Blaze New Trails for Others to Follow: Evidence from Scanner Data[1]

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Abstract

This paper proposes product-based measures to evaluate firms adpoting exploratory and/or exploitative innovation strategies. Tracking more than 110 billion weekly transactions of two million products at the barcode level, we decompose exploratory innovation into radical shocks to the whole economy (pioneers), breakthroughs to the innovating firm itself (followers) and compare the two with their exploitative counterpart (improvers). Firms introducing "pioneer" products are associated with greater future profitability and stock returns than those introducing "improver" who in turn outperform "followers". Price elasticity of demand explains pioneering and improving innovation's operating success while limited investor attention accounts for pioneering firms' superior stock performance. We conclude that exploratory innovation outperforms (underperforms) exploitative one when the former chooses a pioneering (following) strategy.

JEL Classifications : G11, G14, L10, O31, O32

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1. Introduction

Innovation activity is the prime engine of long-run economic growth (Solow 1957) and original innovations can keep improving firm value for several years after they are generated (Hall, Jaffe and Trajtenberg 2005). However, researchers have found significant heterogeneity in the types of innovation investment and thus cast doubt upon the degree to which existing measures captured firms' innovation outcome (Reeb and Zhao 2020). Since the goal of corporate innovation is to introduce cutting-edge products that reap monopolistic profits, we develop a measure based on new products and their price elasticity of demand to better assess overall innovation success.

To gain competitive advantage, businesses either explore new products that are vertically different from rivals or exploit existing product lines to introduce improved new versions (Porter 1996). This is consistent with the notion that when designing a strategy for product innovation, firms generally choose exploration or exploitation[2] (March 1991, Gao, Hsu and Li 2018). We model this process by categorizing firms into three types of new product innovators, including those that tend to lead the market by introducing pioneer products (pure exploration); those that follow the pioneering firms by offering products that are similar to existing products but in new business lines to the firm (exploration but with exploitation), and those that offer new versions of existing products in the same business line as existing products (pure exploitation). By evaluating the outcome of each type of new product, we seek to understand *how and why* innovation strategies differentially affect firm operating and stock performance. To the best of our knowledge, this is the first paper that investigates three unique levels of corporate innovation strategies based on new product introduction.

[2] According to March (1991), an exploratory innovation strategy is vertical innovation that virtually creates a new business segment, whereas an exploitative strategy learns from existing technology to make new products within the same business line.

Evaluating how innovation strategies affect firm performance is of interest yet investing in a particular intangible asset is the result of a firm's optimization problem (Argente, Baslandze, Moreira and Hanley 2019). As such, a single proxy is insufficient to represent the whole innovation process from idea generation to product manufacturing as some firms could use trade secrets to protect their manufacturing process while others apply for patents to defend their products (Reeb and Zhao 2020). By linking patent to product, Argente *et al.* (2019) show that firms use patents in protective or productive ways conditional on size. They also find that non-patenting firms in fact offer many innovative new products. That there are various ways to measure innovation could plausibly explain the finding that assets with technical uncertainty in innovation are difficult to value and lead to underpricing or over-discounting[3]. This paper fills the void by focusing on new products that represent firms' ultimate payoff for innovation efforts to evaluate corporate innovation. Indeed, by combining our sample with patent and trademark, Figure 1 reveals that more than half of our sample firms do not apply for patents or trademarks.

In innovation literature, researchers using different patent-based proxies have found that exploratory or exploitative innovations all lead to superior performance.[4] Our paper's categorization method aims to comprehensively investigate these strategies using a unified product-based measure. In Figure 2, we link the product-based innovation search strategies to traditional measures and profitability. Specifically, we divide sample firms into leaders and laggards[5] by each strategy based on Hoberg and Phillips (2010, 2016) industry groups ("H&P industry" hereafter) and compare their Return on Equity (ROE), R&D investment, innovation efficiency, and trademark introduction rate.

