NEW PERSPECTIVES ON ASSESSING

THE STOCK MARKET VALUE OF INNOVATION

A Dissertation

by

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ABSTRACT

Innovation is considered an imperative for firm survival and growth. Firms invest considerable amount of time and resources on their innovation activities. Consequently, they are willing to inform their investors of the output of these investments, namely their new product releases, so that investors can correctly adjust the price of firms' stock accordingly. For decades, researchers have been studying investors' reaction to firms' new product announcements. However, several aspects of the manner in which these announcements are evaluated by investors are still unexplained. This dissertation attempts to shed light on two important yet overlooked aspects in estimating the value of innovation.

The first essay investigates how firms' success at past new product introductions helps investors form high expectations from the firms' future innovation output, and leads to a smaller investor reaction to subsequent new product announcements by these firms. The second essay shows that concurrently announcing new product releases with other positively valenced corporate news leads to an increase in firms' visibility in the stock market and subsequently it increase firm's stock price. This increase is greater for firms that face a higher investors' expectation or for firms that have a small investor base.

Both essays employ the event study method over large samples of new product announcements and provide hitherto unexplored boundaries for the valuation of new products, as well as helpful insights to managers in terms of when and how to introduce

their new products in order to maximize their firms' investor recognition and stock market value.

DEDICATION

To my kind, loving, and inspiring parents, Shohreh & Manouchehr
who paved the path to my dreams with their sacrifices.

To my closest friend, my confidant, my husband, Caleb
who always understands.

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CHAPTER I

INTRODUCTION

Innovation is critical to the success of firms. In today's competitive business world, firms that fail to innovate run the risk of falling behind and losing business to competitors. Therefore, managers need to have a clear understanding of the effect of their innovation output on the firm's long term performance so that they can make more informed resource allocations and investments for innovation. But how are firms' innovation outcomes evaluated?

Researchers in marketing have long been seeking to quantify the impact of firms' innovation activities on firm value (Sorescu 2012). Many studies have investigated, for instance, the shareholders' reactions to firms' new product announcements, treating the announcement as an outcome of innovation activities (e.g., Chaney, Devinney, and Winer 1991; Kelm, Narayanan, and Pinches 1995; Lee et al.2000; Sharma and Lacey2004; Sood and Tellis 2009; Sorescu, Shankar, and Kushwaha2007). Yet, there are many unexplained aspects about the manner in which shareholders view and evaluate these innovation activities in various scenarios.

This dissertation attempts to shed light on two of the unexplored factors in investors' reaction new product announcements. Specifically, it investigates (1) the effect of investors' expectation of firms' past innovation on their valuation of firms' future innovation output, and (2) the effect of timing and manner of the firms' communication of their innovation to investors.

The first essay examines why investors appear to respond less favorably to announcements issued by firms that are known to be successful innovators. In this essay, I investigate how a firm's history of new product announcements shapes investors' expectations of its future innovation output and how investors react when these announcements materialize.

The results of my first essay suggest that successful innovators receive diminishing abnormal stock returns from subsequent new product announcements, while it also documents higher value already incorporated in these firms stock price before the announcement is made. This result is also supported by my analyses of long-term stock returns, which shows that firms that fall short of investor expectations for their innovation output experience greater losses in the long run. Intuitively those that successfully exceed investor expectations gain more over the long-term.

In my second essay, I investigate the financial consequences of announcements of new products made concurrently with other corporate news by the same firm. I propose that making concurrent new product announcements benefits the firm by increasing the visibility of their stock and consequently the stock price. I then argue that these benefits are greater for firms under certain conditions: (1) firms that have a high value and whose investors have high expectations from (such as firms introduced as successful innovators in my first essay), and (2) firms that have a small investor base and are less recognized in the stock market.

The findings support the argument that concurrent new product announcements increase investor recognition. The results also reveal that the positive change in investor

recognition and the stock market reaction to the concurrent announcements is greater, on average, than that obtained from the sum of similar separate announcements.

This dissertation makes a contribution to the literature in marketing by offering new insight into how investors' assess firms' innovation output. The essays highlight the importance of managing the timing and sequence of new product announcements, as well as their effect on investors' expectations and recognition. From a methodology standpoint, the findings suggest a need to revisit the interpretation of the results of event studies on stock market returns to new product announcements. This dissertation also suggests a way in which a well-established technique, namely, the Propensity Score Matching method, can be leveraged to study the effects of corporate announcements.

While the results for both essays are derived in the context of new product announcements, many of their findings can be extended to a broader class of events. The research framework of the first essay can be applied to investigating investors' expectations that are formed as a result of other marketing actions undertaken by firms. Similarly, the methodology proposed in the second essay can be used to study the effect of other concurrently announced marketing actions of the firm.

Additionally, the results of this dissertation provide helpful insight to managers on how to interpret investors' reaction to their new product announcements and how to evaluate the value of their innovation. The results also help managers strategically decide when and how to leverage concurrent new product announcements in order to increase firm's visibility in the stock market, surpass investors' expectation and grow their investor base.

CHAPTER II

DIMINISHING RETURNS TO NEW PRODUCT ANNOUNCEMENTS: HOW THE PAST SHAPES INVESTORS' EXPECTATIONS OF THE FUTURE

Research shows that innovation raises the market value of firms. However, if firms are active innovators, investors' expectations of such firms' future innovative output will increase. These expectations should cause an ex-ante increase in stock prices and a smaller ex-post market reaction when an actual new product is announced.

I propose a theoretical framework of firm and industry characteristics that influence the formation of investor expectations of events that are part of a corporate strategy. I empirically test this framework using a sample of 4,898 new product announcements made by 833 publicly traded US firms. The results show that the stock market reaction to a new product announcement is negatively related to (1) the number of new products previously announced by the firm, (2) the number of new products previously announced by the firm's competitors, and (3) the average sentiment of past public news issued by the firm. These same three factors are also positively related to the market value of the firm measured immediately prior to each new announcement, controlling for increases in firm value directly attributable to past new product announcements.

The findings suggest that inferences from event studies that examine a special class of events - recurrent events or events that are part of a firm's broader strategy - need to take into account investors' expectations of future occurrences of these events.

The results also suggest that innovation's impact on firm value is best measured in the long term.

INTRODUCTION

Innovation is universally quoted as an imperative for firm survival and growth. Hundreds of articles and books provide advice on how to organize for innovation. Academics urge managers to pursue "unrelenting innovation" (Tellis 2013). And, innovation is associated with an increase in the market value of innovating firms (e.g., Chaney, Devinney, and Winer 1991; Pauwels et al. 2004; Sood and Tellis 2009; Sorescu 2012).

Given the known benefits of innovation, it is surprising that investors do not always respond positively to new product announcements, even when these products are well received in the market place. For example, one industry analyst observes that "Apple routinely sees its stock price take a beating every time it unveils a new product" (Duncan 2011). Another analyst recounts "Nokia CEO Stephen Elop took the stage to unveil two important new Lumia phones powered by Microsoft's new Windows Phone 8 OS. Despite positive reviews of the hardware, the stock collapsed by 16%" (Umiastowski 2012).

What, then, should we infer from negative stock reactions to the introduction of certain new products? Do these products destroy shareholder value? Are investors unable to assess their value-added? In this essay I propose another explanation, namely,

that stock market expectations are higher for more successful innovators[1]. These expectations are built into higher pre-announcement stock prices, leading to lower announcement-day returns.

This essay builds on the findings of Sood and Tellis (2009), who show a negative relationship between announcement-day returns and the quantity of information released about a product prior to its formal introduction. I argue that even in the absence of such product-specific information prior to the announcement, the returns on the day of the announcement can still be affected by investors' expectations of the firm's overall innovation strategy. Indeed, the stock market can reasonably expect a level of innovation activity to occur through time, particularly for firms with an established pattern of innovation and stock prices should already reflect these expectations by the time the new product is announced. Therefore, announcement-day returns will not capture the product's stand-alone contribution to firm value, but only the value of the unexpected information conveyed by the announcement. Viewed in this context, a negative stock return associated with a new product announcement means that the value-added of the product is lower than expected, not necessarily that the product has a negative net present value..

A common methodological approach used in the business academic literature to evaluate corporate actions is the short-term event study methodology (Brown and Warner 1985). The value of a corporate action is measured using Cumulative Abnormal

[1] I define successful innovators as firms that introduce new products more frequently and the announcements of these new products have been received by investors favorably.

stock Returns (CARs), computed as the difference between the actual stock returns and the expected returns that would have occurred in the absence of the event. Returns are typically measured over three- to five-day event windows around the announcement date. This methodology implicitly assumes that expected information is already incorporated in pre-announcement stock prices. Therefore, inferences drawn from the sign and magnitude of announcement-day CARs depend on how pre-announcement expectations are formed.

Accounting for pre-event expectations is a critical step to correctly interpret results from short-term event studies. However, as I will show below, this step is not always followed in the literature. To understand why, consider the entire spectrum of corporate events, classified in terms of pre-event information available to investors. The expectations formation process is usually clear towards the edges of this spectrum, but tends to be more subdued for events that fall in the middle. Event studies for this latter class tend to be more difficult to interpret.

At one end of this expectations spectrum is the class of events that are completely unanticipated. Here, the theory of Rational Expectations predicts that the entire value-added is revealed through CARs on the day of the announcement, so the sign and magnitude of CARs are sufficient to draw inferences about the economic implications of the underlying corporate action. For instance, the first mention of a firm's intention to adopt the Internet as a new channel is an unanticipated event (Geyskens, Gielens, and Dekimpe 2002). A positive announcement-day CAR can be

interpreted as a signal that investors anticipate positive future cash flows as a result of this channel expansion.

At the other end of the spectrum is the class of events whose timing and content are always anticipated. Earnings announcements are a good example since they are usually preceded by several salient and publicly-available forecasts. The date of the next earnings release is known in advance and market observers on the announcement day are known to focus on only the difference between the actual and expected earnings. CARs measured on the announcement day are understood to capture only this unexpected component of earnings (MacKinlay 1997).

The case of new product announcements falls somewhere in the middle of this spectrum. If there is no leakage of information, the first time the market learns of a new product, is on the day it is launched. Unlike earning announcements, there are no pre-established announcement dates that occur at regular time intervals. Yet, it would be difficult to argue that investors form no expectations about a firm's new product pipeline. And, these expectations need not to be too specific (down to the level of launch time and product characteristics) in order to impact stock prices. For instance, investors might not know precisely when Procter & Gamble will launch its next product or what that new product might be, but would nevertheless expect the firm to continue to launch successful new products in the future at a somewhat expected pace and quality.

I argue that new product announcements are a special class of anticipated events, one where expectations pertain to a firm's broader innovation strategy rather

than to event-specific details. As firms engage in innovative activities—which can vary in frequency and quality—investors receive the information that is released gradually from the firm, form expectations about future innovation and incorporate them into stock prices. As a result, a firm that is expected to innovate more and better, should have higher market value even before its next product is launched. In this case, the announcement serves primarily as an opportunity for investors to update their beliefs about the firm's innovation strategy.

Therefore, CARs to new product announcements—and by extension to any other corporate announcements that belong to a broader corporate strategy—should be interpreted differently from CARs measured around announcements that are truly unanticipated. While this appears to be a straightforward implication of the efficient market hypothesis, a review of event studies published in two leading marketing journals reveals that inferences drawn from average event CARs do not always account for pre-event expectations.

I present in the Appendix, findings from several event studies published in the Journal of Marketing Research and the Journal of Marketing during the past ten years. These papers cover events that occur repeatedly over time (such as outsourcing partnerships, alliances, or preannouncements) and likely belong to broader corporate strategies. One hypothesis from each study is selected, the authors' interpretation of the empirical findings is quoted, and a plausible alternative explanation that accounts for pre-event expectations is presented in the Appendix. Although these authors have

correctly applied the event study methodology, their inferences and conclusions appear to assume that the events they study are substantially unanticipated.

For example, Karniouchina, Uslay, and Erenburg (2011) interpret the insignificant CARs surrounding product placements in movies as a sign that this marketing strategy has become ineffective. Yet, many brands in their sample have appeared in multiple movies. It is reasonable to assume that Coca-Cola, whose brands appears 75 times in their sample, and has been one of the iconic symbols of American life that has been featuring in movies since 1916, faces higher expectations for placing products, vending machines, or billboards in movies. If so, investors might not react to Coca-Cola placements announcements even if the underlying movie placement strategy has positive effects on firm value.

The list in the Appendix is necessarily short due to space limitations. However, I have identified additional studies in the literature with similar limitations (see, e.g., Girotra, Terwiesch, and Ulrich 2007; Kalaignanam, Shankar, and Varadarajan 2007; Oxley, Sampson, and Silverman 2009). In addition, a few authors calculate the net present value of new products (Sorescu, Chandy, and Prabhu 2003), new ventures (Rao, Chandy, and Prabhu 2008), or new product alliances (Kalaignanam, Shankar, and Varadarajan 2007) using the stock market reaction to the announcement of these events, without explicitly acknowledging that the measured value pertains to only the unanticipated component of these announcements. Given the many calls to demonstrate accountability for marketing managers, academics should strive to minimize instances

in which the value of marketing goes unrecognized, or is misstated (Rust et al. 2004; Stewart 2009).

In this essay, I propose a set of characteristics that help shape investors' expectations about a firm's product innovation strategy and identify three factors that contribute to these expectations: (1) the number of new products previously announced by the firm, (2) the number of new products previously announced by the firm's competitors, and (3) the average sentiment of past public news issued by the firm.

I then empirically test the proposal using a large sample of new product announcements across industries. I first show that the three proposed factors are positively related to the firm's market value, measured immediately prior to a new product announcement. I do so while controlling for the product-specific information available prior to the event and for the extent to which the firm's past product announcements have exceeded investors' expectations. Second, I show that the three expectation factors are negatively related to announcement-date returns, consistent with the notion that these returns only measure an update from previously-set expectations. To corroborate this conclusion I perform a final test by measuring the long-term stock performance of firms in the sample in relation to their unexpected innovation output. Not surprisingly, I find a positive relationship between performance and output—the opposite of what is found in the case of announcement-day CARs. While active innovating firms have lower announcement-day CARs, they also tend to have higher returns over the long term.

This essay makes three contributions to theory and practice. First, from a conceptual standpoint, it emphasizes the importance of interpreting event-date CARs in the context of broader corporate strategies where investors could use past information to form expectations about the future, even when this information is not explicitly attached to the corporate event being studied. And, for the case of new product announcements, it identifies specific factors that contribute to these expectations. While the focus of this essay is on new products, similar theoretical frameworks can be developed for other strategies such as the choice of alliance partners, the acquisition and disposal of brands, brand licensing and placement decisions, or market expansions.

Second, this research contributes to the literature that studies stock market reactions to new product announcements by showing that firms that are active innovators, firms that perform in innovative industries, and well-performing firms have smaller announcement-day reactions but higher market values before the announcement. In doing so I highlight differences between the short- and long-term effects of innovation on firm value.

Third, the result that frequent innovators have higher increases in long-term market value has important implications for how publicly-traded firms should evaluate the performance of their marketing managers. A focus on short-term stock performance could create sub-optimal incentives, including a disincentive to maintain a fast pace of product introductions. Indeed, recent evidence shows that managers are preoccupied by how they can time product introductions in order to maximize the value of their stock

holdings (Moorman et al. 2012). Governing boards should, therefore, deemphasize short-term performance metrics and focus instead on longer-term returns to innovation.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

New product announcements are manifestations of a firm's innovation strategy. To preserve competitive advantage, firms do not typically articulate the objectives of their innovation strategy, nor do they reveal how they plan to deploy it. Nevertheless, a wealth of information is available to anyone wishing to learn about the strategy. Investors can infer a firm's future innovation output by observing the effectiveness of the firm's prior innovations, accounting for the competitive landscape of the firm's industry. I propose here three factors that shape this expectation-formation process: (1) the number of new products previously announced by the innovating firm, (2) the number of new products previously announced by the firm's competitors, and (3) the average sentiment of past public news affecting the innovating firm.

I do not claim that these three factors are exhaustive. Rather, following a review of event studies of new product announcements, presented in Table 1, I view them as plausible, measurable indicators of pre-announcement expectations. These factors are grounded in theory and are supported by recent research on competitive repertoires, which shows that expectations about strategy deployment depend on how much the strategy is emphasized and how well it has previously been implemented (e.g., Ferrier and Lee 2002; Rindova, Ferrier, and Wiltbank 2010).

Next I provide a detailed justification of the three expectation factors.

TABLE 1
Overview of Event Study Literature in the Area of New Product Announcements

Paper	Sample Size	Sample period	Average CAR
Woolridge and Snow (1990)	241 new product introduction announcements and 52 unrelated R&D project announcements	June 1972-Dec 1987	.69% for new product announcements (p<.01) 1.13% for R&D announcements (p-value NS[a])
Chaney, Devinney, and Winer (1991)	1101	1975-1984	.25% (p<.05)
Kelm, Narayanan, and Pinches (1995)	197 R&D announcements and 304 new product commercialization announcements	1977-1989	.88% for R&D announcements (p<.01) 1.02% for new product commercialization announcements (p<.001)
Zantout and Chaganti (1996)	108	1975-1992	1.15% (p<.01)
Koku, Jagpal, and Viswanath (1997)	334 new product preannouncements and 301 new product announcements	1980-1989	.306% for announcements (p-value NS) .430% for preannouncements (P<.01)
Lee et al. (2000)	24 original new product announcements, 53 announcements of new product imitations	1975-1990	Results range from non-significant for the overall sample to a 2.17% return for the sub-sample of original new announcements (p<.05) for the (-1,1) window
Chen et al. (2002)	384	1991-1995	.59% (p=.002)
Sharma and Lacey (2004)	344 FDA approval of new drugs and 41 FDA rejections	—	1.56% for FDA approvals (p<.005) -21.03% for FDA rejections (p<.005)
Sorescu, Shankar, and Kushwaha (2007)	419	1984-2000	Pre-announcements: .59% (p-value NS)
Chen (2008)	794	1989-1999	1.24% (p<.01)
Sood and Tellis (2009)	5481 announcements related to various stages of innovation, from funding an alliances to launch and awards	1977-2006	.5% (p<.001)
Lee and Chen (2009)	409 new product preannouncements and announcements	1990-1998	3.96% (p<.001) on day (-1) , 1.02% (p<.001) on day zero, and -.3% (p<.05) on day (+1)
Wang, Chen, and Chang (2011)	3061	1997-2005	.194% (p=.004)
Ba et al. (2013)	261 announcements of green vehicle innovations	1996-2009	.45% (p<.05)
Borah and Tellis (2014)	441 announcements of "make" - in house new product announcements	07/01/2002-06/30/2007	.25% for the "make" subsample, (p<.01)

The new product announcement history of the firm

Events that underline the recent implementation of a firm's strategy are among the most important indicators of the future deployment of that strategy. In this essay's context, firms with frequent new product introductions boost investors' expectations of their future innovative output, increasing their stock market value along the way. The announcement of a new product introduction is largely a confirmation of these expectations, leading to a smaller stock market reaction when compared to firms that are not expected to innovate. This factor has two separate effects on firm value measured immediately before the new product announcement. The first is a direct effect resulting from the information conveyed through the CARs associated with past new product announcements. Because these CARs have been shown to be positive, on average (Table 1), this effect produces a mechanical positive relationship between firm value before the announcement and the number of past products launched. The second effect—the one studied in this essay—is the indirect effect of past new products on firm value, which operates through increased expectations about the future. Because my focus is on the latter, I filter out the mechanical effect by controlling for the sum of CARs measured around past product announcements.

Although Chaney, Devinney, and Winer (1991) document a similar negative effect of number of past new products on event-date CARs, the literature as a whole lacks consensus in empirical findings. Table 1 shows that this effect ranges from positive (e.g., Kelm, Narayanan, and Pinches 1995), to non-significant (e.g., Lee and Chen 2009), to negative (e.g., Chaney, Devinney, and Winer 1991). I argue that the

dual empirical test in this essay- which use both Tobin's Q and CARs as dependent variables - provide more conclusive evidence that the negative effect of past new products on CARs is driven by pre-event expectations. Ceteris paribus, I hypothesize that:

> *H_{1a}: The more new product announcements a firm has made in its recent past, the higher its market value measured immediately before a new product announcement.*
> *H_{1b}: The more new product announcements a firm has made in its recent past, the lower the stock market reaction to its new product announcements.*

The new product announcement history of the firm's competitors

Firms do not innovate in a vacuum. When investors form beliefs about a firm's future innovation output they are also likely to learn from product announcements made by other firms in the same industry. While two prior studies have accounted for the presence of competition or industry concentration when measuring the stock market reaction to new product introductions (Rao, Chandy, and Prabhu 2008; Lee et al. 2000), these studies focus on the effect of competition on economic rents, rather than its effect on expectation formation.

