“How broadly do product preannouncement performance effects generalize? Product life cycle and switching cost perspectives”

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HOW BROADLY DO PRODUCT PREANNOUNCEMENT PERFORMANCE EFFECTS GENERALIZE? PRODUCT LIFE CYCLE AND SWITCHING COST PERSPECTIVES

Abstract

Firms use preannouncements to inform customers about the impending introduction of a new product or service. These preannouncements are significant events because they provide customers with product specific information while signaling the health, strategic intent, and future of a company. One important area of research in this field investigates the performance consequences of product preannouncements (PPA). However, a notable gap in our knowledge exists, because the focus of past research has been on studying wealth effects rather narrowly in certain industries, e.g., high-tech, or under certain contingencies. This restrictive approach is surprising, because PPA are observed in a broad range of product categories. Moreover, product life cycle and consumer switching cost theories predict performance effects of PPA irrespective of category or context. The author addresses this lack of generalizability by using switching cost and life cycle theories to hypothesize positive performance effects of PPA independent of context and contingencies. The event study method from finance is used to empirically test the relationship between PPA and stock prices in a broad sample of events comprising multiple product categories. Using events reported in the Wall Street Journal, evidence of a positive effect of PPA on stock prices irrespective of the type of product or context involved is found. Several managerial implications of the study are noted and avenues for further research are outlined.

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INTRODUCTION

The robustness of a firm’s new product pipeline is a vital determinant of a company’s future growth strategy. Hence, companies make every effort to showcase their new product pipeline to customers and interested stakeholders (Flynn & Read, 2003). For example, instead of waiting to announce a new product just before its launch, firms routinely communicate with the market about impending introductions ahead of time. Such advance communications or product preannouncements (PPA) are a well-entrenched and integral component of a firm’s communication strategy.

Given their importance, PPA have attracted the attention of researchers in marketing, economics, and strategy (Calantone & Schatzel, 2000; Heil & Robertson, 1991; Popma et al., 2006; Rao & Turut, 2019; Su & Rao, 2010). Considered as a whole, this literature has studied the nature, antecedents and consequences of PPA. In this vein, one important area of inquiry concerns the performance effects of preannouncements, e.g., the impact of PPA on firms’ security prices. The

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expectation for performance effects is based upon the strong form of the efficient market hypothesis (Titan, 2015), which states that at a given point in time, a firm's security price unambiguously reflects all available information. Hence, any new information released to the market such as PPA should result in a contemporaneous adjustment to a firm's security price. Thus, the performance effect of PPA can be measured ex-post through the change in a firm's share price.

Empirical investigations of the wealth effect of PPA have been conducted primarily in high-tech product categories (Bayus et al., 2001), or in situations where firms deploy contingencies to reduce information asymmetries by signaling intended behavior to the market (Bergh et al., 2019; Connelly et al., 2011; Sorescu et al., 2007). Researchers using the high-tech industry setting argue that products are more prone to disruption by innovators because of short product life cycles, relatively high volatility, steep consumer switching costs, and changing industry standards. Thus, technologically innovative firms, on average, are better placed to disrupt the market and reap wealth gains. Hence, PPA in high-tech industries are expected to result in superior economic performance. Proponents of the information asymmetry school of thought, on the other hand, make a slightly different argument for performance effects. Briefly, information asymmetry theories (Connelley et al., 2011; Sorescu et al., 2017) argue that PPA will yield positive performance effects only when firms provide evidence of an irreversible intention on the part of the announcing firm to follow through on the announcement.

While research about the performance of PPA has yielded several insights as noted above, one critical gap in our knowledge concerns the relatively narrow focus of extant empirical studies that have been confined either to high tech industries, or have used specific contingencies such as evidence to examine wealth effects. In other words, performance effects of PPA appear to have been investigated rather narrowly, leading to a lack of generalizability of findings. Since PPA are observed across the board, and in industries encompassing both consumer and industrial products (Chaudhuri, 2018; Ng, 2013; Ng & Ziobro, 2013; Terlep, 2017), it is imperative to empirically investigate whether PPA create wealth effects across all industries or only in the high-tech product category or in situations involving specific signals.

In view of the preceding observations, the purpose of this paper is to empirically investigate whether PPA performance effects measured using stock market returns generalize broadly across multiple categories or are confined narrowly to certain product categories and situations. In undertaking this study, the paper makes two specific contributions to theory and practice. First, by examining if PPA wealth effects generalize to all product categories, or are limited by context, researchers may be in a better position to refine existing theories and predict PPA effects more accurately. Second, a better understanding of boundary conditions is likely to inform practicing managers about the optimal design and management of preannouncements. For instance, if preannouncement effects are observed to be robust across product categories, managers can refrain from incurring additional costs to make PPA irreversible and costly.