[3] See Eberhart, Maxwell and Siddique (2004); Hall (1993), Chan, Lakonishok and Sougiannis (2001); Lev (2001), Hirshleifer, Hsu and Li (2013, 2018) and Hsu, Li, Li, Teoh andTseng (2020)
[4] See, for example, Hirshleifer, Hsu and Li (2018) and Fitzgerald, Balsmeier, Fleming and Manso (2019)
[5] A firm is a leader (laggards) when its product innovation rate is above (below) its H&P industry average

A cross-sectional comparison among the three product strategies reveals that: (1) Compared to laggards, leaders invest *less* in R&D, yet they are *more* efficient in materializing R&D to patents; (2) leaders in pioneer and improver products generate greater ROE than laggards; (3) leaders in pioneer and follower products introduce more trademarks than laggards, which is intuitive because they seek to introduce vertically new products (pioneers are vertical to the whole market, and followers vertical within itself). Interestingly, improver leaders apply *fewer* trademarks than laggards, which is probably because they tend to focus on innovating existing brands. A key conclusion drawn is that, first, not all innovatively efficient strategies will yield better ROE. Second, although improvers do not apply for many trademarks, they demonstrate superior profitability by optimizing existing product lines through innovation efficiency.

Motivated by these stylized facts, we hypothesize that firms focusing on pioneer innovations tend to have *higher* future profitability due to launching radically new products that are highly exploratory, thereby making them industry leaders that retain monopolistic profits. Second, while follower products exploit the concepts of pioneers, the associated firms are still exploring since the business segment is vertically new to themselves. Given the monopoly of pioneers or market leaders, follower firms have to find their own niche. Therefore, they need to spend significant amount of time and resources differentiating themselves from pioneers, which can harm their short-term profitability. As such, the contribution to profitability by follower products is *unclear*. Last but not least, improver firms are exploiting their knowledge based on existing product portfolios to innovate similar products with improvements. Presumably, if firms choose to improve an existing product, it must be a successful one. To make an improvement, firms collect customers' feedback, either through questionnaire or data analysis of product transactions. As such, firms focusing on improving products will solidify their product line's popularity, thus leading to *better* future profitability.

Our empirical results show that pioneer and improver products are associated with superior future profitability. For example, one-standard-deviation increase in the pioneer product introduction rate, which is the sales of pioneer products divided by those of total new products in a particular year, is associated with a 0.5% increase in the next year's ROA that is slightly higher than that of the Innovation Originality (0.46%[6]), Patent based Innovation Efficiency (0.45%), but lower than Trademark (0.939%), which is a tercile variable instead of a continuous one. Meanwhile, improving product introduction rate is associated with a 1.2% increase in future ROE, while follower product introduction does not have any significant contribution to future profitability.

We are cautious that innovation strategy is a choice by firms, thus subject to endogeneity concerns. Firms that have more liquidity should be able to take risk and afford the high research and development expenses that consequently generate new breakthrough innovations. To address these concerns, we first explore the exogenous variation of innovation activities induced by the staggered changes in state-level corporate tax rates that will reduce innovation activities in affected states (Mukherjee Singh and Žaldokas 2017). A set of difference-in-difference (DiD) experiments supports our findings. Second, motivated by the marketing literature on new product diffusion through word-of-mouth advertising (Horsky and Simon 1983), we identify an instrument, the local firm's average advertising expense per new product, and use it in a two-stage-least-squares (2SLS) analysis. The empirical relation still holds when using the instrumented variable.

Next, we propose that elasticity of demand can explain firms' innovation success. We find that pioneers and firms manufacturing such products are consistently associated with lowest demand elasticity among their respective counterparts. For example, pioneer products on average exhibit 21%

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[6] Although we standardize the independent variable to make it directly comparable with the Innovation Originality (Hirshleifer *et al.*2018), readers should be cautious in interpreting the magnitude of coefficients because our sample is shorter and contains fewer firms than that used for Originality Measure.

absolute value of price elasticity of demand, as compared to 24% and 27% for improvers and followers. This suggests that consumers tend to keep buying pioneer products despite their high prices, which explains why firms focusing on pioneer products gain superior operating performance.

In the second part of this paper, we investigate if the stock market can incorporate different sets of information contained in product innovation strategies, especially for pioneer and improver products that can lead to better future profitability. Using portfolio analysis, we find that a strategy of purchasing the top 70th percentile of pioneer introduction rate and shorting the bottom 30th percentile consistently generates 0.61% monthly alpha from a Fama French 3 factor plus momentum, which is higher than the alpha generated from the same strategy based on the Innovation Originality (Hirshleifer *et al.* 2018) of 0.35%.[7] On the other hand, a trading strategy involving improvers generates significant alphas only in traditional asset price models. However, they are correctly priced after controlling for an innovative efficiency factor (Hirshleifer, Hsu and Li 2013). This could be because traditional models still fail to fully understand improver products by some high-tech firms, which are exposed to specific innovation risk proxied by innovation efficiency.