I argue that the bar is set higher for firms in innovative industries, where effective innovation is almost a prerequisite for survival. These firms often ride waves of technological advances in the industry and benefit from investors' excitement about new technological developments at the industry level. When these firms do innovate, they have a daunting task in cutting through highly competitive clutter. As a result, higher expectations of innovativeness are built into the stock prices of firms that operate in innovative industries. Thus, I hypothesize:

H_{2a}: The more new product announcements a firm's competitors have made in their recent past, the higher the market value of the firm measured immediately before it makes a new product announcement.
H_{2b}: The more new product announcements a firm's competitors have made in their recent past, the lower the stock market reaction to the firm's new product announcement.

Another possibility is that in innovative industries where too many new products are already introduced by competitors, there exists a higher competition for the target firm's new product. Investors might expect a bigger challenge for the firm's new product to be successful and therefore expect a lower NPV for the product. Consequently, the stock market returns to the firm's new product announcement will be lower. Therefore, I still predict a negative relationship between the frequency of firm's competitors' new product and the stock return to firm's new product announcement similar to proposed H2b. However, if investors are expecting a challenging market for the new product and subsequently a lower cash flow for the firm's future product, there should be no positive effects incorporated in firm value before the introduction of the product. In fact, the more firm's competitors announce new products (before firm's new product announcement), the more pessimistic the investors should become about the firm's new product performance in the highly competitive market and this should negatively affect firm value before the new product announcement. Therefore, we should observe that:

H_{A2a}: The more new product announcements a firm's competitors have made in their recent past, the lower the market value of the firm measured immediately before it makes a new product announcement.

Past news sentiment

The last factor is viewed as a proxy for the overall investor assessment of a firm's ability to compete effectively. A positive news sentiment, as captured by a series of predominately favorable public news about the firm, implies that the firm has recently exceled in many areas of activity. Furthermore, investors' perceived effectiveness of firms' corporate actions is likely to have a spillover effect on all other activities of the firm. Therefore, the investors might assume that because the firm has done well in the past, and in other areas, they might do well in their future innovation activities as well. Consequently, investors are more likely to have high expectations from well-managed firms that are prominently featured in the news for doing things right. As a result, these firms should have higher market values and any additional positive news about them is likely to elicit smaller stock market reactions than in the case of less successful firm. This leads to the last set of hypotheses:

> *H_{3a}: The more positive the news sentiment associated with a firm's recent actions, the higher its market value measured immediately before a new product announcement.*
> *H_{3b}: The more positive the news sentiment associated with a firm's recent actions, the lower the stock market reaction to its new product announcements.*

DATA AND SAMPLE

Testing the hypotheses requires a large sample of new product announcements across multiple industries. Most event studies of corporate announcements have used archival searches in Dow Jones, LexisNexis, or Wall Street Journal Index to identify the news (e.g., Chaney, Devinney, and Winer 1991; Sood and Tellis 2009; Sorescu,

Shankar, and Kushwaha 2007; Wang, Chen, and Chang 2011). This method is unwieldy in the context of concurrent announcements. Specifically, to prevent selection bias, a complete sample of corporate announcements made by the firms included in the sample is needed. Archival searches, which typically rely on keywords, cannot guarantee that all corporate announcements are retrieved.

To overcome the challenges associated with archival searches, Icompile the sample from the *RavenPack News Analytics* database. RavenPack is a news provider that collects all major real-time news wires and news from other Internet sources including financial and business websites, such as The Wall Street Journal, Dow Jones, Barron's, blogs and local and regional newspapers. Although RavenPack has been increasingly utilized by researchers in finance and accounting (e.g., Akbas et al. 2016; Kelley and Tetlock 2013; Samadi 2016; Shroff et al. 2013; Shroff, Verdi, and Yu 2014), it has not yet been widely adopted by marketing researchers.

RavenPack has a number of useful features. An important feature of RavenPack is that it categorizes and quantifies all news items according to their sentiment, relevance, topic, and novelty. Among these variables I am particularly interested in the categorization of news items by type. RavenPack classifies all corporate news into specific categories such as product releases, acquisitions, award announcements, executive appointments and other similar categories. Within these categories, I focus on news categorized as "product release," defined by RavenPack as news item where "the company launches a new product or service or an upgrade to an existing one." Therefore, the sample in this study is the totality of news items

classified as “product release” by RavenPack.

I obtain from RavenPack all new product announcements made by publicly traded U.S. corporations between January 2007 and December 2011. The structure of the database requires that a number of filters be applied to obtain a clean, usable sample for this research. Using classifications provided by RavenPack I retain in the sample news items categorized as “press releases” ascribed to the “product release” category. I further ensure that the announcement is correctly ascribed to the specific parent company (and not by another entity which may tangentially refer to the parent firm in one of its press releases). RavenPack provides a “relevance score” between 0 and 100 to address the source of announcements. A relevance score of 100 is always ascribed to the firm issuing the announcement, whereas a lower relevance score may be assigned to a competitor marginally referenced in the announcement. I also use the “novelty score” provided by RavenPack, which captures the newness of the content of each news story. I retain only announcements coded as “product releases” that have a novelty score of 100, as these represent the first mention of the product to appear in any news outlet within a 24-hour time window. This ensures that there is no duplicate announcements in the sample, since some press releases may appear in multiple news wire services. Later in this section I describe how I used archival searches to collect earlier information about these announcements, if such information was available.

After applying these filters a tentative sample of 9,776 press releases is obtained that are classified as new product announcements and are made by 1,600 US firms in 64 industries (defined as two-digit SIC codes), from January 2007 to

December 2011.

Sample validation and content analysis

I perform a detailed content analysis to validate the sample. I do so for two reasons. First, the robustness tests require that I control for pre-event information specific to each product and the "novelty score" variable in RavenPack only looks back 24 hours. Therefore, I search for any information about the product that might have preceded the new product announcement date obtained from RavenPack. Second, I recognize that news items in RavenPack are categorized by computer algorithms that classify announcements as "product releases," and that such algorithms are subject to error. If these errors are random, they would merely introduce noise in the CARs measured around new product announcements. However, if the algorithm systematically misclassifies events with mostly positive sentiments (or mostly negative sentiment) as "product releases," the errors could introduce bias into some of the estimators.

Checks for earlier mentions of products

I begin by reading every press release in the sample to determine if it is correctly classified as a "product release." I find 846 announcements (8.6%) misclassified as "product release" and eliminate them from the sample. I then content analyze the remaining 8,930 announcements and find that 1,503 of them (16.8%) are pre-announcements of future new products, where the introduction is planned at least one week into the future. The remaining announcements are of actual product introductions. I also find that 1,101 announcements (12.3%) refer to multiple products

or to multiple versions of the same product, and I control for these characteristics in the empirical analysis.

Next, I conduct Factiva searches for each new product to search for earlier information about the product. I find that 1,510 announcements (16.9%) refer to products that had been previously mentioned in news wires, blogs, or other press sources.

As a last step, in order to eliminate confounding events I drop all product announcements for which the parent firm issues one or more press releases during the five-day [-2, +2] announcement window. This follows common practice in published event studies (e.g., Borah and Tellis 2014; Lee and Chen 2009; Lee et al. 2000; Wooldrige and Snow 1990).

Additional sample validation

I also consider the reverse-type error, namely that RavenPack might incorrectly classify a new product announcement as a different type of announcement. To investigate this possibility I randomly select twenty firms from the subset of firms that according to RavenPack have made only one new product announcement. Then, I perform archival searches on these twenty firms to determine if new product announcements not reported in RavenPack could be identified through Factiva.

Factiva searches reveal that eleven of these firms did not make any other announcements. Of the remaining nine, five had announced other products; however, because these products were announced along with confounding events they were eliminated from the final sample. For each of the remaining four firms I found one

other new product announcement during the five-year sample period. This suggests that the final sample is not a census of new product announcements. However, because I could not identify any systematic pattern common to the four missing products or the four firms, I conclude that the final sample appears to be representative of the entire census of new product announcements.

Additional data and final sample

To test the hypotheses financial and accounting data for firms in the sample are also required. I collect stock returns from CRSP and financial statement data from COMPUSTAT. All data is aligned at the fiscal year level.

The final sample used in the estimation of the models consists of 4,898 new product announcements made by 833 firms. The 4,898 announcements are made between 2008 and 2011; announcements made in 2007 are used to compute rolling-window variables that capture the history of past new product announcements. Each event in the final sample is subject to the following three filters: (1) I ensured, through content analysis, that the announcement is for a genuine new product, (2) I required complete availability of data for all variables in the statistical models (including R&D and advertising expenditures), and (3) I ensured that no confounding announcements are present. In addition, these remaining events have all been subject to detailed archival searches for earlier mentions of their products.

VARIABLE OPERATIONALIZATION AND METHOD

Measures

To test the hypotheses I develop empirical measures for the two dependent

variables and the three independent variables. I also include control variables that impact the relationship between new product announcements and firm performance. I discuss these measures in this section.

First dependent variable: Tobin's Q

The dependent variable in hypotheses H_{1a}, H_{2a}, and H_{3a} is Tobin's Q, abbreviated here as Q. I use book value of debt as a proxy for market value of debt and compute market value of equity as the product of the number of shares outstanding and the price per share. The market value of assets is computed as the book value of assets plus the difference between the market value of equity and the book value of equity. Q is then computed as the ratio of the market value of assets to the book value of assets, as shown in Equation (1).

$$\text{Tobin's Q} = [(\text{Book value of total assets}) + (\text{Common shares outstanding} \times \text{Stock price}) - (\text{Book value of common stocks})] / (\text{Book value of the total assets}) \quad (1)$$

Because Q should measure firm value as close as possible to the announcement date, the right-hand-side variables in Equation (1) must be those that were available to investors on the day before the announcement window. Two of these variables (book value of assets and book value of equity) are obtained from annual accounting statements. The other two (number of shares outstanding and price per share) are available daily in CRSP. Thus, to estimate Q I use accounting data from the fiscal year immediately preceding the new announcement, and stock market data from the trading day immediately preceding the beginning of the announcement window. This ensures that Q is not contaminated by the stock market reaction to the new product

announcement. The mean value of Tobin's Q in the sample is 1.90, consistent with prior studies (e.g., Krasnikov, Mishra, and Orozco 2009; Morgan and Rego 2009; Sorescu and Spanjol 2008).

Second dependent variable: CAR

The dependent variable in hypotheses H_{1b}, H_{2b}, and H_{3b} is the stock market reaction to new product announcements, obtained through a short-term event study. Within the innovation literature, event studies have been commonly used to assess the stock market reaction to announcements of new product introductions (Borah and Tellis 2014; Chaney, Devinney, and Winer 1991), new product preannouncements (Sorescu, Shankar, and Kushwaha 2007), new product introduction delays (Hendricks and Singhal 1997), and the introduction of new products by competitors (Chen, Ho, and Ik 2005).

I use the market-adjusted returns to estimate the reaction to the introduction of new products (Brown and Warner 1985). Specifically, I estimate abnormal returns associated with each product announcement as follows:

$$AR_{it} = R_{it} - R_{mt} \qquad (2)$$

where AR_{it} is the abnormal return of firm *i* on day *t*, R_{it} is the daily return of firm *i* on day *t*, and R_{mt} is the return of the stock market index on day *t*.

I then compute cumulative abnormal returns (CARs), by cumulating the daily abnormal returns over a time window from t_1 to t_2, which includes the announcement day:

$$CAR_{(t1,\, t2)} = \sum_{t=t1}^{t2} AR_{it} \qquad (3)$$

For robustness, I also compute abnormal returns using the Fama-French-Carhart four-factor model, which augments the market model with three additional risk factors that have been shown to explain the cross-section of stock returns (see Carhart 1997; Fama and French 1993):

$$AR_{it} = R_{it} - (\hat{\alpha} + \hat{\beta}\, R_{mt} + \hat{\gamma}\, SMB_t + \hat{\delta}\, HML_t + \hat{\lambda}\, UMD_t) \qquad (4)$$

where R_{it} and R_{mt} are as previously defined, SMB_t is the return differential between portfolios of small and large market capitalization stocks, HML_t is the return differential between portfolios of high- and low-book-to-market ratio stocks, and UMD_t is the momentum factor computed as the return differential between portfolios of high- and low-prior-return stocks.

To choose the appropriate length of the event window I compute CARs for several windows, beginning with two days before the announcement and ending two days after the announcement, and test their significance in each window. In line with previous studies (e.g., Geyskens, Gielens, and Dekimpe 2002; Swaminathan and Moorman 2009) I select the window with the largest t-statistic: [t-2, t+2].

Independent variables

The new product announcement history of the firm (Firm_NPA): I compute from RavenPack the sum of prior new product announcements made by the firm over rolling windows of twelve months preceding each announcement (e.g., Chaney, Devinney, and Winer 1991; Sood and Tellis 2009).

The new product announcement history of a firm's competitors (Competitors_NPA): I measure competitors' history of new product announcements as

the total number of announcements made by firm's competitors, divided by the number of all of the competitors in the same three-digit SIC code. Again, I use rolling windows of twelve months preceding each announcement. This measure captures the average innovation activity among competitors while effectively controlling for industry size.

Average past news sentiment (News_Sentiment): Past news sentiment is measured using the Event Sentiment Score (ESS) variable from RavenPack. This score measures the valence of the news. The strength of the score is set by a computer algorithm using a coding system established by experts who have classified entity-specific events and determined if these events generally convey positive or negative sentiment to investors and to what degree they do so. ESS ranges from 0 to 100, where values above 50 indicate a more positive sentiment, while values below 50 denote a more negative sentiment. A score of 50 shows that the news is neutral, in the sense that it is believed to not influence the firm's future cash flows[2]. ESS scores are averaged across all news items about the firm published during the twelve months preceding each new product announcement. These news items include all event types, not just the new product announcements. Therefore, if a firm has a high average past news sentiment it indicates that the majority of firm's activities that have been announced

[2] According to details provided by RavenPack, The ESS score is based on ratings that have been obtained from a panel of experts with extensive professional backgrounds in finance and economics. These experts were asked to evaluate over 2000 types of corporate events for their content. The ratings obtained from the training sample are encapsulated in an algorithm that is used to evaluate the content of each new event and generate a score for it. The algorithm uses additional information including ratings scales from all major brokerage firms, investment banks, and credit rating agencies. RavenPack's Event Sentiment Score has been utilized in recent research in finance in a manner similar to ours (e.g., Akbas et al. 2016; Kelley and Tetlock 2013).

publicly were perceived favorably by the investors.

Control variables

Past innovation surprises (Past_Surprises): Earlier in this essay I have discussed the importance of controlling for the direct effect on firm value resulting from the information conveyed through the CARs associated with past new product announcements. I measure the average CARs of past new product announcements made by the firm during the twelve-month period preceding each announcement, computed over the [t-2, t+2] window surrounding each announcement, using the market-adjusted model described previously.

Change in firm value attributed to past product announcements (Total_Past_Surprises): I sum up the CARs of all past new product announcements made in the rolling twelve-month window preceding each announcement. I use this variable in the Tobin's Q regressions to control for the effect of previous new product announcements that have been already incorporated in the stock price of the firm and subsequently in Tobin's Q.

Firm size (Firm_Size): I use the logarithm of the book value of assets to control for the effect of firm size on abnormal returns. This is standard practice in event studies since large firms typically have smaller percentage changes in their stock prices (e.g., Boyd, Chandy and Cunha 2010; Sorescu and Spanjol 2008).

Firm advertising intensity (Advertising): I compute advertising intensity as the ratio of advertising expenditures to book value of assets and use it as a control variable in both the Q and the CAR model. Advertising intensity has been previously linked to

both Tobin's Q and CARs to new product announcements (e.g. Joshi and Hanssens 2010; Wang, Chen, and Chang 2011). The higher the advertising expenditures, the more a firm can support and promote its new products.

Firm R&D intensity (R&D): I compute R&D intensity as the ratio of R&D expenditures to book value of assets and use it as a control variable in both models. R&D intensity has been previously linked to both Q (Krasnikov, Mishra and Orozco 2009) and CARs to new product announcements (Lee and Chen 2009).

Industry R&D intensity (Industry_R&D): Industry R&D intensity is defined as the R&D expenditures summed across all firms in the same three-digit SIC industry divided by the sum of these firms' book value of assets. I use this variable as control in both the Tobin's Q and the CAR model (Chen 2008).

Leverage (Leverage): I compute leverage as the ratio of the book value of long-term debt to the book value of assets. Leverage tends to magnify CARs and is frequently used as a control variable in event studies (e.g., Homburg et al 2014).

Book to market (Book_to_Market): The ratio of book value of equity to market value of equity is used to control for expectations included in the market value of equity that are not captured by the three expectation factors.

Sales growth (Sales_Growth): I use the percentage growth in sales from the previous year to control for the firm's past performance (e.g., Homburg et al 2014).

Herfindahl index (HHI): I compute the Herfindahl index as the sum of the squares of the market shares of all firms in each three-digit SIC code. Herfindahl index is used to control for industry concentration, which can potentially reduce rents to

innovation (Lee and Chen 2009).

T-bill average (T_Bill): Following Chaney, Devinney, and Winer (1991) I use the annual average rate of the 90-day Treasury bill in the CAR model to control for the possibility that CARs may vary through time due to changing economic conditions.

Earlier mention (Early_Mention): I construct a dummy variable whose value is equal to one if information about the new product has been available to investors prior to the formal announcement and zero otherwise. CARs to announcements with prior information available should be smaller than CARs to announcements that contain the first mention of a product in any news source (Sood and Tellis 2009). Likewise, since this prior information is incorporated into firm value when it becomes available, Tobin's Q should be positively related to the availability of earlier information for each product.

Announcement-specific variables: From the content analysis of the RavenPack data I create a dummy variable that takes the value of one if the announcement is an introduction and zero if it is a preannouncement (*Introduction)*. I also compute a second dummy variable that is equal to one if the announcement is about multiple products and zero if it is about a single product (*Multiple*). Finally, I count the number of words in each announcement (*Word_Count*) to account for the possibility that firms use longer press releases to introduce more promising products.

A summary of the operationalization is provided in Table 2.