This paper is organized in the following manner. The first section discusses the literature pertaining to product life cycle and switching cost theories and formulates a hypothesis predicting the generalizability of wealth effects. This is followed by a depiction of the research method, data collection effort, and the event study methodology. The next section describes the results, while the concluding section outlines managerial implications and highlights the scope for further research.

1. LITERATURE REVIEW

The literature on PPA and wealth effects is primarily addressed through the twin lenses of product life cycle theory and consumer switching cost theory. The next subsection describe the essence of these theories, as they pertain to wealth effect predictions for PPA. This is followed by delineation of the relevant hypothesis about the generalizability of PPA wealth effects.

1.1. Product life cycle theory

Product life cycle (PLC) theory is a bedrock framework that is used to formulate marketing interventions at different stages in a product's life (Day, 1981; Golder & Tellis, 2004; Restuccia et al., 2016). Based loosely on the analogy of a human life cycle, the theory advances the idea that over time products move through sequential processes involving birth, growth, maturity, and decline phases. Consequently, at each stage, firms have an incentive to design and deploy interventions to maximize value. For example, at the introduction stage, a new product is in need of early adopters (Palacois & Tellis, 2016). Hence, PLC theory suggests that firms should shun bells and whistles in product design and incorporate basic attributes. Likewise, as a product graduates into the growth phase, it behooves upon firms to differentiate their offerings by adding unique features to thwart competition. At the maturity stage, product sales become sluggish, as firms face the challenges of a saturated market. Market saturation is a direct result of competition. In particular, as per the theory of competitive strategy (Llanes, 2019), entry barriers are trivial, because new entrants experience the benefits of past learning and capitalize on the loss of patent protection of innovators to introduce new products at lower price points. Faced with a new competitive set, it makes sense for incumbent firms to harvest the product or even create line extensions. Finally, facing inevitable decline, firms should plan for strategic exit from the market and target niche marketing opportunities. Notice, however, that the idea of market exit is not a straightforward decision given the significant sunk costs involved in the entire product ecosystem by the focal firm. Typically, over time, incumbents make significant transaction specific investments in their distributor, channel partner, and supply chain relationships (Hoffman et al., 2016). Hence, emerging research (Restuccia et al., 2016) argues that firms facing market share loss at the decline stage may pursue evolutionary strategies such as entering into strategic alliances with ecosystem firms to conceptualize and preannounce new products.

Notice that several limitations and extensions of the original PLC theory have been discussed in the literature. Most notably, researchers have opined that PLC theory is rather deterministic and does not fully account for firms' proactive efforts in creatively extending the life of a product (Rao & Evers, 2015). In this vein, the concept of product evolution is more relevant to understanding the behavior of new products over time. Thus, researchers have suggested that PLC theory should be supplemented by the Product Evolutionary Cycle (PEC) theory to better understand product dynamics (Elberse, 2011; Elberse & Moon, 2011; Keklik, 2018; Lambkin & Day, 1989). For example, consider the Tide detergent brand manufactured by Proctor and Gamble. This product has remained on supermarket shelves since 1946 without succumbing to the extinction prediction of conventional PLC theory. Instead, as posited by PEC theory, Tide has survived because it has evolved over time and successfully adapted to changing customer needs.

At first glance, the basic idea underlying PLC theory appears more suited to explain wealth effects for high-tech PPA. Recall that high-tech products typically face intense obsolescence pressures, since innovations constantly alter the means-end relationship for new technologies. Thus, the fear of short life cycles and imminent mortality is a danger that lurks in the mind of every high-tech product manager. From cell phones being eclipsed by smart gadgets to the possibility of electric cars eventually displacing gasoline vehicles, disruption through innovation is an ever present possibility. Hence, PPA in high-tech industries signal to the market that a firm is conscious of life cycle pressures and is proactively working to overcome mortality challenges. PPA for high-tech products are therefore more likely to positively influence investors, thereby leading to higher stock prices for the announcing firm.

While the PLC logic supporting wealth effects for high-tech products is intuitively apparent, PEC theory predicts that low-tech PPA can also create wealth effects. In fact, firms typically evolve by engaging in minor product modifications just to survive and remain ahead of the competition. For example, consider the success of Chobani, the brand widely credited with popularizing Greek yogurt the world over. As Pannett (2017) notes, "Ulukaya anticipated changing American tastes before the big food conglomerates did, championing the yogurt of his boyhood and helping set

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off the craze for Greek yogurt… Chobani is now the second-best-selling yogurt in America" (p. 2). Hence, from a PEC perspective, Greek yogurt represented an evolution relative to conventional yogurt, and Chobani could successfully pursue incremental innovation in a mature category and achieve wealth gains. In summary therefore, PEC theory explicitly argues for firms' efforts to stay relevant to their consumer segment by adopting product evolution strategies. Furthermore, PEC theory does not confine its argument to just one category of products, e.g., high-tech, but makes a broad prediction that involves all types of products across different product categories. Hence, to stay relevant, we expect firms to engage in product preannouncements irrespective of a particular industry or a specific contingency.