Further, we investigate whether the underpricing is due to unobserved risk factors or a behavioral-based investor inattention theory. Our first proxy for limited attention is advertising expense, which is found to attract investor attention[8]. It is particularly relevant to this study because our focus is on products while advertising increases product exposure. If firms invested heavily on advertising their new products, especially ex ante, analysts would find them easier to value than those who tend to "surprise" the market by offering new products without notice. The second proxy is the number of patents. Since stock market is very responsive to patent approval (Kogan *et al.* 2017), it

[7] Although the alpha is greater than the Innovation Originality (Hirshleifer *et al.*2018), it should be interpreted with caution because they have a longer sample period (1982-2007) while mine is shorter (2008 to 2018).
[8] See Grullon, Kanatas and Weston (2004); Lou (2014)

should have little uncertainty to value the pioneer products associated with these breakthrough patents. On the other hand, if a firm does not apply for any patents related to a newly launched pioneer product, the market would not have any signal about this pioneer product.

We perform portfolio and predictability analyses in subsamples of high and low advertising firms as well as patenting and non-patenting firms. We find that the underpricing effect is stronger in firms that invest less in advertising and those that do not apply for any patents. This shows that without information released through advertising or patents, the market is even more uncertain to value pioneer products. We also tested if the superior stock performance of pioneer innovation is driven by unknown systematic risks – or that pioneer innovation is exposed to some state variables that represent risks associated with technological changes. We create risk factors[9] to proxy for such risk and find that the risk premia are insignificant, indicating that the findings are unlikely to be driven by risk-based explanations.

Our paper contributes to the literature in four ways. First, we document a novel channel of how and why corporate innovations *differentially* create value. Finance and economic researchers have shown a strong relation between innovative activities and firm performance as well as economic growth[10]. Our paper decomposes the aggregate innovation activity and finds that pioneer or improver innovations are driving firm profitability due to low price elasticity of demand. On the other hand, followers are difficult to compete with pioneer peers to gain meaningful superior performance.

Second, we advance the literature of valuation of innovation that identifies it as a premium or mispricing with different measures. Hsu (2009) finds that innovation as a priced risk that carries a premium in the cross-section. Conversely, the underpricing of innovation efficiency, originality and

[9] The factors are constructed by forming long-short hedging portfolio formed by longing top 30th and shorting bottom 70th of firms conducting pioneer/follower/improver product innovation
[10] See Aghion and Howitt (1990), Hsu, Tian and Xu (2014)

trademark is due to investor inattention. With product-level data, we confirm that the innovation premium is time-varying, that it is priced at the beginning stage and is mispriced (or correctly priced with more information transparency) at the product commercialization stage.

Third, we contribute to the innovation search literature by employing a nuanced categorization method of corporate innovation to evaluate explorative and/or exploitative strategies while demonstrating how product innovations differentially affect industry competition[11]. Extant research mainly categorizes exploratory v. exploitative innovation based on patent or trademark classes and scholars have found conflicting results using different measures. By leveraging product-market modules, our method evaluates explorative and exploitative innovations at a finer level based on market pioneer (exploratory), follower (exploitative and exploratory) and improver (purely exploitative). We show that firms should adopt either an exploratory or purely exploitative strategy as followers on average cannot compete with pioneers.

Finally, we introduce a dataset that captures firms' innovation activities at the product level. Researchers have called for more refined proxies because firms conduct different innovative efforts in different dimensions (Kerr and Nanda 2015, He and Tian 2018). On the one hand, new proxies are being developed based on traditional patent and citation measures[12]. On the other hand, a growing number of papers look at alternative sources, such as brand or trademark (Hsu *et al.* 2020). This paper contributes to this debate by showing that the final products, supported by different innovation proxies, have different impacts on firm performance.

2. Data Description, Product Innovation Measures and Summary Statistics

[11] See March (1991), Porter (2008, 1996)
[12]For example, Trajtenberg (1990), Hall, Jaffe and Trajtenberg (2001, 2005), Hirshleifer *et al* .(2013, 2018), Kogan, Papanikolaou, Seru and Stoffman (2017)

2.1 Nielsen Retail Scanner Dataset

We start with the Nielsen Retail Scanner Dataset (RSD) provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. RSD is generated by the point-of-sale systems from more than 90 participating retail chains with 40,000 unique stores across all U.S. markets (See Figure 3). Each store reports product selling prices and quantities per week by scanning the barcode of each product on Saturday of each week. The barcode is a 12-digit Universal Product Code (UPC), which represents the finest level of product identification because it is unique to every product and any change in product attributes will result in a new barcode.[13]

