44	1%	0.38	1%	0.12	10%	0.11	10%	0.12	10%
2011	0.54	1%	0.46	1%	0.32	5%	0.33	5%	0.33	5%
i (firms)	313		313		313		313		313	
F-statistic	4.92		6.35		8.31		11.95		11.23	
R^2-adjusted	0.17		0.24		0.31		0.41		0.42	

Table 10: Multiple regression model for target cumulative abnormal returns and day 0 abnormal return; goodwill is measured in $USD millions.

	Day 0		CAR(-10,10)		CAR(-5,5)		CAR(-1,1)	
	Target	**Significance**	**Target**	**Significance**	**Target**	**Significance**	**Target**	**Significance**
Constant	0.87	1%	0.98	1%	0.93	1%	1.14	1%
Cash/Purchase Price	1.08	1%	1.88	1%	2.11	1%	1.45	1%
ln(goodwill)	1.23	1%	2.65	1%	2.53	1%	1.78	1%
Computer	0.17	10%	0.15	10%	0.16	10%	0.16	10%
Semiconductor	-0.16	10%	-0.17	10%	-0.17	10%	-0.16	10%
Network	-0.15	10%	-0.15	10%	-0.16	10%	-0.15	10%
Q2	0.07	NS	0.07	NS	0.07	NS	0.06	NS
Q3	0.12	NS	0.12	NS	0.13	NS	0.12	NS
Q4	0.14	NS	0.13	NS	0.14	NS	0.14	NS
2003	0.05	NS	0.05	NS	0.05	NS	0.05	NS
2004	0.04	NS	0.03	NS	0.03	NS	0.02	NS
2005	0.11	NS	0.12	NS	0.12	NS	0.11	NS
2006	0.13	NS	0.14	NS	0.14	NS	0.14	NS
2007	0.16	10%	0.17	10%	0.17	10%	0.15	10%
2008	0.05	NS	0.06	NS	0.06	NS	0.04	NS
2009	0.22	10%	0.21	10%	0.22	10%	0.21	10%
2010	0.31	5%	0.29	5%	0.31	5%	0.31	5%
2011	0.34	5%	0.32	5%	0.31	5%	0.33	5%
i (firms)	313		313		313		313	
F-statistic	54.95		32.23		15.39		21.21	
R^2-adjusted	0.75		0.63		0.44		0.52	

Summary of Multiple Regression Model Results

The results for acquirer day-0 ARs and target CARs are very promising. Model A5 explains 42% of the variance in day 0 acquirer ARs (F=11.23), while the day 0 target AR model explains 75% of the target's day 0 AR variance (F=54.95). For targets and acquirers, the industry subsector to which the firm belongs to as well as the year in which the transaction takes place (provided its 2007 or after the 2008 financial crisis) are significant for every model. The percentage of the acquisition financed by cash and the purchase price premium are significant for both types of firms too.

Surprises in the acquirer models include the insignificance of the nonlinear "relative size" regressor, but great predictive power of the concentration index and relative book to market ratios. In fact, my modified concentration index and AR models explain more of the day 0 AR variance than the models developed by Gao and Iyer. For targets, almost all regressors maintained very similar explanatory powers across different models. This implies that most firms that had large/small day 0 abnormal returns also had large/small event window CARs.

Concentration Index

Due to the massive product upselling and R&D synergies that can be realized by combining firms in different layers of the technology stack, I expected the concentration index to be a major arbiter in acquirer ARs. By expanding the software-specific concentration index Gao and Iyer used in their AR regression models to include services (top), intangible capital-heavy firms (middle), and tangible capital-heavy firms (bottom), I developed a concentration index that was significant at the 1% level for all models. The Gao and Iyer (2006) concentration index was significant at 5%. And where the Gao and Iyer adjusted-R^2 and F-statistic were 0.24 and 4.21 respectively, the Model A5 R^2 and F-statistic were 0.42 and 11.23. My concentration index regressor seems stronger at predicting an acquirer's AR, but more importantly, my multiple regression models explain a greater proportion of the AR distribution. Although interesting, the disparity of our datasets makes direct comparison difficult.