1.2. Consumer switching cost theory

Analogous to the PLC and PEC perspectives, switching cost theory also predicts wealth effects of PPA. In particular, firms' PPA can often introduce financial and perceived switching costs for their existing customers who may stick to a known product instead of defecting to a superior competitive offering (Calantone & Schatzel, 2000; Heil & Robertson, 1991; Su & Rao, 2010). Thus switching costs or "the perceived economic and psychological costs associated with changing from one alternative to another" (Jones et al., 2002, p. 441) engendered by PPA are central to firms' customer retention strategies and result in lifetime value maximization (Jain & Singh, 2002; Kumar & Reinartz, 2016). Likewise, an entrenched body of research documents the consequences of switching costs such as their impact on customer satisfaction, repurchase intentions, loyalty and stock-market returns (Blut et al., 2015, Pick & Eisend, 2014). Overall, from a switching cost perspective, PPA are therefore expected to result in positive stock market reaction (Burnham et al., 2003; Yang & Peterson, 2004).

Although switching costs engender customer stickiness and impact performance, the effect of PPA in different industries is explained by two distinct schools of thought, i.e. (a) the industrial organization perspective and (b) the behavioral economics literature. In particular, while industrial economics deals primarily with financial switching costs and argues for the positive effect of PPA primarily in high-tech categories, behavioral economics focuses on the role of consumer biases in determining switching costs for PPA independent of product category.

According to the industrial organization perspective (Lyons, 2010), PPA are forward looking events that showcase and highlight a future new product introduction or improvements to existing offerings. Hence, users exposed to PPA may perceive higher economic costs of switching from an incumbent's product to a competing alternative (Burnham et al., 2003). In a game theoretic sense, faced with the option of migrating to a competitor's product, customers may eventually decide against the switch, because the actual costs of adopting a competitive technology or product may be very high (Choi et al., 2005). For example, in today's technology driven industries, digital connectivity has transformed many products into ecosystem components. In such sprawling inter-connected networks or digital platforms, PPA are being increasingly used by firms to prevent customer switching behavior. In this context, the industrial organization literature discusses the role of financial incentives in switching behavior. For example, Apple successfully preannounced its monthly music subscription service (Beats Music) at an affordable introductory price to minimize defection of its existing ITunes music customers to competitors like Spotify (Smith & Wakabayashi, 2015). Stated differently, economic incentives can directly influence switching costs and affect customer loyalty.

Industrial organization theory also makes an indirect argument for wealth effects of PPA by suggesting that regulation may weed out unethical behavior. In particular, regulation may be deployed by the institutional environment to curb the growth of PPA designed as bluffs. A classic historical example of marketplace bluff is Microsoft's strategy for operating systems in the 1990's. During this time, IBM's operating system, the OS/2 was widely considered to be the best product in the market (Barrett et al., 1993). However, OS/2 never achieved commercial success, and IBM ultimately phased it out because Microsoft froze the market by preannouncing Windows 95 (the precursor to today's Windows 10 operating system) as a bluff even though its operating system was not even at the conceptualization stage. From a technical standpoint, Microsoft's preannouncement was a bluff. However, as a consequence of its announcement, Microsoft's customers thought it prudent to wait for Windows 95 instead of switching to OS 2. Microsoft's behavior, often termed 'vaporware' ushered in a new regulatory regime in the U.S. and other countries, thereby making PPA more honest. Currently, PPA especially in the high-tech sector are regulated, and their strategic use is fairly commonplace. For example, recently, Fitbit which manufactures digital fitness products used PPA to ward off stiff competition from Apple's Iwatch and other competitors in advance of the 2017 holiday season (Koh, 2017). Hence, the industrial economics literature argues for positive effect of PPA in the high-tech industry by focusing on the roles of well-designed financial incentives and the regulatory oversight of the institutional environment.