TABLE 2
Variables and Data Sources for New Product Announcements (2007-2011)

	Conceptual variable	***Measured Variable***	***Data Source***
Dependent Variables	Short-term cumulative abnormal returns (*CAR*)	Cumulative abnormal return (two days before to two days after the announcement) computed using the market adjusted model and the four factor model	*CRSP, Fama French Factors from WRDS*
	Tobin's Q (*Tobin*)	Tobin's Q of the firm measured 3 days prior to the new product announcement	*Merged CRSP/ COMPUSTAT*
Independent Variables	The new product announcement history of the firm (*Firm_NPA*)	Number of the new product announcements made by the firm during the 12 months before the event	*RavenPack News Analytics*
	The new product announcement history of the firm's competitors (*Competitors_NPA*)	Number of new product announcements made by the firm's competitors divided by the number of all firms in the 3-digit SIC code, during the 12 months before the event	*RavenPack News Analytics*
	Past news sentiment (*News_Sentiment*)	Average of event sentiment score (ESS) for all the firm's news published 12 months prior to the event	*RavenPack News Analytics*
Control Variables	Past innovation surprises (*Past_Surprises*)	Average of CARs for all the firm's new product announcements made within 12 months prior to the event	*CRSP*
	Change in firm value attributed to past product announcements *(Total_Past_Surprises)*	Sum of the CARs to new product announcements made within 12 months prior to the event	*CRSP*
	Firm Size (*Firm_Size*)	Natural logarithm of total assets	*COMPUSTAT*
	Firm Advertising Intensity *(Advertising)*	Ratio between a firm's advertising expenditures and its assets	*COMPUSTAT*
	Firm R&D Intensity *(R&D)*	Ratio between a firm's R&D expenditures and its assets	*COMPUSTAT*
	Industry R&D Intensity *(Industry_R&D)*	Ratio of the sum of the R&D expenditures across all firms in the 3-digit SIC code to the sum of their assets	*COMPUSTAT*
	Leverage *(Leverage)*	Ratio of long term book debt to the firm's total assets	*COMPUSTAT*
	Book to market *(Book_to_Market)*	Ratio of book value of equity to market value of equity	*COMPUSTAT*
	Sales growth *(Sales_Growth)*	Percentage growth in sales from the previous year	*COMPUSTAT*
	Herfindahl Index *(HHI):*	Sum of the squares of the market shares of all firms in the 3-digit SIC code.	*COMPUSTAT*
	T-bill average *(T_Bill)*	Annual average of the 90-day Treasury bill rate in the year of the announcement	*CRSP Daily Treasuries*
	Earlier mention of an announcement *(Early_Mention)*	Dummy=1 if information about the new product had been available to investors prior to the announcement	*Factiva and RavenPack News Analytics*
	Introduction (*Introduction)*	Dummy=1 if the announcement refers to an introduction, 0 if preannouncement	*RavenPack News Analytics*
	Multiple (*Multiple*)	Dummy=1 if the announcement refers to multiple products, 0 if single product	*RavenPack News Analytics*
	Announcement word count (*Word_Count*)	Number of words in the press release	*RavenPack News Analytics*

Model development

To test hypotheses H_{1a}, H_{2a}, and H_{3a} I estimate the following model:

$$\begin{aligned} TobinQ_{it} = & \beta_0 + \beta_1 Firm\_NPA_{it} + \beta_2 Competitors\_NPA_{it} + \beta_3 News\_Sentiment_{it} + \\ & + \beta_4 Total\_Past\_Surprises_{it} + \beta_5 Firm\_Size_{it} + \beta_6 Advertising_{it} + \\ & \beta_7 R\&D_{it} + + \beta_8 Industry\_R\&D_{it} + \beta_9 Sales\_Growth_{it} + \beta_{10} Leverage_{it} + \\ & \beta_{11} HHI_{kt} + + \beta_{12} T\_Bill_t + \beta_{13} Early\_Mention_{it} + \Sigma\beta_{14k} Dummy\_SIC_{kt} + \\ & + \mu_i + \varepsilon_{it} \qquad (5) \end{aligned}$$

For hypotheses H_{1b}, $H_{2b,}$ and H_{3b} I estimate the following model:

$$\begin{aligned} CAR_{it} = & \alpha_0 + \alpha_1 Firm\_NPA_{it} + \alpha_2 Competitors\_NPA_{it} + \alpha_3 News\_sentiment_{it} + \\ & + \alpha_4 Past\_Surprises_{it} + \alpha_5 Firm\_Size_{it} + \alpha_6 Advertising_{it} + \alpha_7 R\&D_{it} + \\ & + \alpha_8 Industry\_R\&D_{it} + \alpha_9 Book\_to\_Market_{it} + \alpha_{10} Sales\_Growth_{it} + \\ & + \alpha_{11} Leverage_{it} + \alpha_{12} HHI_{kt} + \alpha_{13} T\_Bill_t + \alpha_{14} Early\_Mention_{it} + \\ & + \alpha_{15} Introduction_{it} + \alpha_{16} Multiple_{it} + \alpha_{17} Word\_Count_{it} + \\ & + \Sigma\alpha_{18k} Dummy\_SIC_{ik} + \mu_i + \varepsilon'_{it} \qquad (6) \end{aligned}$$

where, in both cases, *i* denotes the firm, *t* denotes the time (the day before the CAR measurement window for Tobin's Q and the day of the announcement for CAR), *k* is an industry dummy and the other variables are as previously defined.

RESULTS

Descriptive statistics

Table 3 presents summary statistics computed over the January 1, 2008 to December 31, 2011 period. As mentioned earlier, data from the year 2007 was used to compute the rolling window variables measured over the year preceding each announcement (past new product announcements, past competitors' announcements,

past news sentiment, and past surprises).

The CARs are significantly positive across sample (+.39% for the market-adjusted model, p<.01, +.31% for the four factor model, p<.01), confirming findings from the previous literature summarized in Table 1. The CARs are also significantly positive for the announcement date (+.17% for the market-adjusted model, p<.01, +.14% for the four factor model, p<.01) and for the three day window surrounding the announcement date (+.33% for the market-adjusted model, p<.01, +.28% for the four factor model, p<.01).The magnitude of CARs reported here lies at the lower end of the range from these prior studies. This could be due to the sample of this essay being more comprehensive than those used in past studies, because it includes all types of new product announcements across industries, ranging from product updates to more important innovations.

The final sample includes 780 announcements of products for which I were able to determine that information was available to market participants prior to the formal announcement date in RavenPack; in 612 of these cases I was able to obtain a clear date of the first mention of the product and to compute CARs surrounding this earlier date. These CARs are significantly different from zero (p<.01) and are also significantly larger than CARs surrounding the formal announcement date. This is true for both market-adjusted CARs (+.77% > +.17%, p=.07) and for the four factor CARs (+.91% > +.14%, p=.03). This confirms the findings of Sood and Tellis (2009).

TABLE 3:
Correlation Matrix and Descriptive Statistics for New Product Announcements (2007 to 2011)

	Mean	***St. dev.***	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***	***(8)***	***(9)***	***(10)***	***(11)***	***(12)***	***(13)***	***(14)***	***(15)***	***(16)***	***(17)***	***(18)***	***(19)***	***(20)***	***(21)***
Tobin (1)	1.90	1.04	1																				.
CAR (MA) (2)	.39%	6.31%	-.04	1																			
CAR (Fama French) (3)	.31%	6.21%	-.04	.93	1																		
Firm_NPA (4)	6.10	8.73	.21	-.07	-.07	1																	
Competitors_NPA (5)	2.46	1.36	.05	-.05	-.04	.19	1																
News_ Sentiment(6)	54.15	5.07	.01	-.04	-.03	.01	.00	1															
Past_ Surprises(7)	.38%	4.24%	.06	.00	.01	-.01	.00	.01	1														
Total_Past_ Surprises(8)	1.97%	15.99%	.09	.00	.01	.12	.04	.00	.73	1													
Firm_Size (9)[a]	7.11	2.02	.08	-.08	-.07	.45	-.05	-.09	-.08	-.03	1												
R&D (10)	.09	.09	.17	.03	.02	.00	.18	-.05	.06	.10	-.34	1											
Industry_ R&D (11)	.06	.03	.05	-.01	-.01	.09	.25	-.01	.03	.01	-.14	.36	1										
Advertising (12)	.01	.03	.00	-.03	-.04	.00	-.12	-.01	.00	.00	-.02	-.05	-.17	1									
Leverage (13)	.12	.16	-.11	-.04	-.04	.00	-.11	-.03	-.04	-.05	.30	-.22	-.11	.01	1								
Sales_Growth (14)	.05	.29	.23	-.02	-.02	.03	.01	.06	-.04	-.01	.07	-.04	.00	-.03	-.02	1							
HHI (15)	.05	.04	-.09	.02	.03	-.09	-.11	-.02	-.02	-.02	.10	-.27	-.41	.13	.16	-.01	1						
Book_to_ Market (16)	.58	.56	-.52	.03	.03	-.19	-.03	-.11	-.08	-.09	-.23	-.04	.02	.04	-.05	-.20	.04	1					
T_Bill (17)	.00	.00	-.01	-.04	-.03	-.06	-.04	.06	-.04	-.07	-.05	.03	.12	.02	.05	-.04	-.02	.08	1				
Early_ Mention (18)	.16	.37	.02	.01	.01	.01	.01	.01	.00	.00	.03	.01	-.01	.04	-.03	.02	.01	-.04	.00	1			
Introduction (19)	.83	.37	.01	-.01	-.02	.04	.01	-.02	-.02	-.02	.04	-.02	.00	.03	.01	.00	-.03	-.01	.02	.05	1		
Multiple (20)	.13	.33	-.04	.01	.02	-.04	.00	.01	.02	.00	-.03	-.01	.04	.01	-.01	-.02	-.01	.02	.00	-.06	-.09	1	
Word_Count (21)	765.9	257.3	.11	.00	.00	.06	.06	-.06	.00	.02	.03	.17	.06	.02	-.03	.08	-.11	-.06	-.02	.02	-.05	.05	1

[a] Firm size is measured as the logarithm of total assets measured in $ millions

Test of hypotheses

To test H_{1a}, H_{2a} and H_{3a}, I estimate Equation (5) and present the results in Table 4. The results indicate that the count of past new product announcements ($p<.05$), the recent history of product announcements in the firm's industry ($p=.06$), and the past news sentiment ($p<.05$) are all positively associated with Tobin's Q, even after controlling for the sum of CARs associated with past announcements (which is also positively related to the Q, $p<.01$). This suggests that the three focal factors contribute, at least in part, to firm value associated with expected cash flows, rather than just being positively related to the realized change in market value attributable to the CARs to past announcements. According to the results and the marginally significance of the estimated coefficient for the recent history of product announcements in the firm's industry, although both counteracting mechanisms introduced in H_{2a} and H_{A2a} might be at work, the argument in H_{2a} is more plausible.

In line with prior research I also find that firm R&D intensity and sales growth are positively related to Tobin's Q ($p<.01$). While sales growth can be more directly linked to cash flows that have already accrued to the firm, R&D expenditures could also carry information relevant for assessing firms' future innovation prospects.

To test H_{1b}, H_{2b}, and H_{3b}, I estimate Equation (6) and present the results in Table 5. The first column in Table 5 shows the results with CARs computed using the market-adjusted, estimated over the entire sample of 4,898 observations. The second column repeats the analysis for CARs computed with the Fama-French model. In the third and fourth columns the same models are estimated over the sample that excludes the 780 product announcements for which earlier information was available. Thus, these last two

columns present results for the subsample of announcements that were likely not anticipated in a direct manner, but could be anticipated indirectly, through inferences drawn from firms' past activities.

TABLE 4

Determinants of Tobin's Q Immediately before the Announcement of New Products

	DV: Tobin's Q N=4,898
Firm_NPA	.007 (.003)**
Competitors_NPA	.036 (.019)*
News_ Sentiment	.007 (.003)**
Total_Past_Surprises	.005 (.001)***
Firm_Size	.012 (.021)
R&D	2.077 (.769)***
Industry_ R&D	-1.514 (1.126)
Advertising	-.283 (1.267)
Leverage	-.268 (.185)
Sales_Growth	.721 (.151)***
HHI	.110 (.661)
T_Bill	17.003 (27.376)
Early_ Mention	-.017 (.033)
Wald $\chi 2$	620.28

$*p < 0.10$, $**p < 0.05$; $***p < 0.01$.

Two-way cluster standard errors in parentheses for the coefficients.

Industry dummies (not shown) are also included in the model

TABLE 5
Determinants of Cumulative Abnormal Returns to Announcements of New Products

	DV: Cumulative Abnormal Returns (measured as percentage)			
	Over the entire sample N=4,898		Over the sub-sample without earlier mentions N=4,118	
	Market Adjusted Model	Fama French Carhart Four Factor Model	Market Adjusted Model	Fama French Carhart Four Factor Model
Firm_NPA	-.049(.013)***	-.039(.012)***	-.045(.014)***	-.037(.013)***
Competitors_NPA	-.208(.101)**	-.187(.093)**	-.257(.106)**	-.212(.098)**
News_ Sentiment	-.065(.027)**	-.055(.026)**	-.064(.028)**	-.055(.027)**
Past_Surprises	-.121(.034)***	-..094(.033)***	-.101(.356)***	-.079(.034)**
Firm_Size	-.223(.102)**	-.209(.1)*	-.17(.105)	-.153(.106)
R&D	1.866(2.438)	1.318(2.269)	1.581(2.561)	.962(2.398)
Industry_ R&D	-3.588(5.543)	-4.888(5.462)	-.814(5.858)	-2.286(5.82)
Advertising	-15.07(4.971)***	-15.75(4.604)***	-16.21(5.164)***	-17.14(5.117)***
Leverage	-1.753(.797)**	-1.509(.817)*	-1.653(.817)**	-1.474(.832)*
Sales_Growth	-.664(.395)*	-.573(.382)	-.436(.431)	-.313(.409)
HHI	4.801(4.944)	5.841(4.471)	4.91(5.366)	5.871(4.881)
T_Bill	-435.83 (152.34)***	-276.56 (146.15)**	-486.32 (162.58)***	-352.66 (154.72) **
Book_to_Market	.115(.372)	.105(.344)	.233(.392)	.238(.36)
Introduction	-.048(.253)	-.033(.249)	.005(.281)	.013(.279)
Multiple	.309(.308)	.332(.304)	.26(.327)	.247(.313)
Word_Count	.0002(.0004)	.0003(.0004)	.0002(.0004)	.0003(.0004)
Early_ Mention	.154(.248)	.214(.248)		
Wald $\chi 2$	1086.45	2725.93	965.94	2485.51

**p < 0.10, **p < 0.05; ***p < 0.01.*
Two-way cluster standard errors in parentheses for the coefficients.
Industry dummies (not shown) are also included in the model

I acknowledge that I could not compile complete information about the development of each product, and that prior information about patents and technologies included in the product could have still been available to investors (the information could have perhaps become available before the product was given a formal name, which is why I could not have linked the product with this information through the archival searches). However, the confirmatory results that are obtained controlling for specific mentions of the product that have occurred prior to the firm formally announcing it, provide some reassurance that the main results are not driven by a correlation between the focal expectation drivers and the early availability of information about the product.

In all four models, the results consistently show the same pattern. The counts of past new product announcements ($p<.05$), the recent history of product announcements in the industry ($p<.05$), and the past news sentiment ($p<.05$) are all negatively associated with the announcement CARs. I also control for past CARs, using their average rather than their sum, because I posit that the average success of each past announcement increases expectations for future innovation strategies. The average past CARs are negatively related to current announcement CARs ($p<.01$; the same result is obtained if the total CAR measure is used).

Consistent with prior literature, firm size is negatively related to announcement CARs. In contrast with the Tobin's Q findings, R&D intensity is not a significant determinant of CARs, but advertising intensity is negatively related to CARs ($p<.01$). This negative relationship highlights the main theme in this essay in that it would be erroneous to conclude that firms with high advertising expenditures do not earn rents from new

products. On the contrary, recent evidence indicates that these firms enjoy higher awareness and visibility, have higher liquidity, a larger investment base, and higher firm values (Grullon, Kanatas and Weston 2004). Instead, a more appropriate inference would be that informational updates coming from these high advertisers are less likely to further impact their market value.

It is somewhat surprising to find an absence of a relationship between CARs and announcement content variables (preannouncement, multiple product content, and word length). The effect of these variables could potentially be mitigated by qualitative aspects of the new product (such as radicalness and market potential) which could not be observed and quantified for such a large sample.

Robustness tests and additional analysis

Alternative model specifications

To ensure that the results are not driven by outliers, I perform a 90% winsorization of the dependent variables, of the focal independent variables, and of the variable that captures the CARs to past announcements. This procedure sets observations below the 5th percentile to level of the 5th percentile and observations above the 95th percentile to the level 95th percentile (see, for instance, Leary and Roberts 2014). I then estimate Equations (5) and (6) with these winsorized variables. All factors maintain the original sign and significance, in line with the results of Tables 5 and 6. I also estimate reduced forms of Equations (5) and (6) in which all focal variables are included without control variables. Even though none of the correlations between the variables is higher than .45, and the maximum VIF statistics for all the variables is 1.73,

I took this step to ensure that the results are not affected by potential multicollinearity in the data. The results are qualitatively similar to those presented in Tables 5 and 6. Finally, I repeat all tests with the past history variables measured over six-month rolling windows rather than twelve-month windows. The results for the CAR model are similar to Table 5. For the Q model, competitors' innovation activity and news sentiment preserve their positive sign but are no longer significant. The history of past product announcements remains highly significant.

Differences between high and low output innovators

Of the 833 firms in the sample, 164 have introduced only one product. For these firms I estimate a simple OLS version of the panel models (Equations (5) and (6)) from which I exclude the past count of new products and the CARs to past product announcements. The results show that past news sentiment is still negatively associated with CARs ($p<.05$) and also with Tobin's Q. although this relationship is no longer significant ($p=0.14$). Competitors' innovation output, while carrying the hypothesized sign, is not significant in either model. These lower significance levels could be, at least in part, due to the low power of the test for such small sample. Alternatively, expectations may be more difficult to anchor in past firm activity when there is little or no history that investors could use.

I do find, however, a very strong stock market reaction to the announcements made by these single-product firms. Their average CARs are +1.91%, compared to +.33% for the remaining announcements, a difference that is both substantive and statistically significant ($p<.01$). The distribution of announcements across SIC codes is

very similar for both subsamples, with most innovations coming from SIC codes starting with the digit 3, which includes household appliances and electronic equipment. The similarity of these distributions indicates that the difference in CARs is not driven by industry effects: investors can react strongly to a new product announcement made by a firm that has not been actively announcing new products, even if it belongs to an industry that has a high rate of new product announcements.

Announcements that elicit the strongest market reaction

To answer this question I compute deciles for the CARs to all announcements. In all but the 10th decile the average number of past product announcements per year per firm ranges from 5.14 to 7.79. This average is only 3.13 for the decile with the highest CARs (average CAR=12%). This statistic illustrates nicely the finding that investors react more strongly to announcements coming from firms that have been introducing very few number of new products in the past. The average CARs to past announcements are also smallest for the top CAR decile - indicating that these were firms that had typically underwhelmed investors in the past - but the difference is not as striking as the one obtained for the number of past announcements.

None of the variables that pertain to the content of the announcement provides a clean separation of announcements with high, versus low CARs. In some cases the lack of significance could be due to the low power. For instance, I find that the CARs to preannouncements are .6% and the CARs to introduction announcements are .34%, but the difference is not statistically significant. In other cases, the difference does not appear to be substantive; the press releases for high and low CAR announcements differ,

on average, by only 5 words.

Announcements that beat the odds

The results suggest that firms believed to be successful innovators will find it increasingly difficult to impress investors with new product announcements. An interesting question is whether any firms buck this trend. This is not the focal question in this essay; a conclusive answer would require a set up and data analysis worthy of a separate study. However, to spur additional research in this direction, I provide some preliminary insights into the characteristics of products that generate high CARs despite high pre-announcement expectations.

I begin by narrowing the sample down to announcements that have the highest pre-announcement expectations, as measured by the three independent variables in Equations (5) and (6). I require each of these three variables and the past surprises to be in the highest quartile. From those, I further narrow the sample down to include only announcements with which investors were most pleasantly surprised, both with the previous product introductions and the focal announcement: I require that the past innovation surprises and the announcement-date CARs belong to the top quartile of all CARs.

The subsample of announcements that "beat the odds" contains 42 announcements. I collect a subsample of 42 matching announcements that "do not beat the odds." The matching announcements are randomly selected from those which have the same pre-announcement expectations in the sense that each of the four variables

continues to lie in the highest quartile. However, CARs no longer belong to the top quartile.

I analyze these 84 announcements for content, and code them along eight dimensions that might be used as informational input by investors: (1) radical or incremental innovation; (2) preannouncement or actual introduction; (3) single or multiple product; (4) product developed by the firm alone, or as part of a partnership; (5) endorsement by external entity such as magazine or consumer group; (6) detailed description of the product's features; (7) announcement made by CEO or other top executive; and (8) the presence of details about the consumer needs that the product addresses, or the class of customers that it targets. I then compare announcements across the two subsamples to see if they differ on any of these eight dimensions.

I only observe a significant difference in the last dimension, the presence of specific details about targeted consumer needs or market segments (Specifically, 55% of announcements in the "high CAR" subsample (the one that beats the odds) vs. 39% for the "low CAR" sub-sample, contain one or more statements on how the product meets consumers' needs.)[3] While I am agnostic of the generalizability of this finding to larger samples, it does appear intuitive that uncertainty of demand for the new product is

[3] To exemplify the type of market segment information, an announcement by Symantec stated "We listened to our customers and delivered our award winning NetBackup 7 software in a box that is easy to deploy, easy to configure and tightly integrates management and licensing into their existing NetBackup environment." And Microsemi specified "This product family addresses requests we've had from long-time Microsemi customers to supply LED solutions with the same performance, quality, reliability, service, and supply chain structure they've experienced with Microsemi's proven CCFL complete system solutions."

reduced if the target customer need or market segment clearly mentioned, even when the parent firm is known to be a successful innovator.

Long-term returns to innovation

The main theme in this study—that stock market expectations are higher for successful innovators—also carries a broader implication about the long-term stock performance of innovating firms. I argue throughout this essay that announcement-date CARs are not appropriate performance metrics for innovating firms because rewards to innovation are already reflected in stock prices before the announcement. If so, successful innovators should be rewarded with stronger stock performances over the long term. I test this implication to corroborate the previous findings.

I evaluate the relationship between the long-term stock returns of innovating firms and their unexpected innovation output during the sample period. I measure unexpected innovation as the difference between the number of products introduced during the twelve-month period prior to each announcement and the number of products introduced during the previous twelve-month period. I compute one aggregate value of unexpected innovation for each firm, taking the average of each firm's unexpected innovations during the sample period. I then sort all firms into quintiles based on this aggregate metric of unexpected innovation.