Cash

The percentage of the transaction paid out in cash was significant at 5% for acquirer AR models (Table 9) and at 1% for targets CARs (Table 10). With an adjusted R^2 increase of 0.7 over Model A2 (Table 9) and limited impact on the other continuous independent variables, inclusion of the cash regressor allows Model A3 to explain a greater proportion of the variance of day 0 acquirer abnormal returns.

This finding contrasts with the Kohers and Kohers high-tech event studies (2000, 2001), which found deal financing to be insignificant in M&A transactions. Though my dataset samples acquisitions starting from 2002 (as opposed to the 1980s and 1990s), it is difficult to determine whether timeliness is the main reason for discrepancy.

For targets, non-cash payments may return lower CARs because they entail negotiation initiated by bidders that is not specified in early news leaks (Bouwman 2004). Examples include deciding on the voting status of newly issued shares or whether to use a fixed or floating share exchange ratio. But as negotiation can ultimately favor either party, it seems more likely that the immediacy of capital gains taxes on cash necessitates higher premiums (Asquith 1990).

For bidders, cash transactions are faster to execute and usually signal a competitive M&A environment (Asquith 1990). Acquisitions are highly valued in such settings and may explain bidders' higher abnormal returns. In addition, stock-based transactions hint that bidder shares are overpriced, and given all else equal, adjusts returns downwards (Bouwman 2004). The declining coefficients in years 2007-2011 in Model A3 relative to Model A2 indicate that many deals during that time period were financed with cash (Table 9). In fact, after the 2008 financial crisis, depleted equity prices meant that only companies with strong cash reserves could acquire targets (Ernst and Young 2011). Cash comprised between 37-46% of transaction values in between 2002-2007, but around 66-74% in between 2008-2011 (Table 8).

Industry Subsector

The high-technology subsector dummy was significant at 5% in all five acquirer models (Table 9) and at 10% in all target models (Table 10). Given all else is equal, acquirers and targets within the computer and internet subsectors consistently received higher abnormal returns than those within the semiconductor and networking sectors. Because tangible capital comprises a large percentage of total assets within semiconductor and networking companies, purchase price premiums must naturally be less than those in the other two sectors.

This idea is explicitly demonstrated in Table 9, where inclusion of the goodwill regressor decreases the computer dummy coefficient, but slightly increases the coefficients of semi and networking dummies. The positive correlation between purchase price premium and the computer and internet subsectors found in Table 9 is corroborated by PricewaterhouseCoopers, which found that acquirers in both sectors paid median premiums northwards of 60% in 2011. But even after adjusting for goodwill, all subsector dummies remain significant at 5% (Table 9) or 10% (Table 10), demonstrating that filtering ARs along industry-specific dimensions for both acquirers and targets is crucial for future event studies.

Goodwill

The contribution of the purchase price premium (i.e. goodwill/acquired intangibles as a percentage of the purchase price) is significant at 1% for both acquirer and target ARs. For acquirers, goodwill has a significant curvilinear impact on abnormal returns (Table 9) and starts negatively impacting acquirer returns once premiums reach

64.5% (Model A5). So although my results confirm the 2011 PWC suggestion that premiums may differ by subsector, my results disagree about the median purchase price premiums of each subsector.

Interestingly, the inclusion of the nonlinear goodwill component in Model 2A generates a less negative concentration index regressor. This implies a negative correlation between both variables, as companies that acquiring targets located at polar ends of the tech stack can realize greater synergies from merging. This allows higher purchase price premiums to be paid.

As expected, the logarithmic value of the actual goodwill amount is strongly correlated with target ARs and CARs (Table 10).

More importantly, this paper represents the first use of goodwill in analyzing high-tech acquirer abnormal returns and shows its statistical significance in explaining acquirer returns.

Relative Size

Though the relative size between targets and acquirers was insignificant (Table 9), its inclusion did increase the adjusted-R^2 by 0.01; thus, Model A5 was not eliminated. This is rather surprising as prior studies show that a target to acquirer market cap ratio in excess of 10% can boost acquirer ARs by 2.4% (Asquith et al. 1983). Even though the Asquith dataset samples dissimilar firms from 1963-79, by just looking at the relative size function, each percentage uptick (i.e. unit increase; all variables are percentages) should increase the acquirer's AR until the relative size variable equals 50%, after which point the regressor will negatively impact ARs. This makes sense, as a 50% target to acquirer market cap ratio is just a merger of equals. But given the contribution from all the other regressors, the absolute impact of the function on the acquirer's AR is insignificant.