In contrast to the arguments advanced by industrial organization theory, behavioral economics theory (Fox & Tversky, 1995; Pick & Eisend, 2014) argues that customers systematically overestimate the costs of switching from an existing product to a competitor's offering even if the product in question is rather simple to use. To begin with, switching costs arise from an endowment effect whereby customers value what they possess, e.g., an existing product of a familiar company at a disproportionately higher level than a competing alternative articulated through a rival preannouncement. This endowment effect, which is often the result of in-built biases that people hold, has been shown to be strong and robust across different product categories (Fox & Tversky, 1995). Hence, it is not surprising that endowment effects that prevent defection and increase switching costs are observed across different product categories. For example, the Keurig Green Mountain Company, which manufactures the popular K-Cup coffee brewer and coffee pods, used PPA to minimize customer defection to superior competing alternatives like the Nespresso machine. In particular, as Gasparo (2017) notes, Keurig's chief executive Brian Kelley is "credited with reviving the Waterbury, Vt.-based company's stock since he took over in December 2012 after years at Coca-Cola Co" through pre-announcements much before newer models were introduced (p. 12). Likewise, P&G preannounced several safety features in its upcoming detergent packages to address child safety concerns at a time when competitors had already introduced the product in safe containers (Glazer, 2012). In summary, according to the behavioral economics literature, endowment effects lead to perceived switching costs irrespective of the product category. These costs, in turn, prevent switching behavior and lead customers to remain loyal to a brand. Hence, irrespective of the nature of a product, PPA will lead to higher perceived switching costs, increased customer loyalty, and a positive effect on stock prices.

In view of the preceding discussion, arguments offered by PLC and switching cost theories suggest that considerable advantage accrues to firms engaging in PPA. Moreover, these theoretical perspectives suggest that PPA performance effects are broad based and not confined narrowly to certain industries. In other words, PPA performance effects are expected to generalize across multiple product categories. In view of the preceding discussion, the following wealth effect hypothesis is offered for empirical investigation:

H1: The positive wealth effects of PPA measured by a firm's security price will generalize to encompass multiple products across multiple product categories.

2. RESEARCH METHOD

2.1. Measurement of market value effects

The event study methodology popularized in finance was used to investigate the wealth effect of PPA (Brown & Warner, 1985; Mackinlay, 1997). The basic assumption of this method is that markets are efficient. In particular, the strong form of the efficient market hypothesis (Fama, 1970; Fama, 1980; MacKinlay, 1997; Mikkelson & Partch, 1986) was adopted for investigating wealth effects. The efficient market hypothesis argues that at any point in time, all available information about the announcing firm is fully and accurately reflected in its security price. Hence, any new information is contemporaneously absorbed by the market. Thus,

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changes in stock price are a measure of the impact of a particular event. For example, to begin with, consider PPA in the context of the stock market. There is ample theoretical and empirical evidence to suggest that PPA are significant events that are scrutinized by market participants. Thus, relative to a status quo situation, whenever PPA are received by the market, both buyers and sellers will be incentivized to buy or sell a stock given the potential of PPA to either bolster or constrain the growth of the company. Thus, ceteris paribus, PPA will affect firms' stock prices.

To model this argument, the event study methodology computes the normal return for a stock and compares it to a previous window that does not contain the event. The change in returns or the abnormal return is an adjusted measure of stock price return. The relevant formulae for calculating stock price returns and associated parameters are provided below.

The normal return $R_{i,t}$ for a market portfolio, $R_{m,t}$ for a firm i on day t is specified as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + e_{i,t}.$$

The abnormal return, $AR_{i,t}$, has the following form:

$$AR_{i,t} = r_{i,t} - \left(a_i + b_i R_{m,t}\right),$$

where $r_{i,t}$ represents the specific return on a particular day and a_i and b_i are estimates of α_i and β_i. A time duration of 255 trading days spanning 12 calendar months is used as the baseline for comparison. Data contained in the CRSP (Center for Research in Security Prices, University of Chicago) tapes reflect the market portfolio.

We further assume that the abnormal return, $AR_{i,t}$ with a mean of zero has a variance of $s^2_{AR_{i,t}}$, which can be specified. Note that this estimate follows a maximum likelihood distribution, which is given by the following formula:

$$s^2_{AR_{i,t}} = s^2_{AR_i}\left[1 + \frac{1}{T_i} + \frac{\left(R_{m,t} - \overline{R}_m\right)^2}{\sum_{k=1}^{T_i}\left(R_{m,k} - \overline{R}_m\right)^2}\right],$$

where

$$s^2_{AR_i} = \frac{\sum_{k=1}^{T_i} AR^2_{i,k}}{T_i - 2}.$$

In these formulae, the symbols are explained as under:

$\overline{R}_m$ – average market return, T_i – non-missing returns.