To measure long-term stock returns I use the calendar-time portfolio method, which automatically accounts for cross-sectional clustering of stock returns (Mitchell and Stafford 2000; Srinivasan and Hanssens 2009). I group firms into five portfolios, each corresponding to one of the five unexpected innovation quintiles. Firms in the

highest quintile are those that exceed expectations, and firms in the lowest quintile are those that fall short of expectations, in each case, by the largest margin. I compute abnormal returns for the two extreme portfolios by regressing each portfolio's monthly returns on the four Fama-French-Carhart factors. The intercepts provide the abnormal returns of each portfolio. To assess the statistical significance of the difference in abnormal returns, I build a long-short portfolio that takes long positions in top-quintile stocks and short positions in bottom-quintile stocks, and regress the returns on the same four factors. I also compute a statistic for announcement-day CARs for each portfolio: I sum up all announcement-day CARs for all firms in a portfolio and compute an average across firms of the summed CARs.

I find that firms in the top quintile do quite well during the sample period, with an average long-term abnormal return of +3.95% per year. At the other extreme, stocks in the bottom quintile—those that fall short of expectations—do quite poorly, with an average abnormal return of –3.72% per year. The difference between the two (+7.67% per year) is statistically significant ($p=.003$). Interestingly, the summed announcement-day CARs are negative for firms in the top quintile (−.51% for market-adjusted model and −.83% for Fama-French CARs) and positive for firms in the bottom quintile (+3.04% and +2.31%, respectively), with the differences between the two quintiles being highly significant ($p<.001$).

The long-term results are not surprising in view of published research regarding the long-term rewards to innovation (e.g., Pauwels et al. 2004). However, together with the summed CAR results, they corroborate this essay's main hypotheses by showing that

the relationship between innovation and long-term stock returns remains positive in the sample, despite the negative relationship documented in the case of short-term CARs.

SUMMARY, IMPLICATIONS, AND LIMITATIONS

Event study methodology is addressed as a powerful tool to examine the value generated from strategic investment decisions, (Fang, Lee and Zhang, 2015 in JM) in marketing literature. However, inferences drawn from CARs in event studies do not always carefully account for pre-event expectations. CARs provide a good metric for assessing the value-added of unanticipated events. However, the use of CARs is more problematic for events that are at least partially anticipated. Therefore, inferences drawn from CARs should account for, or at least acknowledge, the way in which pre-event expectations are formed.

Categorizing events as anticipated or unanticipated is not always straightforward. This seems to be the case for a number of events that are of interest to marketers—alliances, brand extensions, or market expansions, to name a few. What makes these events unanticipated is their infrequent and irregular occurrence and the fact that, with the possible exceptions of automobiles, investors do not typically formulate specific forecasts about product launch dates or other product details. What makes them anticipated is the broader underlying strategy that governs each marketing action.

To preserve competitive advantage, firms do not typically release the details of their marketing strategy, so the anticipated nature of most marketing events is not readily apparent. It is perhaps for this reason that prior studies appear to treat them as

completely unanticipated. Indeed, a review of the literature identifies a number of event studies where inferences drawn from announcement-day CARs suggest a simplistic event classification heuristic - one that treats all events as unanticipated unless clear, event-specific information is demonstrably available prior to the announcement date.

I propose here that this simplistic heuristic is inadequate for new product announcements. I show that even in the absence of event-specific information, investors' reaction to new product announcements depends critically on firm and industry characteristics that provide insights into the broader innovation strategy. And, I argue that finding lower announcement-day CARs should not be construed as an unfavorable signal about the value of innovation. Quite to the contrary, I document higher long-term returns for firms that consistently launch high numbers of new products.

While the results are derived in the context of new product announcements, the more general conclusion is relevant to the broader class of events that are part of corporate strategies. Consider, for instance, the case of brand extension announcements (Lane and Jacobson 1995). Investors are more likely to expect brand extensions from firms that have broader brand portfolios, stronger brand equity, more experience with successful brand extensions, from firms that have recently entered into new product categories, and from firms that operate in more competitive product categories. Similar arguments can be made in the case of alliances, product placements, licensing or outsourcing arrangements, category or market expansions, and any other marketing events that can be ascribed to a broader underlying strategy.

Correctly interpreting the stock market reactions to marketing events is also critical for marketing practitioners. An important question in the business literature pertains to performance metrics by which managers should be evaluated. Consider the case of a marketing manager who joins a new firm, perhaps as a replacement for a retired veteran manager with a good track record. If the firm itself is widely recognized as a successful innovator, the value of its innovation strategy is already built into the stock price. What then defines success for this new manager? And how should it be measured? Arguably, from a marketing perspective, the manager's tenure would be judged successful if she can continue the high-quality innovation program initiated by her predecessor. And yet, by performing at that level, all that she can expect from the stock market in reaction to future product announcements is a series of abnormal returns that are essentially zero. Worse, if the manager's performance is good but falls short of expectations, these abnormal returns could turn negative. It is, therefore, difficult to evaluate performance using short-term market signals without observing a relevant counter-factual scenario, such as the one where the job was offered to another candidate.

This essay also highlights the importance of managing expectations. Executives in innovative firms might want to manage investors' expectations to avoid irrational exuberance. To illustrate, assume that an innovation strategy produces economic rents at a rate of 3% per year and the firm is expected to launch a number of new products each year. If expectations are carefully managed, the firm would expect the risk-adjusted firm value to increase from, say, $100 to $103 during the year, without further market reactions on the announcement days. However, if expectations are irrationally exuberant,

firm value could first overshoot to $110 before dropping toward the intrinsic value of $103. The drop would occur gradually, with each new product announcement, as investors' expectations become more realistic. The former price pattern is desirable because it keeps stock prices more informative, which facilitates the implementation of meaningful performance metrics.

The latter, bubble-like pattern is more problematic. A stock price that is not informative should not be used as a performance metric. Doing so could create moral hazard. For example, managers might be tempted to overpromise, especially if their compensation is linked to short-term stock value. Additional nefarious consequences are possible if the stock market is particularly illiquid; the correction phase of the bubble could overshoot on the down side and the value of the firm could temporarily drop below its $103 fundamental value, as margin calls would trigger additional sell orders. In rare cases of acute illiquidity this decline could become self-fulfilling and cause real economic losses to an otherwise healthy company.

I argue, therefore, that performance metrics linked to short-term stock returns are likely inappropriate for marketing managers, particularly for firms that are already successful innovators. Instead, the results of this study recommend the adoption of metrics that are linked to longer-term stock value, and also of metrics that are non-financial in nature, such as market share, units sold, customer satisfaction, and profit margins.

In this essay, my focus has been on new product announcements. It would be worthwhile to examine the effect of investors' expectation about other marketing

activities that are part of a broader marketing strategy in future studies. This essay was restricted by the size of the sample from content analyzing the new product announcements in depth. Future research can also expand the horizon of this study by examining other product-specific factors that can affect investors' expectation.

CHAPTER III

WHEN 1+1>2: HOW INVESTORS REACT TO CONCURRENTLY ANNOUNCED NEW PRODUCT RELEASES AND OTHER CORPORATE NEWS

Firms routinely press release the launch of their new products. An examination of these press releases shows that in about 7% of cases firms issue new product announcements concurrently with another corporate announcement. However, academic evidence on the consequences of these actions is lacking, because concurrent announcements are routinely eliminated from event studies in an attempt to avoid their confounding effects.

I use a comprehensive sample of press releases issued by publicly traded U.S. firms to document the consequences of firms announcing the release of a new product concurrently with other positively valenced corporate news item. Drawing on Merton's model of capital market equilibrium with incomplete information I first present two conditions under which firms benefit more from issuing concurrent new product announcements. I then verify that under these conditions, the increase in shareholder value from concurrent announcements is higher than the total increase from issuing two similar announcements separately. This research provides managerial insights on how corporate communications can be leveraged to increase stock prices.

INTRODUCTION

New product announcements are important events for their parent firms. Managers issue these announcements in the hopes that investors will notice, recognize, and reward their new product development efforts. As a result, most new product announcements are carefully choreographed, stand-alone press releases. However, in a nontrivial number of cases, firms announce new products concurrently with other corporate news. For example, on October 26, 2010, Juniper Networks announced the introduction of Junos Pulse Mobile Security Suite while also announcing the opening of the Juniper Global Threat Center, a facility based in Columbus, Ohio. Similarly, on March 18, 2003, findwhat.com announced both the launch of AdAnalyzer and the hiring of Ernst & Young as its new independent auditor.

These examples raise two important questions: Under which conditions are concurrent announcements more likely to occur, and when are firms more likely to gain from announcing new products concurrently with other unrelated, positively valenced corporate news, rather than separately?[4] At first glance, the theory of efficient markets suggests that, all else being equal, the effect of concurrent announcements should equal the sum of the effects of the two announcements issued separately; thus, managers should be indifferent between the two options (Fama 1970). Alternatively, prospect

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[4] I focus on the combination of two *positively valenced* news items because concurrently announcing new products with a *negatively valenced* news item is a rare occurrence. I found that in this extensive, multi-industry sample which spans 11 years of announcements less than .05% of new product introductions are announced concurrently with a negatively valenced news item. Throughout this essay, when I refer to concurrent new product announcements it means one new product announcement and one other, distinct positively valenced corporate announcement made on the same day by the same firm, but in separate press releases.

theory suggests that managers prefer to enjoy the stock market gains from positive announcements separately and, as such, should avoid making concurrent announcements (Linville and Fischer 1991; Thaler 1985). Yet the data in this essay show that concurrent announcements are not rare occurrences: approximately 7% of new products are announced concurrently with other news. Are these managerial actions beneficial to firms?

Notwithstanding a substantial research stream of event studies of new product announcements, the economic implications of concurrent announcements are not well understood. Previous event studies have opted to exclude concurrent announcements from analysis rather than study them in isolation, because of their confounding effects on stock returns (e.g., Borah and Tellis 2014; Lee and Chen 2009; Lee et al. 2000; Wooldrige and Snow 1990). As a result, the financial consequences of concurrent announcements, despite being of potential substantive interest to managers, remain unknown. Insights are also lacking into their prevalence and the conditions that make them more desirable. If at least some concurrent announcements elicit more positive stock market reactions than the sum of two comparable separate announcements, firms should actively use this communication tool when circumstances warrant it. Conversely, this strategy should be avoided if concurrent announcements have a negative effect on shareholder value. To the best of my knowledge, this study is the first to investigate the determinants and consequences of new product announcements made concurrently with other positively valenced corporate news. I aim to answer the following research questions:

1. Under which conditions are firms more likely to make concurrent announcements?
2. When concurrent announcements are made under these conditions, what is their financial value? Specifically, do concurrent announcements generate higher abnormal returns when compared to the sum of abnormal returns obtained from similar stand-alone announcements?

I start by proposing that concurrent new product announcements meet the characteristics of events that Barber and Odean (2008) identify as "attention-grabbing". As such, concurrent announcements can increase the investor base of the firm more than stand-alone announcements. In turn, an increase in the relative size of a firm's investor base can reduce the firm's cost of capital and increase its market value. But this effect differs across firms, as Robert Merton shows in his model of capital market equilibrium with incomplete information, which provides the theoretical foundation for this essay (Merton 1987). I leverage Merton's model to propose two conditions when concurrent new product announcements are more likely to occur and when they can lead to a higher increase in firm value relative to an increase in the investor base of the firm.

I empirically document the additional value that accrues to stock prices due to concurrent new product announcements. I do so by disentangling the effects of the two combined announcements and by estimating the average treatment effect (ATE) of concurrently issuing the new product release with one other positively valenced corporate news item. Using propensity score matching (PSM) I create matched counterparts for each of the two combined announcements among the news that were announced stand-alone. I then compare the effects of concurrent announcements with those of stand-alone announcements (Guo and Fraser 2010; Rosenbaum and Rubin 1983). I empirically test the hypotheses on a sample that includes concurrent and stand-

alone new product releases, and other positively valenced corporate announcements made by U.S. publicly traded firms from January 2003 to December 2013. The results show that the stock market reaction to concurrent announcements is greater than the sum of the reactions to similar stand-alone announcements.

This study makes three contributions to marketing theory and practice. First, from a theory standpoint, it contributes to an emerging stream of research on firm communications with investors. Much has been written about how firms can improve their communications with consumers; researchers are now examining how effective firms are at capturing investors' attention (e.g., Chemmanur and Yan 2009; Grullon, Kanatas, and Weston 2004; Kaniel, Starks, and Vasudevan 2007). I theorize and provide empirical support for the assertion that issuing a new product release on the same day with one other positively valenced announcement increases the likelihood that these announcements will stand out in the stock market and be noticed by investors. This finding opens the door for additional research on how other types of marketing announcements can be sequenced and leveraged to maximize their stock market impact.

Second, concurrent announcements have been routinely eliminated from event studies in the marketing literature, but I argue that they should not be. Eliminating them yields an incomplete picture of the phenomenon being studied and could lead to inaccurate results. Indeed, their consequences could add new insights to the literature and may provide managers with a new set of strategic actions that could be occasionally used to benefit their firms.

Third, this essay identifies two conditions when concurrent new product announcements are beneficial to firms and can lead to an increase in shareholder value. The decision to issue such announcements entails a cost-benefit analysis: for instance, there may be costs associated with unduly delaying a product announcement in order to issue it concurrently with a positively valenced announcement that will be released at a later date (Moorman et al. 2012). Guided by the findings of this essay and the contingencies that characterize them, managers can better assess the benefits of issuing concurrent new product announcements and, potentially, of other types of concurrent announcements.

The remainder of this essay proceeds as follows: First, the theory is introduced that underlies the hypotheses on the occurrence of concurrent new product announcements and on the stock market reaction to these announcements. Next, the data is described, the method used to empirically test the hypotheses is explained, and the results are presented. Finally, the theoretical and managerial implications from this research essay are explained.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

It is not obvious that combining positively valenced announcements benefits firms more than issuing the same announcements separately. On the one hand, the efficient market hypothesis (EMH) suggests that the total gains from the two announcements should be the same, whether they are combined or issued separately. Specifically, EMH posits that investors have access to all publicly available information

needed to estimate the expected returns of all the stocks in the market (Fama 1970; Sharpe 1964). When new information becomes available, EMH assumes that investors only react to its content, regardless of the timing or the source of this information (assuming that these factors do not in themselves carry additional informational content). Thus, all else being equal, the stock market returns from announcing new product introductions concurrently with other news should be equal to the combined stock returns from announcing the news items separately; that is, the two options should be financially equivalent.

On the other hand, prospect theory suggests that people prefer to segregate positively valenced events. Specifically, the hedonic editing hypothesis (Thaler 1985) and its variant, the gain-savoring hypothesis (Linville and Fischer 1991), predict that people prefer to savor gains separately but integrate losses. In this context, this means that managers may prefer to announce positively valenced news separately, to enjoy gains in the stock market on different occasions.

To address this apparent puzzle, I propose another possibility; concurrent announcements may increase stock prices by making investors more aware of the firm's stock. In the following sections I draw on research on "attention-grabbing stocks" to propose that concurrent announcements increase the investor recognition of the firm's stock (Barber and Odean 2008). I then rely on Robert Merton's model of capital market equilibrium with incomplete information, to identify the conditions under which firms benefit most from an increase in investor recognition or its investor base (Merton 1987

uses the terms investor recognition and investor base interchangeably and I do the same in this essay).

Concurrent announcements and investor recognition

Finance researchers argue that it is unrealistic to expect investors to access and process all publicly available information. Kaniel, Starks and Vasudevan (2007) note that "even if news is publicly available, it is not incorporated into investment decisions until investors pay attention." (p.1) Indeed, there is evidence that investors tend to ignore good news if the manner in which it is made publicly available is not particularly salient (Huberman and Regev 2001). What, then, can firms do to attract investors' attention?

Researchers have linked investor attention and breadth of stock ownership to advertising, news coverage, or media coverage of the CEO (e.g., Barber and Odean 2008; Grullon, Kanatas, and Weston 20004; Nguyen 2015). For instance, Barber and Odean (2008) show that investors are more likely to buy stocks that are in the news than stocks that are not. They also show that investors are more likely to pay attention to and buy stocks that exhibited extreme one-day returns on the previous day, irrespective of their performance on the focal day. This is in part because of their performance, in part because these stocks are more likely to be highlighted in various news outlets such as Wall Street Journal's previous day's big gainers column. I argue that concurrent announcements share the characteristics of the events highlighted by Barber and Odean: first, they are news, and second, they have a higher chance of moving the stock of the firm in an attention-grabbing territory than does a stand-alone positively valenced

announcement. For instance, if a stand-alone new product announcement increases the price of a stock by 2% and another positively valenced announcement increases it by 1%, the 3% increase that should, at a minimum, be obtained by releasing the two announcements together has a higher chance of attracting investors' attention than the increase produced by either one of the stand-alone announcements.

Thus, I propose, and later in this essay I show empirically, that issuing a new product announcement concurrently with other positively valenced announcement increases investor recognition more than separately issuing two comparable announcements. However, firms do not equally benefit from the increase in investor recognition.

Specifically, I build my arguments on the main take-away from Merton's theoretical model: the required rate of return for each firm's stock depends on the investor recognition of the stock and this rate decreases as investor recognition increases (Merton 1987). This means that companies with higher investor recognition are able to raise money through the stock market at lower costs. Merton demonstrates this argument mathematically in equation (33) in his paper. He presents a set of determinants of the marginal increase in firm value due to the increase in investor recognition for that firm's stock. In the next section I identify two of these determinants that can serve as a theoretical foundation for the hypotheses in this essay. One factor is the value of the firm, captured by the term V_k which appears in the numerator of the right hand side of equation (33) and the second factor is investor recognition, q_k, which appears in the denominator of the right hand side of equation (33). Merton argues that

firms with higher value (i.e., firms facing higher expectations of cash flows), and firms with lower investor recognition will benefit more from an increase in investor recognition and their firm value will increase more. I expand this argument in the following subsections.

Conditions under which concurrent announcements are more likely to occur, and their financial consequences

Firms with high values

The stock of firms with high values or firms facing high investor expectations of future cash flows is likely to trade at a price that is a higher multiple of the firm's earnings. The expensive price of this stock makes it less likely that individuals who are part of the firm's current investor base buy additional stock in that firm. As a result, this type of firm will benefit more from expanding its investor base and adding new potential buyers who previously have not considered the stock (Merton 1987).

I select two proxies that correspond to firm value and to expectations of the future cash flows. First, I use Tobin's Q, measured as the ratio of firm value to the book value of assets. Second, I use the news sentiment - the investor sentiment associated with past corporate announcements - as a determinant of investors' expectations of future firm performance[5]. Specifically, when a firm consistently makes announcements over a period of time that are positively perceived by investors, investors gradually build expectations that this firm will continue to do well in the future. If investors'

[5] I formally define news sentiment at time t as the cumulative strength of the valence of the totality of news that has been released by the firm over a specified period that immediately precedes time t.

expectations are high, the price of that firm's stock is also likely to be high (relative to its current earnings) as it incorporates higher expectations about future earnings. This argument applies equally to firms with high news sentiment and to firms with a high Tobin's Q. Therefore, firms with high investor sentiment or high Tobin's Q are more likely to take an action that expands their investor base and attracts new investors, such as issuing concurrent new product announcements. Thus, I hypothesize that:

> *H_{4a}: Firms that have experienced a higher news sentiment associated with their recent corporate announcements are more likely to issue concurrent new product announcements than firms whose recent announcements have elicited a lower news sentiment.*
>
> *H_{4b}: Firms with a higher Tobin's Q are more likely to issue concurrent new product announcements than firms with lower Tobin's Q.*

<u>Firms with low investor recognition</u>

I now turn to the second condition identified from Merton's model where he proposes that the lower the investor recognition, the more the firm benefits from increasing it. Intuitively, a firm that is known to a majority of investors has a limited upside potential from further expanding its investor base. In contrast, the potential to find new interested buyers is relatively higher for a firm that is less known to investors and has smaller base of current investors.

I therefore propose that firms are more likely to make concurrent new product announcements when they are relatively unknown (the stocks of these firms have been called neglected, or generic stocks: Arbel 1985; Arbel, Carvell, and Strebel 1983). The intuition behind this contingency is supported by research that has documented a positive link between investor recognition and a reduced cost of capital (e.g.,

Christensen, De la Rosa, and Feltham 2010; Easley and O'Hara 2004). This literature suggests that firms in this category have the strongest incentive to leverage a communication strategy that can place them on the radar screen of investors who are unaware of their stock. I use two commonly used proxies for the size of investor base: institutional investor holdings and the number of analysts following a firm (e.g., Arbel 1985; Baker, Powell, and Weaver 1999). Thus, I hypothesize that:

> *H_{5a}: Firms with a lower percentage of shares held by institutional investors are more likely to issue concurrent new product announcements than firms with a higher percentage of shares held by institutional investors.*
>
> *H_{5b}: Firms that are followed by a smaller number of analysts are more likely to issue concurrent new product announcements than firms followed by a larger number of analysts.*

I note that the conditions highlighted in H_{4a}, H_{4b} respectively H_{5a}, H_{5b} are not dependent on one another. As an illustration, consider a young biotech firm that has a small following of investors who believe that the firm will produce a blockbuster drug at some point in the future. This expectation would result in a relatively high firm value despite its investor base being low.