Relative Book to Market

The relative book to market ratio (B/M) was significant at 1%. Whenever the acquirer's market-to-book value is larger than the target's (i.e. a high relative book to market ratio), investors view the acquisition as a well-managed acquirer buying a poorly-managed target (Lang et al. 1989). If this is true, firms should experience higher day 0 abnormal returns as synergies should be quickly realized. But such managerial efficiency also has a downside. Oftentimes, companies with fast-rising share prices become overconfident and overpay for targets (Roll 1986). This is demonstrated in Model A4, where the statistically significant B/M ratio is positively correlated with the purchase price premium.

Seasonality

With respect to seasonality, only Q4 provides significant abnormal returns in every acquirer AR model (Table 9). This may be explained by investors looking for firms with rising end-of-year sales to make advantageous acquisitions that earlier were financially unfeasible (Ernst and Young 2011). When goodwill is introduced in Model A2, the Q4 coefficient becomes less significant ($p<0.1$ instead of $p<0.05$), meaning that goodwill explained at least some portion of Q4's impact on day 0 AR in Model A1 (Table 9). Basically, when profits are high, premiums tend to follow.

None of the multiple regression models for targets displayed a significant seasonality effect.

Year

Though the coefficients for successive years are rising, 2007 and 2009-2011 are the only years with significant betas in all acquirer AR (Table 9) and target CAR models (Table 10). Though 2002-2006 and 2007 shared a similarly strong economy, 2007 had the greatest purchase price premium (57% as per Table 8). As expected, inclusion of goodwill in Model A2 dropped the 2007 coefficient from 0.28 to 0.22 and reduced its significance from $p<0.05$ to $p<0.1$ (Table 9). Goodwill was also positively correlated with 2010 (47%) and 2011 (53%), but the explanatory power of both dummy variables dropped when the "cash as a percentage of purchase price" regressor was introduced (Table 9) as both years had upwards of 70% of deal financing done in cash.

Though 2008 may suffer from a small sample size, its changing coefficient in the acquirer AR models is very interesting. Conservative M&A dealflow and depressed premiums boosted the 2008 dummy variable's coefficient from 0.08 (Model A1) to 0.13 (Model A2), but as cash payments are positively correlated with the 2008 regressor, the coefficient declined from 0.13 (Model A2) to 0.04 (Model A3).

For all target CARs, the years 2007 and 2009 are significant at the 10% level and the years 2010-2011 are significant at 5% (Table 10). Because 2007, 2010, 2011 comprised 45% of all sampled deals, acquirers may have been pressured to acquire firms just to keep up with their competitors (Harford 2004). In the frenzy to buy appreciating target shares, investors may have bid up prices without fully considering goodwill, method of payment, or probability of deal closure.

IV. Conclusion

This paper aimed to discover whether high-tech M&A transactions generated value for acquirers and targets, and if so, determine what factors contributed to that value creation. Using an event study method, I found that acquirers and targets both realized statistically significant day 0 ARs (with targets experiencing significant CARs as well). After developing multiple regression models that explained nearly 42% of the variance in day 0 acquirer ARs and 75% of the target's day 0 AR variance, I realized how important purchase price premiums, industry subsector dummy variables, and concentration within the technology industry are. Though this paper updates the historically pre-21st century data used in event studies, focuses on the undercovered high-tech sector, and makes key refinements to AR and CAR multiple regression models, there are still many areas of future work.

Expanding the study to test returns for firms that have already interacted through prior alliances or have longstanding M&A expertise, would give a better sense of how efficiently synergies would be realized. Determining technological complementarity in terms of R&D, rather than just revenue, is also critical in accelerating a product's time to market. Finally, ascertaining the type of M&A deal (e.g., acquiring a firm due to industry consolidation or merging to expand sales internationally) and including the deal binary variables within the acquirer models might enhance the models' predictive powers.

V. References

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