Under these specifications in the econometric model, the standardized abnormal return $SAR_{i,t}$ and the average standardized abnormal returns $\left(ASAR_t\right)$ are specified as follows:

$$ASAR_t = \frac{1}{N}\sum_{i=1}^{N} SAR_{i,t},$$

$$SAR_{i,t} = \frac{AR_{i,t}}{s_{AR_{i,t}}}.$$

In the formulae above, N represents the number of firms announcing a product. Under relevant assumptions of the central limit theorem, the Z and t values used to compute statistical differences are calculated as follows:

$$Z = \sqrt{N}\left(ASAR_t\right),$$

$$t = \frac{ASAR_t}{SE\left(SAR_t\right)}.$$

In interpreting our results, it is important to clarify that the Jackknife Z statistic was used for gauging statistical significance of AR's instead of the conventional Z estimate. Typically, for small sample sizes, the underlying distribution of data may not be normal and can result in biased estimates for the standard Z statistic. To deal with this problem, researchers have advocated the use of a Jackknife Z measure (Shao & Tu, 1995). This statistic is computed using a re-sampling method that eliminates bias by deleting one datum each time from the original data set and recalculating the estimator based on the rest of the data. The description of the Jackknife procedure is provided in Appendix A.

2.2. Sample data

The sample was collected from announcements made in the Wall Street Journal, which is widely

Table 1. Descriptive statistics

Variable	N	Mean	Median	Standard deviation	Minimum	Maximum
Sales[a]	214	16403.95	7582.92	23061.48	2.96	122081.00
MVE[b]	200	11480.48	6027.85	13947.99	17.615	72710.74
TA[c]	206	21514.31	7584.79	38065.39	18.45	213701.00
Adv/Sales[d]	181	.06	.04	.05	.01	.20
NetP/Sales[e]	177	.17	.18	.03	.03	.24

Notes: a – aggregate sales volume ($ million), b – market value of equity ($ million), c – total assets ($ million), d – ratio of advertising expenses to net sales volume, e – ratio of net profits to aggregate sales volume.

considered to be an authoritative avenue for documenting new product preannouncements. To ensure that the sample did not contain data that were influenced by extraneous events, they were systematically examined to identify confounding situations. For example, if an event date had multiple major announcements, e.g., the preannouncement itself and additional information about earnings, that data point was eliminated. Using this approach, we originally started with a sample of 260 firms, which eventually resulted in 219 firms for the present study.

Additional data pertaining to the characteristics of announcing firms were collected from the COMPUSTAT tapes provided by Standard and Poor's Corporation (S&P). Data for several variables of interest such as sales, market value of equity, total assets, advertising to sales ratio, and net profits to sales ratio were collected for the firms' fiscal year immediately preceding the year of the preannouncement. The summary statistics for the sample are presented in Table 1.

Descriptive statistics are computed using information from the COMPUSTAT tapes. Data from the fiscal year that ended immediately preceding the year in which the preannounced event took place were used in computing all the variables. The number of firms is less than 219, because data of interest for some firms are missing on the COMPUSTAT tapes.

As can be noted from Table 1, the typical firm in the sample has high sales ($ 16.40 billion), a large market value of equity ($ 11.48 billion), and substantial total assets ($ 21.5 billion). Furthermore, a firm earns net profits amounting to 17% of its sales, while it spends 6% of sales on advertising. Hence, advertising expenses are approximately 33% of a firm's net profits. This substantial outlay on advertising implies that communicating information to external stakeholders is an important part of a firm's promotional strategy. Hence, product preannouncements, a form of communication directed at external audiences, constitute significant firm events and are likely to elicit stock market reaction.

2.3. Classification of announcements

Table 2 depicts the classification scheme used in the present study. The classification exercise was conducted in a systematic manner using independent raters (trained professionals in business

Table 2. Examples of product preannouncements

Industry	Preannouncement
Consumer products (staples)	"The buzz [for its Yeezy Boost shoes] is a welcome change for Adidas...Boost soles use a proprietary plastic from German chemicals company BASF... Gerd Manz, vice president at Adidas said [upon wearing it] his blood pressure rose... pounding the material to simulate running and jumping, he saw that it released far more of the energy input than any other material he had known of... I got that we were on to something... he said" (Jervell, 2015)
Consumer products (staples)	"Proctor and Gamble Co., Under assault by penny-pinching consumers... [will] quietly roll out a version of the Tide detergent that the company freely admits isn't new and improved" (Byron, 2009)
Consumer products (staples)	"MillerCoors LLC has begun testing the sale of $20 draft-beer systems for consumers to drink at home, part of a string of products..." (Kesmodel, 2009)
Consumer products (durables)	"Standing on stage in front of a large New York audience, Amazon Chief Executive Jeff Bezos Wednesday unveiled a music and video playing tablet dubbed the Kindle Fire" (Woo & Trachtenberg, 2011)
Industrial products	"The Food and Drug Administration approved the first generic version of the big-selling blood thinner Lovenox, hitting Sanofi-Aventis SA and bringing a victory to Novartis AG's generics unit..." (Mundy, 2010)
Industrial products	"Fujitsu Ltd. and Xerox Corp. subsidiary Palo Alto Research Center said they will work together to develop next-generation data networks, in a move they say brings them closer to realizing futuristic scenarios..." (Dvorak, 2004)