Finally, the last hypothesis follows directly from Merton (1987) and from the previous hypotheses. As argued before, concurrent announcements have the potential to increase investor recognition more than their stand-alone counterparts. The increased investor recognition, in turn, leads to an increase in stock liquidity investor base, a decrease in the cost of capital of the firm and an increase in firm value (Gervais, Kaniel, and Mingelgrin 2001; Grullon, Kanatas, and Weston 2004; Merton 1987). Thus, when firms are in a position to benefit more from investor recognition, issuing concurrent

announcements will yield higher returns than their stand-alone counterparts. Specifically:

> *H_6: The stock market reaction to a concurrent new product announcement made under the conditions described in $H_{4a,b} – H_{5a,b}$ is greater, on average, than the sum of the reactions to a similar stand-alone new product announcement and a similar stand-alone positively valenced corporate news item.*

DATA AND SAMPLE

Testing the hypotheses requires a comprehensive sample of positively valenced corporate announcements, including new product announcements. Most event studies of corporate announcements have used archival searches in Dow Jones, LexisNexis, or Wall Street Journal Index to identify the news (e.g., Chaney, Devinney, and Winer 1991; Sood and Tellis 2009; Sorescu, Shankar, and Kushwaha 2007; Wang, Chen, and Chang 2011). This method is unwieldy in the context of concurrent announcements. Specifically, to prevent selection bias, a complete sample of corporate announcements made by the firms included in the sample is needed. Archival searches, which typically rely on keywords, cannot guarantee that all corporate announcements are retrieved.

To overcome the challenges associated with archival searches, I compile the sample from RavenPack News Analytics that is described in the first essay.

RavenPack has a number of useful features described in prvious essay. Relevant to this research is the classification of all corporate news into specific categories. To test the hypotheses, I compile all the announcements in the “product release” category in RavenPack which includes announcements of new products, new services, or upgrades

of existing products or services. In addition to product releases, I compile all other types of news, such as acquisitions, award announcements, executive appointments and other similar categories, announced on the same day as the product releases. I define concurrent announcements as events that are issued on the same day by the same firm. The events do not need to be announced simultaneously; I define them as concurrent news as long as the two events are announced during the same day. Future research could expand the window used to define concurrent announcements and study the impact of an expanded class of concurrent announcements.

I use the RavenPack database to obtain all new product releases and other types of positively valenced announcements by U.S. publicly traded companies from January 2003 to December 2013. For each announcement in the sample, the database provides the date when it was issued, the name of the parent company, and an event specific sentiment score (ESS) as described previously[6].

To obtain a clean, usable sample the following steps were employed: First, the focus of this essay is on events whose timing the firm can control; as a result, the sample is limited to announcements made directly by the firm through a press release. Second, in order to confirm that the press release is generated by the specific parent company I only use announcements with relevance score of 100 as explained in the first essay.

I assemble two subsamples of firm announcements. The first subsample includes all product releases and the second subsample includes all other positively valenced

[6] The features and collection process of the event sentiment score (ESS) is described in the first essay in details. Please refer to page 27.

corporate announcements, where their sentiment score (ESS) is greater than 50[7]. I collect the stock return data from CRSP and financial data from COMPUSTAT.

I eliminate announcements for which I could not collect the financial data from COMPUSTAT or their stock returns from CRSP. Finally, following previous research (e.g., Chen, Ganesan, and Liu 2009; Geyskens, Gielens, and Dekimpe 2002; Homburg, Vollmayr, and Hahn 2014) to cleanly measure the stock market reaction to the concurrent announcements, if the firm has announced any other news items a day before or a day after the concurrent announcements, I eliminate the announcements from the sample to prevent confounding effects.

The final sample contains two subsamples. The first subsample includes 28,758 new product announcements. Of these, 27,596 were stand-alone announcements (they were the only press releases issued by the firm on that day) and 1,162 were announced concurrently with one other positively valenced corporate news (other than new product releases) issued on the same day.

The second subsample consists of positively valenced corporate news from many different categories such as partnerships, acquisitions, awards, facility upgrades, executive appointments, etc. This sample includes 53,600 announcements, of which 52,438 are stand-alone and 1,162 are announced alongside the 1,162 new product releases identified earlier.

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[7] I only collect news sentiment scores above 50. This follows directly from the RavenPack's definition of the news sentiment variable that adding a neutral-sentiment news item to a new product introduction is not likely to significantly change the stock market reaction to the new product announcement. I also eliminate concurrent news with a negative news sentiment (ESS < 50). These are extremely rare occurrences, representing less than .05% of the announcements in the sample.

Announcements included in the two subsamples are press releases from 2,873 firms in 58 industries classified by 2-digit SIC codes. I use the complete set of firms that have made at least one new product announcement, whether they have made concurrent announcements or not, because these are the firms that have the ability to make concurrent new product announcements.

VARIABLE OPERATIONALIZATION AND METHOD

Measures

To test H_{4a} to H_{5b}, I use two logistic regressions as follows: (1) one that models the probability that a new product announcement will be made concurrently with another corporate announcement or stand-alone and (2) one that models the probability that a corporate announcement, other than a new product announcement, will be made concurrently with a new product announcement or stand-alone. In each model, the dependent variable is a categorical, dummy variable. These variables are:

In the first model, *Concurrent_NPA* equals 1 if the new product has been announced concurrently with another corporate news item and 0 if the new product announcement is stand-alone.

In the second model, *Concurrent_News* equals 1 if the corporate news (other than products releases) has been announced concurrently with a new product release and 0 if the corporate announcement is stand-alone.

Independent variables

The independent variables included in the logit models are as follows:

News sentiment (News_Sentiment): I use firms' average news sentiment prior to the announcements as a proxy for firm value and for investors' expectations of the firm's future cash flows. If a firm has recently undertaken a string of positively received actions, investors expect the firm to continue to do so and to generate high cash flow in the future. I measure news sentiment by averaging the Event Sentiment Scores (ESS) for all announcements, of all types, made by a firm, six months prior to each announcement under consideration. For robustness, I report later in the essay results obtained with the same variable computed over rolling windows of 3, respectively 12 months prior the event.

Tobin's Q (*Tobin_Q*): I measure firms' Tobin's Q prior to each announcement as a proxy for the value of the firm (e.g., Morgan and Rego 2009; Rubera and Kirca 2012; Sorescu and Spanjol, 2008). Tobin's Q is defined as the ratio of firm's market value to its book value for the year prior the announcement and is calculated as:

$$\text{Tobin's Q} = \frac{AT + (CSQ \times Price) - CEQ}{AT} \qquad (7)$$

where AT is the book value of the total assets, Price is the price of the stock, CSQ is the number of common shares outstanding, and CEQ is the book value of common stocks, all measured prior to the announcement.

Data used to compute Tobin's Q is obtained from COMPUSTAT.

Investor recognition: Arbel (1985) refers to the stock of the firms with small institutional holdings, and firms with small or no number of analysts following as "neglected stocks". In line with previous research I use two proxies for investor recognition: percentage of shares held by institutions (*Institutional_Holdings*) and

number of analysts following the firm (*Analysts*) (Arbel 1985; Arbel, Carvell, and Strebel 1983; Jain and Kim 2006; King and Segal 2009). Institutional holdings data is obtained from Thomson Reuters and data on analyst following is obtained from IBES.

Control variables

Frequency of firms' recent news: To benefit from concurrent announcements, in addition to the proposed conditions, firms also need to have the ability to make such announcements. Firms that seldom make new product announcements or any other types of positively valenced corporate news may need to delay their press releases to be able to issue them concurrently, which may not be optimal from a competitive standpoint (Moorman et al. 2012). Conversely, firms that frequently make corporate announcements will not need to significantly alter the timing of these announcements in order to issue them concurrently. These firms have more degrees of freedom as they decide whether to combine announcements and which announcements to pair. I account for the ability of the firms to make concurrent new product announcements by controlling for frequency of firms' recent new product announcements and other types of positively valenced corporate news:

a) *New product announcements* (*Firm_NPA*): To capture the frequency of firms' new product announcements in the recent time, I compute rolling window measurements of the number of new product announcements that firms made in the six months preceding each new product announcement included in the sample.

b) *Other corporate news* (*Corporate_News*): Similar to new product

announcements, I control for the frequency of firm's recent corporate news (other than product releases) and compute this variable as a rolling-window measurement of the number of all the firms' corporate announcements (other than new product announcements), that firms made in the six months preceding the announcement of each corporate news item included in the sample.

Past concurrent announcements: Firms that have used concurrent announcements in the past might be in a better position to understand the conditions under which these announcements are effective at increasing the investor recognition and might be more likely to identify when these conditions occur and leverage concurrent announcements accordingly. I use relative number of concurrent announcements to total announcements of the firm as a proxy for such factors and I use two rolling-window variables, *Relative_Concurrent_NPA* and *Relative_Concurrent_News*, computed as the ratio of the counts of the concurrent new product announcements (other corporate announcements) to the counts of stand-alone new product announcements (other corporate announcements) made by the firm in the six months preceding each new product announcement from the firm. I use a relative measure because the absolute number of concurrent announcements is correlated with the total number of announcements, which is also included in the model estimated.

Firm-specific factors: The propensity to combine announcements may be different for firms of different size and financial status. I control for the firm's size (*Firm_Size*) using the logarithm of firm assets (e.g., Lin and Chang 2012). I account for firms' financial status by controlling for firm's financial leverage (Luo, Homburg, and Wieseke

2010) and return on assets (Rego, Billett, and Morgan 2009).

Industry-specific factors: To control for the effects of industry-specific factors on managers' decision making I include three control variables corresponding to the industry's innovativeness, communication baseline with the investors, and competitiveness:

a) *Competitor's recent new product announcements* (*Competitors_NPA*)*:* Industry's innovativeness is controlled by computing rolling-window measurements for the counts of new product announcements made by the firm's competitors in the six months preceding each new product announcement; I define competitors as all firms operating in the same three-digit SIC code.

b) *Competitors' communication baseline with investors (Competitors_News*): To control for the industry's communication baseline with investors, I compute rolling-window measurements for the counts of the competitors' corporate announcements (other than new product releases) in the six months preceding each corporate announcement.

c) *Industry concentration (Industry_Concentration):* I control for the industry concentration as a measure of the Herfindahl index (e.g., Lee and Grewal 2004; Lin and Chang 2012). Similar to previous studies, I calculate the Herfindahl index as the sum of the squared percentage of sales of firms in the same SIC code.

Table 6 summarizes the dependent, independent, and control variables used in the empirical analysis.

TABLE 6
Variables and Data Sources for Evaluating Concurrent New Product Announcements

	Conceptual Variable (label)	***Measured Variable***	***Data Source***
Dependent variables	Probability of adding a positively valenced corporate announcement to a new product announcement *(Concurrent_NPA)*	A dummy variable that equals1 if the new product has been announced concurrently with another corporate news item and 0 if the new product announcement is stand-alone.	*RavenPack News Analytics*
	Probability of adding a new product release to a positively valenced corporate announcement (*Concurrent_News)*	A dummy variable that equals 1 if the corporate news has been announced concurrently with a new product release and 0 if the corporate announcement is a stand-alone.	*RavenPack News Analytics*
	Short-term cumulative abnormal returns (*MAR_CAR, MM_CAR, FFC_CAR)*	Cumulative abnormal return (one day before to one day after the announcement, computed using, respectively, the (1) market-adjusted model, (2) market model , and (3) Fama_French_Carhart model	*CRSP/ Fama French and Liquidity Factors/*
Independent variables	Firm's news sentiment (*News_Sentiment*)	Firm-level average of the ESS scores for all the firm's news that were published in the six months preceding the announcement	*RavenPack News Analytics*
	Firm's previous Tobin's Q *(Tobin_Q)*	Firm's Tobin's Q for the year preceding the announcement	*COMPUSTAT*
	Percentage of shares held by institutional investors *(Institutional_Holdings)*	Number of firm's share in institutional holdings divided by firm's total number of shares in the fiscal quarter preceding the announcement	*Thomson Reuters*
	Number of analysts following the firm *(Analysts)*	Total number of analysts following the firm in the fiscal quarter preceding the announcement	*IBES*
Control variables	Number of recent new product announcements (*Firm_NPA*):	Number of new product announcements made by the firm in the six months preceding the announcement	*RavenPack News Analytics*
	Number of other corporate announcements (*Corporate_News*)	Number of corporate news (other than product releases) made by the firm in the six months preceding the announcement	*RavenPack News Analytics*
	Relative number of recent concurrent new product announcements to recent stand-alone new product announcements (*Relative_Concurrent_NPA*)	Number of the concurrent new product announcements to the counts of stand-alone new product announcements made by the firm in the six months preceding the announcement	*RavenPack News Analytics*

TABLE 6 Continued

	Conceptual Variable (label)	***Measured Variable***	***Data Source***
Control variables	Relative number of recent positively valenced corporate news concurrently announced with product releases to recent stand-alone corporate news (*Relative_Concurrent_News*)	Number of the positively valenced corporate news announced concurrently with new product announcements to the counts of stand-alone corporate news made by the firm in the six months preceding the announcement	*RavenPack News Analytics*
	Number of competitors' recent new product announcements (*Competitors_NPA*)	Number of new product announcements made by firms in the same industry (based on 3-digit SIC codes) in the six months preceding the announcement	*RavenPack News Analytics*
	Number of competitors' recent corporate news (*Competitors_News*)	Number of corporate news (other than product releases) announced by firms in the same industry (based on 3-digit SIC codes) in the six months preceding the announcement	*RavenPack News Analytics*
	Industry concentration *(Industry_Concentration)*	Herfindahl index: Sum of squares of the market shares of all firms in the same industry (based on 3-digit SIC codes)	*COMPUSTAT*
	Firm size (*Firm_Size*)	Logarithm of total assets	*COMPUSTAT*
	Financial leverage *(Leverage)*	The ratio of long term book value of debt to the firm's total assets	*COMPUSTAT*
	Return on assets *(ROA)*	The ratio of income before extraordinary items to the firm's total assets	*COMPUSTAT*
	Year *(year)*	Year of the announcement	*RavenPack News Analytics*

Model Development

Testing H_{4a}– H_{5b}

To test H_{4a}– H_{5b} I run two separate logit models that estimate the probability of new product announcements being made concurrently with other types of corporate news. The first equation estimates the probability that a new product announcement is

made concurrently with another positively valenced corporate announcement, as opposed to stand-alone. The second equation estimates the probability that a corporate announcement (other than a new product release) is made concurrently with a new product announcement, as opposed to stand-alone. Thus, in the first model, the focus is on product releases, and in the second model, the focus is on other types of corporate news:

$$\left[\Pr(\text{Concurent\_NPA}_{\text{ij}} = 1 \mid \text{Covariates}_{pij}, e_{pij}) = \frac{1}{1+\exp(-X\beta_{pij})}\right], \qquad (8)$$

where $X\beta_{\text{pij}} = (\beta_{p1} + \beta_{p2}News\_Sentiment_{ij} + \beta_{p3}Tobin\_Q_{ij} + \beta_{p4} Investor\_Recognition_{ij} + \beta_{p5}Firm\_NPA_{ij} + \beta_{p6}Relative\_Concurrent\_NPA_{ij} + \beta_{p7}Competitors\_NPA_{ij} + \beta_{p8}Industry\_Concentration_{ij} + \beta_{p9}Firm\_Size_{ij} + \beta_{p10}Leverage_{ij} + \beta_{p11}ROA_{ij} + \beta_{p12}Year_{ij} + e_{pij})$.

$$\left[\Pr(\text{Concurent\_News}_{ij} = 1 \mid \text{Covariates}_{cij}, e_{cij}) = \frac{1}{1+\exp(-X\beta_{cij})}\right], \qquad (9)$$

where $X\beta_{\text{cij}} = (\beta_{c1} + \beta_{c2}News\_Sentiment_{ij} + \beta_{c3}Tobin\_Q_{ij} + \beta_{c4}Investor\_Recognition_{ij} + \beta_{c5}\ Corporate\_News_{ij} + \beta_{c6}Relative\_Concurrent\_News_{ij} + \beta_{c7}Competitors\_News_{ij} + \beta_{c8}Industry\_Concentration_{ij} + \beta_{c9}Firm\_Size_{ij} + \beta_{c10}Leverage_{ij} + \beta_{c11}ROA_{ij} + \beta_{c12}Year_{ij} + e_{\text{cij}})$.

In both models, i, and j index the firm and the announcement date, p and c index the new product announcement variables and positively valenced corporate announcement variables, respectively. The terms e_{pij} and e_{cij} are random firm and time-specific effects, and other variables are as previously defined. *Investor_Recognition* refers to *Institutional_Holdings*, respectively *Analysts*, which are included in the models one at a time, as they are highly correlated. *Year* is a linear time trend included to control for the possibility that concurrent announcements have increased in recent times. In both models,

I adjust the standard errors for possible simultaneous correlations across both firms and time in the residuals using two-dimensional clustered standard errors (Petersen 2009)[8].

Testing H_6

To test H_6 I verify that the stock market reaction to a concurrent new product announcement made under the conditions described in H_{4a}– H_{5b} is greater, on average, than the sum of the reactions to the new product announcement and the positively valenced corporate news, had they been announced separately. I use the short-term event study methodology to compute the stock market reaction to concurrent announcements. Short-term event studies are commonly used to measure the stock market reaction to a firm's financial, strategic, or marketing announcements. They have been widely used for new product announcements (e.g., Chaney, Devinney, and Winer 1991; Sood and Tellis 2005; Sorescu, Shankar, and Kushwaha 2007), acquisitions (e.g., Asquith 1983), partnerships (e.g., Kale, Dyer, and Singh 2002), channel additions (e.g., Homburg, Vollmayr, and Hahn 2014), and brand acquisitions (e.g., Wiles, Morgan, and Rego 2012). The methodology is well specified over short-term horizons (see Brown and Warner 1985).

Specifically, I estimate abnormal returns (AR) for the firms in the sample as

$$AR_{it} = R_{it} - E(R_{it}) \tag{10}$$

[8] Following Peterson (2009), I assume that $e_{pij} = \gamma_{pi} + \lambda_{pj} + u_{pij}$ and $e_{cij} = \gamma_{ci} + \lambda_{cj} + u_{cij}$, where γ_{pi} and γ_{ci} are firm-specific components, λ_{pj} and λ_{cj} are time-specific components, and u_{pij} and u_{cij} are idiosyncratic components unique to each observation. I estimate the variance–covariance matrix as $\hat{V}ar(\hat{\beta}) = \hat{V}_{(\text{firm})} + \hat{V}_{(time)} - \hat{V}_{(firm\text{-}time)}$.

where R_{it} is the realized rate of return of stock i on day t and $E(R_{it})$ is the estimated return of the stock i on day t in the absence of the event. I use three alternative ways to compute $E(R_{it})$ and provide results obtained with all these measures:

$$E(R_{it}) = R_{mt} \tag{11}$$

$$E(R_{it}) = R_{ft} + \beta(R_{mt} - R_{ft}) \tag{12}$$

$$E(R_{it}) = R_{ft} + \beta_1(R_{mt} - R_{ft}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(UMD_t) \tag{13}$$

where R_{mt} is the average rate of return of all stocks trading on the US stock market, R_{ft} is the risk-free rate of return on a US Treasury bond on the day t, SMB is the difference between the rate of returns of small and big stocks, HML is the difference in returns between high and low book-to-market stocks, and UMD is the momentum factor, all during day t.

Equation (11) corresponds to the market-adjusted model, (12) to the market model, and (13) to the Fama-French-Carhart model (Brown and Warner 1985; Carhart 1997).

I calculate AR_{it} as the abnormal return of firm i on day t using each of the models above. The daily abnormal returns are then cumulated over a time window (t_1, t_2) around the announcements day, as follows:

$$CAR_{(t1,\, t2)} = \sum_{t=t1}^{t2} AR_{it}. \tag{14}$$

I use a three-day window around the event date ($t_1 = t - 1$, $t_2 = t + 1$) to account for possible information leakage during the day before the announcement and for possible delays in the dissemination of news during the day after the announcement. I compute the CARs for each of the different methods used to estimated expected returns:

MAR_CAR are the CARs for the market adjusted model, MM_CAR are the CARs for the market model, and FFC_CAR are the CARs for the Fama-French-Carhart model.