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management) who were provided with definitions of product preannouncements by the principal investigator. In addition, the raters were also given several unique keywords to more precisely identify the preannouncement. The classification approach was conducted across different product categories, i.e., consumer staples, consumer durables, and industrial products. A few representative announcements are depicted in Table 2.

3. EMPIRICAL RESULTS

As can be seen from the abnormal returns in Table 3, they are positive and significant on the announcement day (day 0), thereby supporting the generalizability hypothesis articulated in *H1*. Specifically, on the day of the announcement, the mean abnormal return is positive (0.66%) and statistically significant ($Z = 3.212$, $p < 0.05$; Jackknife–$Z = 2.415$, $p < 0.001$). Thus, firms making preannouncements experience a wealth gain on an average of 0.66% on the day when they make such announcements. In addition, the ratio of positive to negative returns (87:74) suggests that the returns are not skewed and not driven by a few extreme values. Since the positive results are observed in a broad sample of preannouncements, irrespective of the product category (consumer or industrial goods), it is apparent that wealth effect of PPA generalize broadly and are not narrowly confined to certain kinds of products.

Table 3. Abnormal returns from days –5 to +5

Day	Abnormal return (%)	Positive to negative returns	*Z* statistic[a]	Jackknife *Z* statistic[b]
–5	.32	81:80	1.408	.962
–4	.20	76:85	0.837	.206
–3	.21	84:77	1.147	1.295
–2	–.08	71:90	–0.345	–.700
–1	.39	89:72	1.965**	.904
0	.66	87:74	3.212*	2.415**
+1	.17	88:73	1.215	1.113
+2	.20	77:84	1.759***	.643
+3	–.18	71:90	–1.164	–1.588
+4	.25	76:85	1.365	.462
+5	.15	85:76	1.311	1.670***

Notes: a – based on non-parametric test, b – based on re-sampling, *p < 0.05, **p < .001, *** p < .0.001, day 0 represents the event date.

Further support for the robustness of our results is provided by Table 4, which depicts the cumulative abnormal returns (CAR) over selected time windows. The CAR measure provides estimates of the abnormal return over a window of time as opposed to a particular day. The advantage of computing CAR is that it is less biased than abnormal returns and can account for extraneous events like lawsuits and boycotts that firms may face. In the present situation, the CAR for two different windows, i.e., (–1, +1) and (–2, +2), are positive and statistically significant.

Table 4. Cumulative abnormal returns over selected windows

Day	Cumulative abnormal return (%)	Positive to negative returns	*Z* statistic[a]	Jackknife *Z* statistic[b]
(–1, +1)	1.23	91:70	3.69*	2.488**
(–2, +2)	1.35	88:73	3.49**	1.951***

Notes: a – based on non-parametric test, b – based on re-sampling, *p < 0.05, **p < .001, *** p < .0.001, day 0 represents the event date.

In particular, as may be seen from Table 4, for the (–1, +1) window, the CAR is 1.23% with a statistically significant *Z* and Jackknife *Z* statistic ($Z = 3.69$, $p < 0.05$; Jackknife–Z= 2.488, $p < 0.01$), while the corresponding values for the (–2, +2) window are also positive (1.35%) and statistically significant ($Z = 3.49$, $p < 0.01$; Jackknife – $Z = 1.951$, $p < 0.001$). Furthermore, as can be seen from Table 4, the ratio of positive to negative returns for both windows suggest that the CAR's are not being driven by extreme values.