To test H_6, I need to show that the CARs to the concurrent announcements are significantly higher than the sum of the CARs to stand-alone announcements:

$$\text{CAR\_Concurrent} > \text{CAR\_NPA}_{(\text{stand-alone})} + \text{CAR\_Corporate\_News}_{(\text{stand-alone})} \quad (15)$$

If firms randomly made some announcements concurrently and some separately, inequality (15) could have been tested using t-tests of the mean differences between CAR_Concurrent and ($\text{CAR\_NPA}_{(\text{stand-alone})}$ +$\text{CAR\_Corporate\_News}_{(\text{stand-alone})}$). However, firms do not randomly select announcements to be announced concurrently or stand-alone; rather, they make concurrent announcements only under specific circumstances that need to be accounted for. To eliminate selection bias, I would ideally need to observe, in relation to each concurrent announcement, the counterfactual stand-alone new product announcement and the counterfactual stand-alone corporate announcement that constitute the concurrent announcement. Because these counterfactual announcements are not available, I employ an appropriate statistical matching method, namely Propensity Score Matching (PSM), to control for the potential endogeneity resulting from the non-randomly-assigned treatments (Angrist, Imbens, and Rubin 1996; Verbeek 2008). PSM has been widely used in economics (e.g., Dehejia and Wahba 1999), information systems (Rishika et al. 2013), strategic management (e.g., Chang, Chung, and Moon 2013), and marketing research (e.g., Garnefeld et al. 2013; Wangenheim and Bayón 2007). This method leverages matching techniques that identifies the “statistical twin” of each treated observation in the pool of untreated ones

(Guo and Fraser 2010; Rosenbaum and Rubin 1983).

Several matching techniques have been proposed in the literature (for a review, see Caliendo and Kopeinig 2008). I present the main results using matching done with the *nearest neighbor with caliper.* In the robustness section I report results using an alternative method, *Kernel matching*. The nearest neighbor method is a one-on-one matching method that has been shown to be the most effective in reducing bias (the difference between the treated and untreated group) and is preferred when researchers have large samples of untreated observations relative to the treated group.

PSM uses a propensity score as the criterion to find the most similar match to the treated observation. I use the estimated probability obtained from equations (8) and (9) as the propensity score used for matching. Nearest neighbor PSM matches each treated announcement (concurrent) with the untreated one (stand-alone) that has the closest propensity score to the treated announcement (e.g., Bronnenberg, Dubé, and Mela 2010; Huang et al. 2012; Rosenbaum and Rubin 1983). To increase the quality of matching and to ensure that the propensity scores in the control samples are reasonably close to those in the treated samples, nearest neighbor with caliper requires that the absolute distance between the two propensity scores be less than a predetermined caliper (ε), calculated as $\varepsilon = .25\sigma_P$, where σ_P is the standard deviation of the propensity score (Guo and Fraser 2010).

To increase the similarity between announcements in the treated and control groups and to account for the unobservable industry- and firm-specific factors not included in the logit models, I conduct two separate types of matching. In the first

matching method, I require that the matched announcements belong to the same industry. In the second matching method, I require that the announcements belong to the same firm. This second type of matching is more conservative and may lead to a loss of data that can be used to test H_6, but it offers a cleaner comparison between the treated and control groups because it helps control for unobserved firm heterogeneity.

For each one of the matching methods (within the same industry or within the same firm) I run two matching procedures. The first PSM runs through the sample of new product announcements and finds the *Matched_NPA* for each treated new product announcement according to the estimated probability from the logit model of equation (8). The second PSM runs through the sample of other positively valenced corporate news and finds the *Matched_News* for each concurrent corporate news item according to the estimated probability from the logit model of equation (9).

After obtaining the two control groups for each type of matching, I align the Matched_NPA and Matched_News with the corresponding concurrent announcements to calculate the treatment effect as follows:

$$\text{Treatment effect} = \text{CAR\_Concurrent} - [\text{CAR\_Matched\_NPA} + \text{CAR\_Matched \_News}] \quad (16)$$

The average of these differences for all the announcements in the treated group is the average treatment effect (ATE):

$$\text{ATE\_CAR} = \text{Average}\ \{\text{CAR\_Concurrent} - [\text{CAR\_matched\_NPA} + \text{CAR\_Matched\_News}]\} \quad (17)$$

To test H_6 I run t-tests on the ATE_CAR defined in (11) above.

RESULTS

Descriptive statistics

Table 7 reports descriptive statistics. Panels A and B of Table 7 show descriptive statistics for the subsample of new product announcements and, respectively, positively valenced corporate news (other than product releases). The second and third columns include means of variables for the concurrent and the stand-alone announcements.

The average CARs are positive and significant for all three subsamples: concurrent, stand-alone new product announcements, and stand-alone other announcements (all p-values <.001). In terms of the new product announcements, the findings are in line with prior research which has found that investors reward, on average, new product introductions. In terms of the other types of corporate announcements, the significantly positive average CARs provide face validity for the ESS score that was used to determine the valence of these announcements.

Table 7 also reports the correlations matrix for each subsample. The correlations between the three CAR variables are high (.93% or higher) indicating that the abnormal returns measured with the three alternative methods are similar. The correlation between institutional holdings and number of analysts is also high in both subsamples (.60 in panel A and .70 in panel B). This is consistent with research in accounting that has documented a strong link between analysts' decisions to follow firms and institutional investors' decisions to hold the same firms in their portfolios (e.g., O'Brien and Bhushan 1990). Therefore, I use them as alternative measures of investor recognition in separate models.

TABLE 7
Descriptive Statistics for the Sample to Evaluate the Concurrent New Product Announcements (2003-2013)

A: Descriptive Statistics for the Subsample of New Product Announcements

Variables	*New Product Announcements*				*Correlations*[a]													
	Concurrent		*Stand-Alone*		*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*
	N=1,162		*N=27,596*															
	Mean	**SD**	**Mean**	**SD**														
MAR_CAR (%) (1)	.423	5.4	.310	5.1	1													
MM_CAR (%) (2)	.505	5.4	.357	5.0	.95	1												
FFC_CAR (%) (3)	.421	5.4	.305	5.0	.93	.95	1											
News_Sentiment(4)	59.25	3.8	57.04	4.1	-.03	-.03	-.03	1										
Tobin_Q (5)	2.07	1.3	2.11	1.5	-.00	-.01	-.00	.09	1									
Institutional_Holdings (6)	.43	.49	.55	.46	-.03	-.03	-.03	.03	.04	1								
Analyst (7)	12.08	12.1	8.58	10.9	-.04	-.03	-.04	.23	.11	.60	1							
Firm_NPA (8)	8.55	10.1	3.61	5.6	-.02	-.02	-.03	.45	-.01	.04	.35	1						
Relative_Concurrent_NPA (9)	.14	.19	.06	.15	-.01	-.01	-.01	.21	.01	.01	.16	.33	1					
Competitors_NPA (10)	176.6	176.8	162.6	172.9	.00	.00	.00	.20	.19	-.00	.07	.08	.06	1				
Industry_Concentration (11)	.21	.18	.18	.16	-.01	-.01	-.01	-.031	-.13	-.00	.00	.07	.03	-.45	1			
Firm_Size (expressed in billion dollars) (12)	107.17	297.7	29.29	142.3	-.08	-.08	-.08	.23	-.19	.11	.48	.45	.25	-.19	.20	1		
Leverage (13)	.16	.18	.15	.20	-.01	-.01	-.01	-.054	-.11	-.06	-.04	.03	.010	-.21	.13	.21	1	
ROA (14)	.024	.22	-.041	1.4	.00	-.00	.00	.01	.01	.052	.05	.02	.02	.01	.01	.11	.01	1

[a] Correlations are based, in each case, on the full sample corresponding to that panel (stand-alone + concurrent announcements)

TABLE 7 Continued

B: Descriptive Statistics for the Subsample of Other Positively Valenced Corporate News

Variables	*Other Corporate Announcements*				*Correlations*													
	Concurrent[b] *N=1,162*		*Stand-Alone* *N=52,438*		*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*
	Mean	**SD**	**Mean**	**SD**														
MAR_CAR (%) (1)	.423	5.41	.500	6.92	1													
MM_CAR (%) (2)	.505	5.36	.508	6.91	.95	1												
FFC_CAR (%) (3)	.421	5.37	.522	6.93	.93	.95	1											
News_Sentiment(4)	59.25	3.82	56.11	4.15	-.03	-.03	-.03	1										
Tobin_Q (5)	2.07	1.34	1.97	1.43	-.00	-.01	-.00	.09	1									
Institutional_Holdings (6)	.43	.49	.53	.49	-.03	-.02	-.03	.03	.04	1								
Analyst (7)	12.08	12.07	6.99	9.25	-.04	-.04	-.04	.23	.11	.60	1							
Corporate_News (8)	15.87	12.43	8.25	6.02	-.02	-.02	-.03	.45	-.01	.04	.35	1						
Relative_Concurrent_News (9)	.19	.19	.08	.14	-.01	-.01	-.01	.21	.01	.01	.16	.33	1					
Competitors_News (10)	643.6	667.4	488.6	616.2	.00	.00	.00	.20	.19	.00	.07	.08	.06	1				
Industry_Concentration (11)	.21	.18	.20	.18	-.01	-.01	-.01	-.03	-.13	.00	.01	.07	.03	-.45	1			
Firm_Size (expressed in billion dollars) (12)	107.2	297.7	35.68	178.47	-.08	-.08	-.08	.23	-.19	.11	.48	.45	.25	-.19	.20	1		
Leverage (13)	.16	.18	.17	.20	-.01	-.01	-.01	-.05	-.11	-.06	-.04	.03	.01	-.21	.13	.21	1	
ROA (14)	.024	.22	-.056	1.48	.00	.00	.00	.01	.01	.05	.05	.02	.01	.01	.01	.11	.01	1

Test of hypotheses

Results for H_{4a}– H_{5b}

Table 8 shows the results for the logit models. Panel A of Table 8 shows the results for equation (8). The first two hypotheses (H_{4a} and H_{4b}) postulate a positive effect of the news sentiment and Tobin's Q on the likelihood that the new product will be announced concurrently with other news. The coefficients for the firm's news sentiment and Tobin's Q are positive and significant in both models A-1 and A-2 (β_{p2} = .058 (for A-1) & .062 (for A-2), p<.01 for news sentiment, and β_{p3} = .056 (for A-1) & .061 (for A-2), p<.05 for Tobin's Q). The results support H_{4a} and H_{4b}: firms are more likely to issue concurrent announcements when they face high expectations about future cash flows.

H_{5a} and H_{5b} focus on the effect of investor recognition on the likelihood that the new product will be announced concurrently with other news. The coefficient for the institutional holdings is negative and significant in model A-1 (β_{p4} = -1.69, p < .01). Similarly, the coefficient for the number of analysts following is negative and significant in model A-2 (β_{p4} = -.022, p < .01). These results are consistent with H_{5a} and H_{5b}: firms that are less recognized by investors are more likely to make concurrent announcements in hopes of increasing their investor recognition and subsequently their firm value.

Panel B of Table 8 provides the results for equation (9). The coefficients for all independent variables are consistent with these presented in Panel A (β_{c2}=.076 in B-1 & .083 in B-2, β_{c3} = .091 in B-1 & .081 in B-2, p<.01 for all, β_{c4} = -1.45 p<.01 in B-1, and β_{c4} = -.014 p<.05 in B-2). Therefore, H_{4a} – H_{5b} are supported in both subsamples.

TABLE 8
Determinants of the Propensity to Make Concurrent Announcement

A: Determinants of the Propensity to Concurrently Announce New Product Announcements with Other Corporate Announcements

DV : *Concurrent_NPA* (N=28,758)	**Model A-1**	**Model A-2**
News_Sentiment	.058*** (.011)	.062*** (.011)
Tobin_Q	.056** (.027)	.061** (.027)
Institutional_Holdings	-1.69*** (.23)	-
Analyst	-	-.022*** (.0060)
Firm_NPA	.010 (.0091)	.015* (.0090)
Relative_Concurrent_NPA	.31 (.19)	.43** (.19)
Competitors_NPA	.0011*** (.00028)	.0011*** (.00026)
Industry_Concentration	.79*** (.30)	.71*** (.26)
Firm_Size	.25*** (.023)	.27*** (.024)
Leverage	.019 (.015)	.062 (.018)
ROA	.068 (.18)	-.0089 (.018)
Year	-.0031 (.015)	-.013 (.013)
Wald χ^2	243.91	315.03
Log-likelihood	-4325.10	-4393.05
Pseudo R^2	.19	.14
AIC	8676.20	8812.11

*$p < .10$, **$p < .05$, ***$p < .01$.

TABLE 8 Continued

B: Determinants of the Propensity to Concurrently Announce Other Corporate Announcements with New Product Announcements

DV : *Concurrent_NPA* (N=53,600)	**Model B-1**	**Model B-2**
News_Sentiment	.076*** (.010)	.083*** (.0094)
Tobin_Q	.091*** (.031)	.081*** (.029)
Institutional_Holdings	-1.45*** (.21)	-
Analyst	-	-.014** (.0071)
Corporate_News	.018** (.0072)	.019** (.0075)
Relative_Concurrent_News	.60** (.27)	.73*** (.26)
Competitors_News	.00055*** (.00010)	.00050*** (.00009)
Industry_Concentration	.63* (.36)	.51 (.31)
Firm_Size	.28*** (.034)	.24*** (.029)
Leverage	-.38 (.31)	-.31 (.28)
ROA	.17 (.28)	.0026 (.027)
Year	.032** (.015)	.0061 (.015)
Wald χ^2	406.29	296.06
Log-likelihood	-4537.05	-4639.70
Pseudo R^2	.22	.14
AIC	9100.10	9305.41

*$p < .10$, **$p < .05$, ***$p < .01$.

The coefficients for competitors' innovation output are positive and significant ($p < .01$ in models A1 and A2). The coefficients for the extent to which other firms in the industry issue announcements are also positive and significant ($p < .01$ in models

B1 and B2). These results indicate that managers of firms operating in innovative industries and these with a high volume of announcements are more likely to make concurrent new product announcements to increase the likelihood that they will be noticed against a larger volume of competitor news and new product announcements. The coefficient for firm size is positive and significant in all models ($p < .01$) which shows that larger firms are more likely to concurrently announce their new products with other positive corporate news than smaller firms. The coefficient for industry concentration is positive in models A1 and A2 only: since this variable is measured using the HHI index, and in conjunction with the positive effect of size, this effect suggests that concurrent announcements are more likely to occur in industries in which a few large firms are competing for investors' attention. Firm's financial leverage and ROA have no significant effects on the likelihood to make concurrent new product announcements.

Results for H_6

I examine the impact of concurrent announcements on abnormal returns by verifying that ATE_CAR>0. First, to perform the matching, I extract estimated probabilities from the logit models presented in the previous section. The estimated probabilities can be chosen from models A-1 and B-1 or from models A-2 and B-2. To choose the propensity score, I compare the explanatory power and goodness of fit for the two groups of models. The goodness of fit measures for logit models are provided in the last four rows of Panel A and B in Table 8. Pseudo R^2 statistics are higher for A-1 (.19) compared to A-2 (.14) and for B-1 (.22) compared to B-2 (.14). Additionally, A-1

and B-1 have lower AICs compared to A-2 and B-2, respectively. Therefore, I use estimated probabilities of the logit models A-1 and B-1 as propensity scores for the matching procedure. Results obtained from models A-2 and B-2 are not reported but are substantively similar to the ones I present in this essay.

After running PSM and obtaining the two matched groups I follow previous research and test the quality of matching by calculating the percentage reduction in bias (PRB) (Granefeld et al. 2013; Wangenheim and Bayón 2007). PRB shows how much the bias (the difference of mean of covariates between treated and untreated group) has been reduced after matching. Rosenbaum and Rubin (1985) define PRB as:

$$\text{PRB}= 1- \left|\frac{(XA-XA')}{(XB-XB')}\right| \qquad (18)$$

where
XA = the mean for the treatment group after matching (treated observations that have a match)
XA'= the mean for the non-treatment group after matching (matched observations),
XB = the mean for the treatment group before matching (all treated observations)
XB'= the mean for the non-treatment group before matching (untreated observations).

Table 9 shows the PRB of the matching for both new product announcements and other positively valenced corporate news when matched within the same firm. The average PRB is 88.82% for the sample of new product announcements, and 82.93% for the sample of the other positively valenced news. The average PRB indicates that the matching has reduced the bias by more than 82%. That is, the differences between the mean of variables in treated and matched sample is 82% less than the differences in means of variables between the sample of treated and untreated announcements. This compares favorably with previous research and suggests the matching is good (e.g.,

Granefeld et al 2013; Wangenheim and Bayón 2007).

TABLE 9
Means Before and After Matching and Percentage Reduction in Bias (PRB) for Concurrent New Product Announcements

A: Mean Differences and PRB for the Matching Of New Product Announcements (Within the Same Firm Nearest Neighbor With Caliper) [a]

	Before Match N(treated)=1,162 N(untreated)=27,596		**After Match** N(treated)=916[b] N(matched)=916		**PRB**
Variables	**Mean difference** (treated – untreated)	**t**	**Mean difference** (treated – matched)	**t**	**(%)**
News_Sentiment	2.2	17.76	0.12	0.73	94.55
Tobin_Q	-0.036	-0.82	-0.014	-0.23	61.11
Institutional_Holdings	-0.12	-8.76	0.0015	0.047	98.75
Analysts	3.5	10.59	-0.79	-1.32	77.43
Corporate_NPA	4.95	28.01	0.04	0.092	99.19
Relative_Concurrent_NPA	0.078	16.80	-0.013	-1.43	83.33
Competitors_NPA	13.97	2.69	2.76	0.35	80.24
Industry_Concentration	0.034	7.00	-0.0042	0.52	87.65
Firm_Size	1.84	24.98	-0.021	-0.18	98.86
Leverage	0.017	2.90	0.00022	0.028	98.71
ROA	0.065	1.61	-0.0018	-0.18	97.23
Average PRB for the matching model					**88.82**

[a] The PRB table for matching within the same industry is not shown due to space limitations. The average PRB for within-industry matching is 68.9% for matching of new product announcements and 74% for matching of other corporate news. Matching has a lower quality compared to matching within the same firm because the procedure does not account for unobservable firm-specific variables.
[b]: I was able to match 78.8% of concurrent announcements. 246 observations are omitted due to the restrictions of the matching method: when the matching is within the same firm and it uses a caliper not all treated observations have a match that meets all imposed matching conditions. The restrictions are less stringent in matching within industry and I match 1,050 (90.4%) of the concurrent announcements.

TABLE 9 Continued

B: Mean Differences and PRB for the Matching Of Other Corporate Announcements (Within the Same Firm Nearest Neighbor With Caliper)

	Before Match N(treated)=1,162 N(untreated)=52,438		**After Match** N(treated)=916 N(matched)=916		**PRB**
Variables	**Mean difference** (treated – untreated)	**t**	**Mean difference** (treated – matched)	**t**	**(%)**
News_Sentiment	3.13	24.06	-0.015	-0.86	99.52
Tobin_Q	0.099	2.34	-0.031	-0.51	68.69
Institutional_Holdings	-0.1	6.79	-0.01	-0.45	90.00
Analysts	5.09	18.42	-0.99	-1.66	80.55
Corporate_News	7.62	41.23	0.24	0.45	96.85
Relative_Concurrent_News	155.07	8.47	-0.49	-0.016	99.68
Competitors_News	0.11	27.06	-0.012	-1.38	89.09
Industry_Concentration	1.9	25.02	0.014	0.12	99.26
Firm_Size	0.011	2.11	0.0048	0.58	56.36
Leverage	-0.0081	-1.33	0.0046	0.61	43.21
ROA	0.08	1.84	-0.0088	-0.93	89.00
Average PRB for the matching model					**82.93**

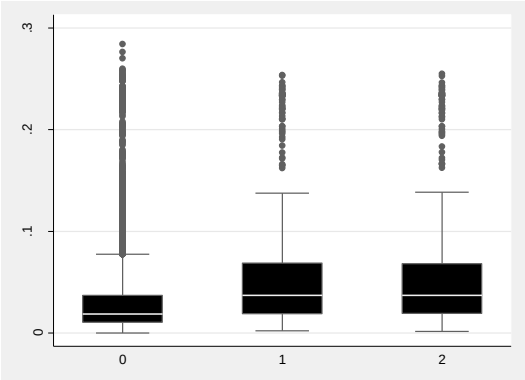
I also conduct a Kolmogorov-Smirnov test to compare the distribution of the propensity score in the treated and untreated group versus in the treated and matched group. The p-value of the Kolmogorov-Smirnov test that compares the concurrent announcements with the untreated stand-alone announcements, is less than.001 while the p-value of the test that compares the concurrent announcements and matched stand-alone announcements is equal to 1 (for both matching within firm and within industry). These statistics provide evidence of similarity of propensity score distributions in the

treated and matched groups. The visual evidence for the distribution of propensity to announce concurrently in each group (treated- matched and unmatched) are also provided in Figure 1.

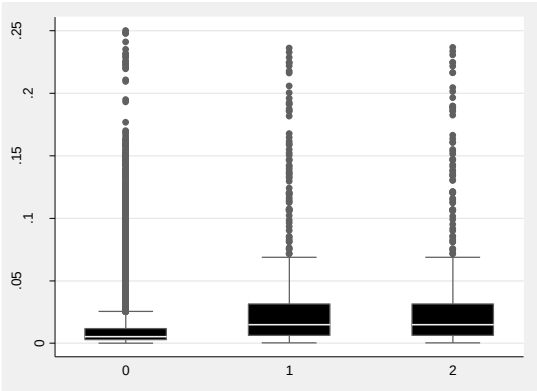
FIGURE 1
Distribution of Propensity to Announce Concurrently

A: Histograms for the Matching with Nearest Neighbor with Caliper – Within the Same firm

Sample of New Product Announcements



Sample of Other Positively Valenced Corporate News

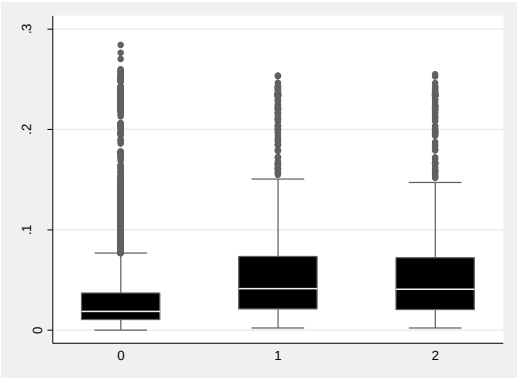


Category 0 = Un-matched stand-alone announcements
Category 1 = Concurrent announcements
Category 2 = Matched stand-alone announcements

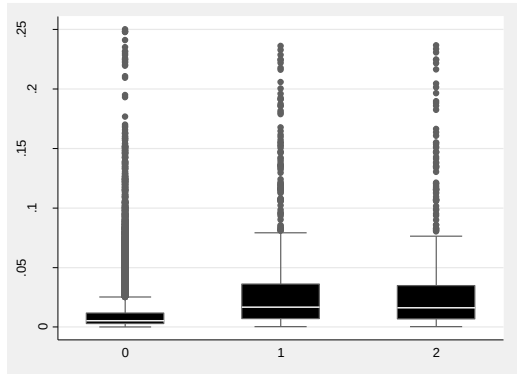
FIGURE 1 Continued

B: Histograms for the Matching with Nearest Neighbor with Caliper – *Within the Same industry*

Sample of New Product Announcements



Sample of Other Positively Valenced Corporate News



Category 0 = Un-matched stand-alone announcements
Category 1 = Concurrent announcements
Category 2 = Matched stand-alone announcements

Finally, I proceed with the matched samples to calculate the ATE_CAR defined in (17) and to test that ATE_CAR > 0. Panel A of Table 10 shows the test of ATEs for all three CAR models. The ATEs for all three CAR models are positive and significant. These results indicate that the average CARs for the concurrent announcements are on average .4% higher than the sum of the CARs for stand-alone new product announcements and stand-alone positively valenced corporate news. Thus, concurrent announcements positively contribute to firm value when made under the conditions previously described and incorporated in the logit model.

TABLE 10
Average Treatment Effects of Concurrent New Product Announcements

A: Average Treatment Effects of Concurrent New Product Announcements on Stock Market Returns

Average Treatment Effects	***PSM variables (Nearest Neighbor with Caliper)***	
$CAR_{concurrent}$ - [$CAR_{matched\text{-}NPA}$ + $CAR_{matched\text{-}corporate\text{-}news}$]	***Match within the same industry*** N=1,050 treated vs. 1,050 matched	***Match within the same firm*** N=916 treated vs. 916 matched
ATE_MAR_CAR (%)	.400**	.475**
ATE_MM_CAR (%)	.446**	.424**
ATE_FFC_CAR (%)	.387**	.375**

*p < .10, **p < .05, ***p < .01.

B: Average Treatment Effects of Concurrent New Product Announcements on Investor Recognition

Average Treatment Effects	***PSM variables (Nearest Neighbor with Caliper)***	
	Match within the same industry N=1,050 treated vs. 1,050 matched	*Match within the same firm* N=916 treated vs. 916 matched
ATE_Change_Institutional_Holding (%) $CIH_{concurrent}$ - [$CIH_{matched\text{-}NPA}$ + $CIH_{corporate\text{-}news}$]	1.03**	1.11**
ATE_Change_Analysts $CA_{concurrent}$ - [$CA_{matched\text{-}NPA}$ + $CA_{corporate\text{-}news}$]	.063**	.077**
ATE_Change_TradingVolume$_{event\ window}$ (%) $CTVE_{concurrent}$ - [$CTVE_{matched\text{-}NPA}$ + $CTVE_{corporate\text{-}news}$]	8.75***	6.87***
ATE_Change_TradingVolume$_{quarterly}$ (%) $CTVQ_{concurrent}$ - [$CTVQ_{matched\text{-}NPA}$ + $CTVQ_{corporate\text{-}news}$]	3.72**	3.61**

*p < .10, **p < .05, ***p < .01.
CIH= Changes in institutional holdings in the fiscal quarter, CA= Changes in number of analysts in the fiscal quarter, CTVE=Changes in trading volume in the event window, CTVQ=Changes in trading volume in the fiscal quarter.

Process check: Are concurrent announcements associated with changes in investor recognition?

For each concurrent announcement and its matched stand-alone counterpart I calculate the changes in the institutional holdings and number of analysts from the period before to after the announcements. These two metrics are available on a quarterly basis. I therefore, compare the value of these variables in the quarter immediately preceding the announcement with the one that immediately follows it. If concurrent new product announcements increase firm value due to an increase in investor recognition, as Merton (1987) indicates, a higher growth should be observed in institutional holdings and number of analysts after concurrent announcements rather than the sum of changes after the matched stand-alone announcements.

As a robustness check I also calculate the changes in the trading volume. Trading volume, defined as the total number of shares that changes hands during each trading day, has been used in previous research as a proxy for visibility of the firm's stock (Barber and Odean 2008; Gervais, Kaniel, and Mingelgrin 2001). Trading volume captures not only awareness, but also expectations of higher stock returns (Gervais, Kaniel, and Mingelgrin 2001), and therefore is a weaker proxy than the main independent variables. However, it is the only proxy for investor recognition for which data is available on a daily basis. Hence, it enables the researchers to calculate the changes in investor recognition inside the window of the focal event, and allows documenting a more precise association between the concurrent announcement and the increase in investor recognition. I measure changes in trading volume as the difference

between the average daily trading volume of the stock for the three day window of the event (1 day before to 1 day after, i.e., the measurement window for CARs) and the three day window immediately preceding the event. For robustness, I also calculate this variable for the quarter before to the quarter after the announcement in line with the measurement window used to assess changes in institutional holdings and in the number of analysts following the firm.

In a similar manner with the test conducted to assess the relative CARs that accrue to concurrent announcements I run a t-test on the ATE for changes in investor recognition for each of the four alternative proxies described above. The results appear in Panel B of Table 10. The ATEs for all four variables are positive and significant ($p<.05$ or better), suggesting that after making concurrent new product announcements, firms experience, on average, an increase in their institutional holdings, number of analysts following their firm, and the volume of their shares trading in the stock market. This process check provides empirical evidence for the investor recognition mechanism presented in support of the hypotheses. The positive ATE for trading volume measured in the window of the announcements also confirms the assertion derived from Barber and Odean (2008); concurrent new product announcements are indeed more likely to turn the firms' stocks into attention-grabbing stocks than their stand-alone counterparts. Overall, the results are in line with the predictions of Merton's (1987) model and highlight one manner in which firms can leverage their corporate communications to increase shareholder value.

A summary of the significant effects of all analyses is presented in Table 11.

TABLE 11
Summary of Results for Evaluating the Concurrent New Product Announcements

Conditions under which concurrent announcements are more likely to occur				
Theory driven				
High expectations of future cash flows			Low investor recognition	
Positive news sentiment associated with recent corporate announcements		High Tobin's Q	Small percentage of shares held by institutional investors	Small number of analysts following the stock
Empirical: Control variables with significant coefficients				
Firm level			Industry level	
Large firms	Firms who have more frequently made concurrent announcements in the past	Firms with a large volume of corporate announcements	Lower concentration industries	High volume of corporate announcements made by competitors
Consequences of concurrent announcements made under the conditions identified in the essay				
Concurrent announcements increase firm value		Concurrent announcements increase investor recognition		
Higher CARs than the sum of CARs from stand-alone similar announcements		Higher increase in volume of trade during the event window compared to the sum of increases associated with stand-alone similar announcements	Higher increase in the percentage of shares held by institutional investors in the post-announcement quarter compared to the previous quarter relative to the sum of increases associated with stand-alone similar announcements.	Higher increase in analysts following the stock in the post-announcement quarter compared to the previous quarter relative to the sum of increases associated with stand-alone similar announcements.

Robustness tests and additional analysis

Alternative PSM technique

To establish the robustness of the results I conduct the empirical analysis using an alternative matching technique in the PSM analysis used to obtain the ATEs. Specifically, I run a weighted matching method, Kernel matching, within the same firm and the same industry. In this method, each treated observation is paired with each untreated observation, one at a time, and a weight that reflects the closeness of the propensity scores for the two observations is assigned to each pair. Each treated observation is then matched with a weighted combination of all untreated observations, reducing the possibility that treated observations remained unmatched. The ATE is obtained by subtracting the effect of the treated observation from the weighted average of the effect of the untreated group. This method leads to a smaller reduction in bias but is useful when researchers have small samples of untreated observations and risk having a significant portion of the treated observations being left unmatched. While this is not the case in the context of this essay, I nevertheless check the robustness of the results by using the Kernel method and I find that the results obtained with the two matching methods are similar for the sample.

Controlling for time and sequence of announcements

In addition to calculating the ATE for the overall sample, to control for the effect of the distance in time between announcements, I test H_6 on three smaller subsamples: (i) one where announcements are matched within the same firm and the same year; (ii) one where announcements are matched within the same year only; and (iii) a subsample

for which news are at most three months apart. Although these three subsamples constitute only a fraction of the original sample, the ATEs for CARs in all three subsamples are also positive and significant ($p < .05$ or better).

Furthermore, I repeat the analysis controlling for the sequence of stand-alone announcements matched with the concurrent news. I divide the sample into two groups: (1) the announcement date of Matched_NPA is *before* the announcement date of Matched_News (50.2% of announcements) and (2) concurrent news matched with a new product announcement published *after* the other positively valenced corporate news (49.8% of announcements). The difference between ATEs for the two samples is not statistically different from zero. Next, I examine whether the timing and order of the two concurrent announcements affect the main result. Recall that the concurrent announcements are separate press releases made by the same firm on the same day, but RavenPack provides the exact time of the day when the press release is issued. I found no difference in average CARs between the group in which the new product announcement was issued earlier in the day of announcement than the other corporate announcement, and the group in which the other corporate announcement was issued first.

Controlling for the content of announcements

The PSM technique I used in the empirical analysis ensures that the concurrent announcements are comparable to their stand-alone counterparts on all observable variables included in the two logit models. Furthermore, I matched announcements within firm and year, which controls for firm and time heterogeneity. However, this

method does not control for the unobservable heterogeneity that pertains to the content of each announcement. To partially address this limitation, I conduct one last robustness test on a subsample of the data. I randomly select 200 concurrent new product announcements, 200 stand-alone new product announcements selected from the matched group (Matched_NPAs) of the PSM analysis, and 200 stand-alone new product announcements not selected as part of the matching sample (untreated group). I content-analyze these announcements to determine whether they differ in terms of content. I code each announcement on the following six dimensions: (1) the innovativeness of the product announced, coded using a dictionary of words from prior research (Sorescu, Shankar, and Kushwaha 2007); (2) whether the announcement is a preannouncement or the announcement of an actual introduction; (3) whether the announcement was made by a chief executive officer (CEO) versus another firm representative; (4) whether the announcement was made by any top-level executive versus a public relations representative[9]; (5) the number of words in each announcement; and (6) whether the announcement is about a product developed in-house or through an alliance. The last four dimensions may provide some indication of the significance of the product to the firm. I then compare the subsamples on each dimension.

I found that approximately 14% of concurrent new product announcements are for radically innovative products, compared with 11% for matched stand-alone new

[9] Top-level executives identified in the sample announcements are: Chief Executive Officer, Chief Marketing Officer, Chief Finance Officer, Chief Information Officer, Chief Technology Officer, and Chief Operation Officer

product announcements. In addition, 26% of concurrent new product announcements are preannouncements, compared with 20% for matched group. Approximately 14% of concurrent announcements are announced by CEOs and 22% by top executives, while 15% of matched stand-alone new product announcements are announced by CEOs and 24% by top executives. The average number of words in the press releases is 769.7 for the concurrent group and 746.5 for the matched group. 15.5% of the concurrent and 17% of the matched new product announcements are developed through an alliance. All differences are statistically nonsignificant.

Alternative control variables

Finally, I also checked whether the results are robust to the length of the time period used to compute the backward-looking, rolling-window variables that measure past corporate activities of the firms in the sample. I recompute all rolling-window variables over 12-month, respectively 3 months windows, in addition to the 6-month time frame used to report the main results, and reestimate the logit models and the ATEs. The results remain consistent with those obtained with the 6-month window.

SUMMARY, IMPLICATIONS, AND LIMITATIONS

The analysis of a large sample of new product announcements shows that almost 7% of new product introductions are announced concurrently with another corporate news item. However, extant research provides no guidance to managers to either avoid or encourage concurrent new product announcements. The financial consequences of concurrent announcements are unexplored in the marketing literature because all event

studies of new product announcements eliminate them to avoid confounding effects. The current research is a first attempt to explain when these announcements occur and to measure their effect on stock prices.

The nature of the data does not allow determining whether the concurrent announcements were intentionally issued on the same day or were simply the product of chance. However, I interviewed several executives who confirmed that most firms closely control the release of all announcements by ensuring that they are issued from a unique public relations office[10]. Therefore, most firms are likely to carefully manage their press releases. This may be particularly true for good news, the type of announcements I focus on in this essay. Firms do not have an unlimited supply of good news, and therefore concurrent announcements are unlikely to be just a by-product of a high volume of unimportant corporate news.

The data indicate that concurrent new product announcements are more likely to occur when firms have high stock market values, have a history of corporate announcements that have been positively received by investors, and have low investor recognition. I argue that issuing announcements concurrently makes their content stand out from the informational flow facing investors. I verify that firms are successful in this endeavor, as investor recognition of their stock increases more after concurrent new product announcements than after stand-alone ones. And, the stock market reaction to

[10] Specifically, at the 2015 Theory + Practice in Marketing conference in Atlanta I interviewed 6 upper management individuals employed by firms in industries ranging from the financial sector to gaming and entertainment.

concurrent new product announcements made under these conditions is higher, on average, than the sum of the stock market reactions to similar stand-alone announcements.

This research contributes to the marketing literature by providing a rationale for the decision to make concurrent corporate announcements, as well as a contingent framework for when they are most beneficial to firms. I focused on new product announcements to keep the theory simple and the data analysis manageable. However, new product announcements are not the only marketing actions that firms announce concurrently. Other types of concurrent corporate announcements have likewise been discarded in empirical research. The method I propose here can also be used to investigate the financial consequences of other types of concurrent announcements, such as announcements of brand extensions, partnerships, business contracts, acquisitions, and market expansions. This essay also contributes to the finance literature by providing an empirical test of Merton's model of capital market equilibrium with incomplete information in a unique context that has not been previously studied (Merton 1987).

The average firm in the sample made approximately three new product announcements and eight other positively valenced announcements in a six-month period: this indicates that concurrent announcements are not infeasible given the flow of corporate communications documented in this essay. The contribution resides in pointing out when this feasible action is valuable; specifically, I offer prescriptive implications for the managers of two very different types of firms: niche firms with a low investor base and high value firms that are striving to meet high investor

expectations. The theory in this essay predicts that concurrent announcements occur more frequently and are more beneficial under these conditions, but future research could pinpoint alternative mechanisms that link corporate communications to shareholder value and additional conditions when they yield an increase in value.

This essay provides novel insights into concurrent new product announcements, but many other aspects of these announcements could be investigated further. First, a more detailed content analysis of two announcements made concurrently could help further qualify the financial gains of these announcements. Second, I explored the consequences of combining two positively valenced announcements, mainly because few new product announcements are paired with negative news. However, other types of positively valenced corporate announcements could be announced alongside bad news. If so, it would be fruitful to determine the financial consequences of these types of concurrent announcements.

CHAPTER IV

CONCLUSION

Although stock market reactions to the announcements of firms' marketing actions have been studied for many years, there are many aspects that are yet to be explained. This dissertation focuses on a critically important corporate activity that has relevance to marketing, namely innovation and new product development, and investigates two aspects of the stock market reaction to innovation announcements that have been overlooked in previous studies.

The first essay sheds lights on the expectation formation of investors about the firms' future activities based on their past actions. The findings show that the stock market reaction to a new product announcement is negatively related to (1) the number of new products previously announced by the firm, (2) the number of new products previously announced by the firm's competitors, and (3) the average sentiment of past public news issued by the firm. These same three factors are also positively related to the market value of the firm measured immediately prior to each new announcement, controlling for increases in firm value directly attributable to past new product announcements. These results suggest that investors' expectations need to be accounted for, when making inferences from the results of event studies that examine events that are part of a broader strategy.

The second essay investigates the effect of concurrently announcing new products with positively valenced corporate news (unrelated to the new product release).

The results document a positive difference in abnormal returns (relative to the sum of the abnormal returns obtained by separate similar announcement) for firms that issue concurrent new product announcements when (1) they face high investors' expectation or have high value, and/or (2) they have a small investor recognition, and they are in need of an increase in their investor recognition.

This dissertation contributes to marketing literature by offering new insights into how new product announcements influence firm value. Additionally, the results of this dissertation provide helpful insights to managers on when and how to introduce their new products in order to maximize the firm's financial value and their investor recognition.

REFERENCES

Akbas, Ferhat, Ekkehart Boehmer, Bilal Erturk and Sorin Sorescu (2016), "Short Interest, Returns, and Fundamentals," working paper, University of Kansas, available on SSRN at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2216919

Angrist, Joshua D., Guido W. Imbens, and Donald B. Rubin (1996), "Identification of Causal Effects Using Instrumental Variables," *Journal of the American Statistical Association*, 91 (434), 444-55.

Arbel, Avner (1985), "Generic Stocks: An Old Product in a New Package," *The Journal of Portfolio Management,* 11(4), 4-13.

_____, Steven Carvell, and Paul Strebel (1983), "Giraffes, Institutions and Neglected Firms," *Financial Analysts Journal,* 39(3), 57-63.

Asquith, Paul (1983), "Merger Bids, Uncertainty, and Stockholder Returns," *Journal of Financial Economics,* 11 (1), 51-8.

Ba, Sulin, Ling Lei Lisic, Qindong Liu, and Jan Stallaert (2013), "Stock Market Reaction to Green Vehicle Innovation," *Production and Operations Management,* 22(4), 976-990.

Baker, H. Kent, Gary E. Powell, and Daniel G. Weaver (1999), "Does NYSE Listing Affect Firm Visibility?" *Financial Management,* 46-54.

Barber, Brad M. and Terrance Odean (2008), "All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors," *Review of Financial Studies,* 21(2), 785-818.

Borah, Abhishek, and Gerard J. Tellis (2014) "Make, Buy, or Ally? Choice of and Payoff from Announcements of Alternate Strategies for Innovations," *Marketing Science* 33(1) 114-133.

Boyd, Eric D., Rajesh K. Chandy, and Marcus Cunha Jr. (2010), "When Do Chief Marketing Officers Affect Firm Value? A Customer Power Explanation," *Journal of Marketing Research,* 47(6), 1162-1176.

Bronnenberg, Bart J., Jean-Pierre Dubé, and Carl F. Mela (2010), "Do Digital Video Recorders Influence Sales?" *Journal of Marketing Research,* 47(6), 998-1010.

Brown, Stephen J. and Jerold B. Warner (1985), "Using Daily Stock Returns: The Case of Event Studies," *Journal of Financial Economics,* 14, 3–31.