In addition to computing AR's and CAR's, we also conducted an additional statistical test to ascertain the generalizability of our findings. In particular, we directly compared the abnormal stock price returns of preannouncing firms across different industry groups to study if abnormal returns were dependent on a certain product category. However, in conducting this analysis, an important caveat is in order. For comparing industry adjusted sales and profits, the COMPUSTAT tapes contain two digit industry classification (SIC) data that permit easy comparisons. However, classifying preannouncements in our sample into industry groups based upon industry SIC codes is virtually impossible given that at a minimum, we have to fit

Table 5. Industry effect of preannouncements

Feature	Industrial products (N = 68)	Consumer products (N = 151)	
		Consumer staples (N = 62)	Consumer durables (N = 89)
Focus	Business to business	Business to consumer	Business to consumer
Characteristics	Long product life cycle Infrequent purchase Purchasing teams Large capital outlay	Moderate to short product life cycle Individual purchase Frequent purchase	Moderate to short product life cycle Individual purchase Infrequent purchase
Examples	Aircraft engines Medical equipment	Food Beverages Household products	Toys Electronics Books
Preannouncement examples	General Electric GEnx engines Johnson and Johnson's stent	Anheuser Busch's beer product Gillette's razor blades	Apple Ipad Amazon Alexa
Abnormal return (Z, p)	0.58 (2.212, p < .05)	0.41 (1.416, p < 0.10)	0.42 (1.371, p < 0.05)
MANOVA results	Wilks Lambda = 0.99, F = 0.929, P = 0.483; Pillai's Trace = 0.009, F = 0.929, p = 0.483. (H_0: The vector of group abnormal returns across the three industry groups are equal)		

219 observations into 48 two digit SIC categories. Hence, we adopted an ad-hoc procedure used in prior studies (Cavusgil & Zao, 1994). Specifically, we created broad categories (industrial versus consumer goods) and compared the abnormal returns across these groups. We present the results of our analysis in Table 5.

As may be noted from Table 5, the AR for each category is positive and statistically significant, and a MANOVA analysis suggests that the hypothesis of equal mean vector of AR's across the three categories cannot be rejected. In other words, consistent with our finding from the main event study, abnormal returns do not differ significantly across industry groups for the firms in our sample. Hence, the positive effect of PPA generalize across all product categories and are not limited by context.

4. DISCUSSION

4.1. Implications for researchers and practitioners

The basic purpose of this study has been to gain a better understanding of product preannouncements. At the outset, we noted that PPA represent significant communication events for firms. Given their importance, a growing body of literature in marketing and adjacent disciplines such as economics, strategy, and management has investigated the nature, antecedents, and consequences of product preannouncements (PPA). From a performance angle, a question that is often asked is: since preannouncements are significant events, are they consequential enough? Broadly speaking, PPA performance effects are expected, because technological disruptions engendered by innovation displace low-tech products and create economic value that is reflected in the disruptor's stock price. Hence, extant studies argue in favor of a positive relationship between PPA and a common metric of economic performance, e.g., a firm's security price.

Despite the performance insight, we noted that most empirical investigations have been limited in context by focusing primarily on high-tech announcements. Since PPA are observed across different product categories, we drew upon product life cycle and switching cost theories to hypothesize that stock market returns as a consequence of PPA are expected to generalize more broadly across all products. The results of our empirical tests conducted on a sample of PPA events confirm the generalizability effect. Next, we focus on the managerial and research implications of this study.

From a managerial standpoint, the fact that PPA create wealth effects across the board provides an actionable basis for managing such announcements judiciously. For example, the conventional wisdom in low-tech product categories is that saturated markets, declining market shares and obsolescence concerns do not provide a firm basis for managers to exploit the benefits of minor product modifications. In contrast to this general expectation of trivial returns, the results of this study show that the stock market does indeed

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value PPA in the same way across all categories. This valuation is justified in part, because consistent with the predictions of modern product life cycle theory, PPA serve as signals for a product's evolutionary pathway. As noted earlier, anecdotally we know that several low-tech products like Chobani yogurt, Harry's razor, and Tide detergent that have benefited from announcing minor modifications. Hence, managers should pay more attention to these announcements and consider them to be part of their integrated marketing communications strategy. For example, instead of allocating their entire advertising budget to informing customers about product changes, some resources can be diverted toward creating compelling communication narratives for the preannouncement itself. Such an approach, initiated before a product is actually introduced in the market will likely create buzz and wealth gain. Consequently, managers will be in a better position to use their advertising resources more efficiently.

From a research angle, the main implication of these findings is that performance effects of PPA generalize more broadly. Hence, it is imperative for scholars to conduct additional empirical studies in other contexts and update their beliefs about the consequences of PPA. Notice that currently the literature is somewhat biased toward recognizing wealth effects for high-tech products. Thus, arguments used by researchers center on theories about product innovation and marketplace disruption. However, to gain a more well-rounded and holistic view of PPA, researchers should incorporate prescriptions form product life cycle, product evolutionary cycle, and switching cost theories that argue for wealth effects more broadly.