Caliendo, Marco, and Sabine Kopeinig (2008), "Some Practical Guidance for the Implementation of Propensity Score Matching," *Journal of Economic Surveys,* 22(1), 31-72.

Carhart, Mark M. (1997), "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52(1), 57-82.

Chaney, Paul K., Timothy M. Devinney, and Russell S. Winer (1991), "The Impact of New Product Introductions on the Market Value of Firms," *Journal of Business,* 64(Fall), 573–610.

Chang, Sea-Jin, Jaiho Chung, and Jon Jungbien Moon (2013), "When Do Wholly Owned Subsidiaries Perform Better than Joint Ventures?" *Strategic Management Journal*, 34(3), 317-337.

Chemmanur, Thomas J. and An Yan (2009), "Advertising, Attention, and Stock Returns," working paper, Carroll School of Management, Boston College.

Chen, Sheng-Syan (2008), "Organizational Form and the Economic Impact of Corporate New Product Strategies," *Journal of Business Finance & Accounting*, 35(1-2), 71-101.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), "Does a Firm's Product-Recall Strategy Affect its Financial Value? An Examination of Strategic Alternatives during Product-Harm Crises," *Journal of Marketing*, 73(6), 214-226.

Chen, Sheng-Syan, Kim Wai Ho, and Kueh Hwa Ik (2005), "The Wealth Effect of New Product Introductions on Industry Rivals," *Journal of Business*, 78(May), 969–996.

Christensen, Peter O., Leonidas E. de la Rosa, and Gerald A. Feltham (2010), "Information and the Cost of Capital: An Ex Ante Perspective," *The Accounting Review,* 85(3), 817-848.

Dehejia, Rajeev H., and Sadek Wahba (1999), "Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs," *Journal of the American Statistical Association*, 94(448), 1053-1062.

Duncan G. (2011), "Why does Apple Stock Fall with New Products?" (Accessed November 10, 2012) [Available at http://www.digitaltrends.com/apple/why-does-apple-stock-fall-with-new- products/#ixzz2DAI1nEXh]

Easley, David, and Maureen O'Hara (2004), "Information and the Cost of Capital," *The Journal of Finance*, 59(4), 1553-1583.

Fama, Eugene F., and Kenneth R. French (1993), "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics,* 33(1), 3-56.

Ferrier, Walter J., and Hun Lee (2002), "Strategic Aggressiveness, Variation, and Surprise: How the Sequential Pattern of Competitive Rivalry Influences Stock Market Returns," *Journal of Managerial Issues,* 162-180.

Fornell, Claes, Sunil Mithas, Forest V. Morgeson III, and Mayuram S. Krishnan (2006), "Customer Satisfaction and Stock Prices: High Returns, Low Risk," *Journal of Marketing*, 70(1), 3-14.

Garnefeld, Ina, Andreas Eggert, Sabrina V. Helm, and Stephen S. Tax (2013), "Growing Existing Customers' Revenue Streams Through Customer Referral Programs." *Journal of Marketing*, 77(4), 17-32.

Geyskens, Inge, Katrijn Gielens, and Marnik G. Dekimpe (2002), "The Market Valuation of Internet Channel Additions," *Journal of Marketing*, 66(2), 102–119.

Geyskens, Inge, Katrijn Gielens, and Marnik G. Dekimpe (2002), "The Market Valuation of Internet Channel Additions," *Journal of Marketing*, 66(2), 102-119.

Girotra, Karan, Christian Terwiesch, and Karl T. Ulrich (2007), "Valuing R&D Projects in a Portfolio: Evidence from the Pharmaceutical Industry," *Management Science*, 53(9), 1452-1466.

Green, Jeremiah, John R. M. Hand, and Michael W. Penn, Jr (2011), "Disseminating Business Information: The Attention-Grabbing Role of Bad News," (Working Paper SSRN No. 1780162). Retrieved from http://ssrn.com/abstract=1780162

Grullon, Gustavo, George Kanatas, and James P. Weston (2004), "Advertising, Breadth of Ownership, and Liquidity," *Review of Financial Studies*, 17(2), 439-461.

Guo, Shenyang and Mark W. Fraser (2010), *Propensity Score Analysis: Statistical Methods and Applications*. Thousand Oaks, CA: Sage Publications.

Hao, Jiang and Zheng Sun (2013), "Understanding the Illiquidity of Corporate Bonds: The Arrival of Public News," Working Paper, Retrieved from http://ww.leadershipreview.org/fei/2013ZhengSun.pdf

Hendricks, Kevin B. and Vinod R. Singhal (1997), "Delays in New Product Introductions and the Market Value of the Firm: The Consequences of Being Late to the Market," *Management Science*, 43(4), 1258–1274.

Ho, Kin-Yip, Wai-Man Raymond Liu, and Jing Yu (2013), "Public News Arrival and Cross-Asset Correlation Breakdown: Implications for Algorithmic Trading," (Working Paper SSRN No. 2023079). Retrieved from http://ssrn.com/abstract=2023079

_____, Yanlin Shi, and Zhaoyong Zhang (2013), "How Does News Sentiment Impact Asset Volatility? Evidence from Long Memory and Regime-Switching Approaches," *North American Journal of Economics and Finance,* 26(December), 1–21.

Homburg, Christian, Joseph Vollmayr, and Alexander Hahn (2014), "Firm Value Creation through Major Channel Expansions: Evidence from an Event Study in the United States, Germany, and China," *Journal of Marketing*, 78(3), 38-61.

Huang, Qingyi, Vincent R. Nijs, Karsten Hansen, and Eric T. Anderson (2012), "Wal-Mart's Impact on Supplier Profits," *Journal of Marketing Research*, 49 (2), 131-43.

Huberman, Gur, and Tomer Regev (2001), "Contagious Speculation and a Cure for Cancer: A Nonevent that Made Stock Prices Soar," *The Journal of Finance* 56(1), 387-396.

Jain, Pankaj K., and Jang-Chul Kim (2006), "Investor Recognition, Liquidity, and Exchange Listings in the Reformed Markets," *Financial Management* 35(2), 21-42.

Joshi Amit and Dominique M. Hanssens (2010), "The Direct and Indirect Effects of Advertising Spending on Firm Value," *Journal of Marketing,* 74(1), 20-33.

Kalaignanam, Kartik, Venkatesh Shankar, and Rajan Varadarajan (2007), "Asymmetric New Product Development Alliances: Win-Win or Win-Lose Partnerships?" *Management Science*, 53(3), 357-374.

Kale, Prashant, Jeffrey H. Dyer, and Harbir Singh (2002), "Alliance Capability, Stock Market Response, and Long-Term Alliance Success: The Role of the Alliance Function," *Strategic Management*, 23(8), 747-67.

Kaniel, Ron, Laura T. Starks, and Vasudha Vasudevan (2007), "Headlines and Bottom Lines: Attention and Learning Effects from Media Coverage of Mutual Funds," working paper, Simon Business School, University of Rochester.

Karniouchina, Ekaterina V., Can Uslay, and Grigori Erenburg (2011), "Do Marketing Media Have Life Cycles? The Case of Product Placement in Movies," *Journal of Marketing*, 75(3), 27-48.

Kelley, Eric K., and Paul C. Tetlock (2013), "*Retail Short Selling and Stock Prices,"* Columbia Business School Research Paper, 13-70.

Kelm, Kathryn M., V. K. Narayanan, and George E. Pinches (1995), "Shareholder Value Creation during R&D Innovation and Commercialization Stages," *Academy of Management Journal*, 38(June), 770- 786.

King, Michael R., and Dan Segal (2009), "The Long-Term Effects of Cross-Listing, Investor Recognition, and Ownership Structure on Valuation," *Review of Financial Studies*, 22(6), 2393-2421.

Koku, Paul S., Harsharanjeet S. Jagpal, and P. V. Viswanath (1997), "The Effect of New Product Announcements and Preannouncements on Stock Price," *Journal of Market Focused Management*, 2, 183–199.

Krasnikov, Alexander, Saurabh Mishra, and David Orozco (2009), "Evaluating the Financial Impact of Branding Using Trademarks: A Framework and Empirical Evidence," *Journal of Marketing*, 73(6), 154-166.

Lane, Vicki, and Robert Jacobson (1995), "Stock Market Reactions to Brand Extension Announcements: The Effects of Brand Attitude and Familiarity," *Journal of Marketing* (1995): 63-77.

Leary, Mark T., and Michael R. Roberts (2014), "Do Peer Firms Affect Corporate Financial Policy?" *Journal of Finance*, 69(1), 139-178.

Lee, Hun, Ken G. Smith, Curtis M. Grimm, and August Schomburg (2000), "Timing, Order and Durability of New Product Advantages with Imitation," *Strategic Management Journal*, 21, 23-30.

Lee, Ruby P. and Qimei Chen (2009), "The Immediate Impact of New Product Introductions on Stock Price: The Role of Firm Resources and Size," *Journal of Product Innovation Management*. 26, 97–107.

_____ and Rajdeep Grewal (2004), "Strategic Responses to New Technologies and their Impact on Firm Performance," *Journal of Marketing*, 68(4), 157-171.

Lin, Wen-Chun and Shao-Chi Chang (2012), "Corporate Governance and the Stock Market Reaction to New Product Announcements," *Review of Quantitative Finance and Accounting*, 39(2), 273-91.

Linville, Patricia W. and Gregory W. Fischer (1991), "Preferences for Separating or Combining Events," *Journal of Personality and Social Psychology*, 60(1), 5-23.

Luo, Xueming, Christian Homburg, and Jan Wieseke (2010), "Customer Satisfaction, Analyst Stock Recommendations, and Firm Value," *Journal of Marketing Research*, 47(6), 1041-1058.

MacKinlay, A. Craig (1997), "Event Studies in Economics and Finance," *Journal of Economic Literature, 35*(1), 13–39.

Merton, Robert C. (1987), "A Simple Model of Capital Market Equilibrium with Incomplete Information," *Journal of Finance,* 42(3), 483-510.

Mitchell, Mark L., and Erik Stafford (2000), "Managerial Decisions and Long-term Stock Price Performance," *Journal of Business,* 73(3), 287-329.

Moorman, Christine, Simone Wies, Natalie Mizik, and Fredrica J. Spencer (2012), "Firm Innovation and the Ratchet Effect among Consumer Packaged Goods Firms," *Marketing Science,* 31(6), 934-951.

Morgan, Neil A. and Lopo L. Rego (2009), "Brand Portfolio Strategy and Firm Performance," *Journal of Marketing,* 73(1), 59-74.

Nguyen, Bang Dang (2015), "Is More News Good News? Media Coverage of CEOs, Firm Value, and Rent Extraction," *Quarterly Journal of Finance,* 5(4), 1-38.

O'Brien, Patricia C., and Ravi Bhushan (1990), "Analyst Following and Institutional Ownership," *Journal of Accounting Research,* 55-76.

Oxley, Joanne E., Rachelle C. Sampson, and Brian S. Silverman (2009), "Arms Race or Détente? How Interfirm Alliance Announcements Change the Stock Market Valuation of Rivals," *Management Science,* 55(8), 1321-1337.

Pauwels, Koen, Jorge Silva-Risso, Shuba Srinivasan, and Dominique M. Hanssens (2004), "New Products, Sales Promotions, and Firm Value: The Case of the Automobile Industry," *Journal of Marketing,* 68 (October), 142-56.

Petersen, Mitchell A. (2009), "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches," *Review of Financial Studies,* 22 (1), 435-80.

Raassens, Néomie, Stefan Wuyts, and Inge Geyskens (2012), "The Market Valuation of Outsourcing New Product Development," *Journal of Marketing Research,* 49(5), 682-695.

Rao, Raghunath Singh, Rajesh K. Chandy, and Jaideep C. Prabhu (2008), "The Fruits of Legitimacy: Why Some New Ventures Gain More from Innovation Than Others," *Journal of Marketing,* 72(July), 58–75.

Rego, Lopo L., Matthew T. Billett, and Neil A. Morgan, (2009), "Consumer-Based Brand Equity and Firm Risk," *Journal of Marketing,* 73(6), 47-60.

Rindova, Violina, Walter J. Ferrier, and Robert Wiltbank (2010), "Value from Gestalt: How Sequences of Competitive Actions Create Advantage for Firms in Nascent Markets," *Strategic Management Journal*, 31(13), 1474-1497.

Rishika, Rishika, Ashish Kumar, Ramkumar Janakiraman, and Ram Bezawada. (2013), "The Effect of Customers' Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation," *Information Systems Research*, 24(1), 108-127.

Rosenbaum, Paul R. and Donald B. Rubin (1983), "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70(1), 41–55.

_____and _____ (1985), "Constructing a Control Group Using Multivariate Matched Sampling Models That Incorporate the Propensity Score," *American Statistician*, 39(1), 33-38.

Rubera, Gaia, and Ahmet H. Kirca (2012), "Firm Innovativeness and its Performance Outcomes: A Meta-Analytic Review and Theoretical Integration," *Journal of Marketing*, 76(3), 130-147.

Rust, Roland T., Tim Ambler, Gregory S. Carpenter, V. Kumar, and Rajendra K. Srivastava (2004), "Measuring Marketing Productivity: Current Knowledge and Future Directions," *Journal of Marketing*, 68(4), 76-89.

Sabherwal, Sanjiv, Salil K. Sarkar, and Ying Zhang (2011), "Do Internet Stock Message Boards Influence Trading? Evidence from Heavily Discussed Stocks with No Fundamental News," *Journal of Business Finance & Accounting*, 38 (9&10), 209–1237.

Samadi, Mehrdad (2016), "Intermarket Competition: Evidence from Trading Venue Short Sales," working paper, University of North Carolina Chapel-Hill, available on SSRN at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2619839

Sharma, Anurag and Nelson Lacey (2004), "Linking Product Development Outcomes to Market Valuation of the Firm: The Case of the U.S. Pharmaceutical Industry," *Journal of Product Innovation Management*, 21, 297–308.

Sharpe, William F. (1964), "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk," *Journal of Finance*, 19(3), 425-42.

Shroff, Nemit, Amy X. Sun, Hal D. White, and Weining Zhang (2013), "Voluntary Disclosure and Information Asymmetry: Evidence from the 2005 Securities Offering Reform," *Journal of Accounting Research*, 51(5), 1299-1345.

_____, Rodrigo S. Verdi, and Gwen Yu (2014), "Information Environment and the Investment Decisions of Multinational Corporations," *The Accounting Review*, 89(2), 759-790.

Srinivasan, Shuba, and Dominique M. Hanssens (2009), "Marketing and Firm Value: Metrics, Methods, Findings, and Future Directions," *Journal of Marketing Research*, 46(3), 293-312.

Sood, Ashish and Gerard J. Tellis (2005), "Technological Evolution and Radical Innovation," *Journal of Marketing*, 69(3), 152-68.

_____, and _____ (2009), "Do Innovations Really Pay Off? Total Stock Market Returns to Innovation," *Marketing Science*, 28(3), 442-456.

Sorescu, Alina (2012), "Innovation and The Market Value of Firms," in the *Handbook of Marketing and Finance*, edited by Shankar Ganesan. Edward Elgar Publishing.

_____, Rajesh K. Chandy, and Jaideep C. Prabhu, (2003), "Sources and Financial Consequences of Radical Innovation: Insights from Pharmaceuticals," *Journal of Marketing*, 67(4), 82–102.

_____, Venkatesh Shankar, and Tarun Kushwaha (2007), "New Product Preannouncements and Shareholder Value: Don't Make Promises You Can't Keep," *Journal of Marketing Research*, 44(August), 468–489.

_____, and Jelena Spanjol (2008), "Innovation's Effect on Firm Value and Risk: Insights from Consumer Packaged Goods," *Journal of Marketing*, 72(2), 114–132.

Stewart, David W. (2009), "Marketing Accountability: Linking Marketing Actions to Financial Results." *Journal of Business Research* 62(6), 636-643.

Swaminathan, Vanitha and Christine Moorman (2009), "Marketing Alliances, Firm Networks, and Firm Value Creation," *Journal of Marketing*, 73(September), 52–69.

Tellis, Gerard J. (2013), *Unrelenting Innovation: How to Build a Culture for Market Dominance*, San Fransisco, CA: Jossey-Bass.

Thaler, Richard (1985), "Mental Accounting and Consumer Choice," *Marketing Science*, 4(3), 199-214.

Tuli, Kapil R., Sundar G. Bharadwaj, and Ajay K. Kohli (2010), "Ties that Bind: The Impact of Multiple Types of Ties with a Customer on Sales Growth and Sales Volatility," *Journal of Marketing Research*, 47(1), 36-50.

Umiastowski, Chris (2012), "What to Think About Nokia after Yesterday's 16% Stock Price Collapse," (Accessed November 14, 2012) [Available at http://www.wpcentral.com/what-think-about-nokia-after-yesterday%E2%80%99s-16-stock-price-collapse]

Verbeek, M. (2008), *A Guide to Modern Econometrics*, 3d ed. Chichester, UK: John Wiley& Sons.

Wang, Chi-Feng, Li-Yu Chen, and Shao-Chi Chang (2011), "International Diversification and the Market Value of New Product Introduction," *Journal of International Management*, 17, 333–347.

Wangenheim, Florian V., and Tomás Bayón (2007) "Behavioral Consequences of Overbooking Service Capacity," *Journal of Marketing*, 71(4), 36-47.

Wiles, Michael A. and Anna Danielova (2009), "The Worth of Product Placement in Successful Films: An Event Study Analysis," *Journal of Marketing*, 73(4), 44-63.

_____, Neil A. Morgan, and Lopo L. Rego (2012), "The Effect of Brand Acquisition and Disposal on Stock Returns," *Journal of Marketing* 76(1), 38-58.

Wooldrige, J. Randall and Charles C. Snow (1990), "Stock Market Reaction to Strategic Investment Decisions," *Strategic Management*, 11(5), 353–363.

Yglesias, Matthew (2009), "The Decline of Product Placement?" Think Progress, (accessed October 21, 2009), [available at http://yglesias.thinkprogress.org/archives/2009/01/the_decline_of_product_placement.php]

Zantout, Zaher and Radha Chaganti (1996), "New Product Introductions, Shareholders' Wealth, and First- Mover Advantages," *Journal of Financial and Strategic Decisions*. 6(3) 49–61.

APPENDIX

Excerpts from Published Event Studies that Examine Events that Can Have Past Occurrences (First Essay)

Paper	Focal event	Event Part of a Strategy-Driven Sequence of Events?
Raasens, Wuyts, and Geyskens (2012)	NPD outsourcing announcements	Yes: Firms can potentially outsource the development of several new products through time.
Boyd, Chandy, and Cunha (2010)	Announcement of a CMO appointment	Yes: The authors cite statistics stating that the average CMO tenure is 23 months, thus CMO announcements can occur relatively frequently. (p. 1162) The authors also state that only 19% of their sample constitutes announcements of newly created CMO positions.
Sorescu, Shankar, and Kushwaha (2007)	The preannouncement of a new product.	Yes: Many firms have a history of preannouncing their products.
Homburg, Vollmayr, and Hahn (2014)	Announcement of an increase in distribution intensity ("an expansion of the number of channel entities at a particular level within an existing channel, such as wholesalers or retailers" p. 41) or the addition of a new channel.	Yes: Firms can increase their number of wholesalers or retailers on more than one occasion.
Wiles, Morgan, and Rego (2012)	Announcement of acquisition or disposal of brands from a firm's portfolio.	Yes: Firms can repeatedly buy new brands or sell old ones.
Karniouchina, Uslay, and Erenburg (2011)	Product placement in movies. The effect of product placement is assessed in a window around the movie release date.	Yes: Firms repeatedly place products in movies. For instance, the authors report that Coca Cola was placed in 75 movies included in their sample.
Chen, Ganesan, and Liu 2009)	The announcement of a product recall by the Consumer Product Safety Commission (CPSC). The authors distinguish between proactive recalls, done at the initiative of the firm, and passive recalls, which are issues only after serious consumer complaints have been made to the firm or the CPSC.	Yes: Many firms have issued multiple recalls through time, or have faced product harm crises that may or may have not involved recalls.
Wiles and Danielova (2009)	Product placement in movies. The effect of product placement is assessed in a window around the movie release date.	Yes: Firms repeatedly place products in movies.
Rao, Chandy, and Prabhu (2008)	The announcement of a new product introduction in the biotech industry (FDA approval announcement). The sample includes both products that were introduced by single firms and products introduced by alliances.	Yes: Firms typically have a history of product introductions.
Fornell et al. (2006)	"The ACSI [score release] announcement for a firm as (simultaneously) published in The Wall Street Journal and on the ACSI Web site." (p.7)	Yes: ACSI scores are announced at regular intervals of time.