4.2. Scope for further research

Future research may gain from consideration of additional variables that might influence wealth effects. For example, information asymmetry perspectives encompassing transaction cost, agency, and signaling theories argue for the role of evidence in determining wealth effects. In particular, a preannouncement may not always result in actual product introduction because of a number of reasons. For instance, firms might paint an inaccurate picture and throw a competitor's new product strategy off balance. Hence, a key question that emerges is whether the market penalizes such behaviors or not. One way in which such conditions can be tested is by considering the degree of irreversibility contained in preannouncements. In other words, firms that provide evidence in the preannouncement by incurring up-front sunk costs such as investments in land and assets will suffer a financial penalty if they fail to introduce a product. Thus, firms making preannouncements that possess evidence content are less likely to renege on their intentions given the sizeable sunk investments involved. As a consequence, the degree of evidence in a preannouncement will likely affect wealth effects. In addition, researchers can also consider the impact of additional variable such as marketing buzz on a firm's security price. For example, firms like Apple routinely benefit from publicity because of the buzz created in their preannouncements much ahead of actual product introduction.

CONCLUSION

The basic purpose of this study has been to investigate if the performance effects of PPA generalize across different industries and products or are narrowly confined to certain sectors, e.g., the high-tech industry. We drew upon product life cycle and consumer switching cost theories to predict that firms' product preannouncements will be positively valued by the stock market irrespective of the industry in which PPA are made or the type of product involved. Our results indicate that the stock market values PPA positively. Moreover, as hypothesized, the financial markets do not distinguish between preannouncements based upon industry or product characteristics.

The most dominant paradigm in product management relates to issues surrounding the actual introduction of new products. Several streams of research have considered various aspects of the new product development process like market testing, forecasting, and designing product launches. These actions pertaining to the new product process are expected to yield tangible strategic benefits to a firm. However, our study provides a rationale for researching product preannouncements as well. Much in the same way that actual introduction decisions add value to a firm, successful preannouncements are also important. These announcements create shareholder wealth, and researchers should pay more attention to the various processes underlying the preannouncement decision. For instance, our study shows that the preannouncement process is not a straightforward phenomenon. Specifically, what our study shows is that any kind of preannouncement will be valued positively by the stock market. In a sense, this raises issues mainly with respect to potential antitrust and legal issues. However, as noted below, the practical benefits of preannouncements to managers are also tremendous.

Given that PPA indeed yield positive performance effects, managers should have a better basis to divert advertising and promotion resources to design better preannouncements. For example, instead of making vanilla announcements, firms can experiment with different levels of detail such as type of evidence and other specifics such as the product details.

Several additional avenues for conducting research in this area exist. First, researchers can systematically incorporate variables pertaining to reversibility and credibility of PPA by surveying managers through structured questionnaires. Surveys can also be sent to financial analysts who critically assimilate information about product preannouncements almost on a daily basis. Second, it would be interesting to note how the stock market valuation perspective compares to perceptions of managers and financial analysts about the value of PPA.

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APPENDIX A

The Jackknife technique

For small sample sizes, parameter estimates are often biased. However, the Jackknife technique can estimate the bias of an estimator by deleting one datum each time from the original data set and recalculating the estimator based on the rest of the data. Hence, the Jackknife approach essentially combines two or more biased estimators of a parameter to yield an overall unbiased estimate. As a simple illustration, consider $\hat{p}_1$ and $\hat{p}_2$ to be biased estimators of a parameter p. In the simplest case, the generalized Jackknife $G(\hat{p})$ is defined as:

$$G(\hat{p}) = \frac{\hat{p}_1 - R\hat{p}_2}{1-R}, \qquad (1)$$

where R is a weighting factor normally set equal to $\{(N-1)/N\}$ to remove bias that is inversely proportional to sample size.

Suppose there is a sample $x = x_1, x_2, ..., x_n$ and an estimator $\hat{\theta} = s(x)$. The Jackknife focuses on those samples that leave out one observation at a time. These Jackknife samples are given by:

$$x_i = x_1, x_2, ...x_{i-1}, x_{i+1}, ..., x_n, \qquad (2)$$

where $i = 1, 2, ..., n,$ define the Jackknife samples. The i Jackknife sample represents the data set where the i observation has been removed. Let $\hat{\theta}_{(i)} = s\left(x_{(i)}\right)$ be the i Jackknife replication of $\hat{\theta}$. The Jackknife estimate of the standard error is defined by:

$$\hat{s}e_{jack} = \left[\frac{n-1}{n}\sum\left(\hat{\theta}_{(i)} - \hat{\theta}_{(\cdot)}\right)^2\right], (3)$$

where

$$\hat{\theta}_{(\cdot)} = \sum_{i=1}^{n}\frac{\hat{\theta}_{(i)}}{n}.$$