Currently, RSD reports around 2.6 million UPCs' weekly sales from 2006 to 2019 that consists of more than 110 billion transactions at the UPC-weekend-store level with a total of 2 trillion in product sales. The participating stores are in grocery, drug, mass merchandise and others that take up to more than 50% of total sales volume of U.S. grocery and drug stores and more than 30% of U.S. mass merchandiser sales volume.[14]

2.2 GS1 U.S. Data Hub

To connect firms with products, we link RSD to GS1 U.S. Data Hub (GS1) as GS1 is the only official source of UPCs and provides firm name of all UPC owners. If a firm wants to get UPCs for its products, it will contact GS1 to purchase a company prefix, which will be combined with a product number to form a 12-digit UPC code. The company prefix varies from five- to ten-digits to identify unique firms and their products. Intuitively, the digits of company prefix determine the maximum number of products a firm can launch since the total number of UPC digits is 12. From Figure 4, we see that if a firm purchases a nine-digit company prefix (right side), this firm can launch at most 100

[13] One possible concern is that a new UPC might not always represent a new product. However, Nielsen notes that if they detect a new UPC in this scenario, they would assign this to its prior UPC.
[14] Source : https://www.chicagobooth.edu/research/kilts/datasets/nielsen

products with 00 to 99 as the two digits product number. On the contrary, if a firm purchases a six-digit prefix, this firm can launch up to 100,000 products because six-digits as product number allows 10^5 possible combinations. Naturally, the nine-digit company prefix is cheaper to obtain than a six-digit prefix.

Because GS1 links firm name to firm prefix, we connect firm prefix with UPCs from Nielsen to obtain the ultimate owner's name of the UPCs. We perform all the matching at the parent level as some firms can own many firm prefixes through merger and acquisition. GS1 also further provides this firm's address, city, state and zip code.

2.3 Merge RSD/GS1 with CRSP/COMPUSTAT

Next, we merge the combined RSD/GS1 to CRSP/COMPUSTAT to obtain firm financial and stock information. Because GS1 does not provide unique firm identifier such as Gvkey or Permno, we use fuzzy matching on firm names between GS1 and CRSP, with additional checks on address, state and zip code. After matching, we are able to identify 442 unique firms at the intersection of RSD/GS1/CRSP/COMPUSTAT from 2006 and 2019. In addition to the firm year level tests, we match the CRSP individual firm return data at monthly level and Compustat data at quarterly level in monthly return predictability tests.

2.4 Identification and Categorization of New Products

Following the economics literature (Argente *et al.* 2018, Broda and Weinstein 2010), a new product is defined as the first time a UPC has recorded sales in the RSD data in that particular week. However, the way to identify new products suffers from a truncation bias. Nielsen started collecting data for RSD in 2006 and the latest available sample year is 2019, with updating occurring every two years. The issue is that for products identified as new in 2006, they could be entering into the data in

2006 for the first time, or they could already be in the market, but the data starts from 2006. To address this issue, we delete all data from 2006, and our final data set is from 2007 and 2018.

RSD organizes them into more than 1100 time-varying modules that belong to 125 groups that are further segmented into 10 departments. To model the exploratory and/or exploitative strategies, we identify all new products as (1) pioneer when its introduction was so new that RSD had to create a new module; (2) follower when the firm introduced it for the first time although there has already been pioneer products in related modules; (3) improver when it is an improvement to the focal firm's existing product module.

Appendix 2 shows a set of pioneer, follower and improver product examples. For pioneers, Nielsen added three new modules about electronic cigarettes to account for their mass-commercialization around 2013. We categorize all the products associated with these modules as pioneer products. For followers, Tyson Foods, a company primarily specializing in prepared meats, acquired the brand "Three Happy Cows" in 2014, announcing its entry into the yogurt market. We regard all these products as follower products. For improver products, Apple keeps introducing new version of iPhone and all of these versions are improver products.

We aim to measure the abnormal market reaction around each new product's introduction. Since we only know the product's first appearance in a specific week, we run event studies for all new products based on a [0, +4] window from Monday to Friday and calculate the Cumulative Abnormal Return (CAR) against the Fama-French three factor model. Then we multiply the CAR by last Friday's market value of equity to obtain the dollar-based value creation, in the sprit of Kogan et al (2017). We aggregate such dollar value at monthly level and annual level to conduct empirical tests.

2.5 Samples Construction and Control Variables

To ensure that our results are not driven by other innovation inputs, we control for two innovation-related variables, including innovation efficiency (Hirshleifer *et al.*2013) and trademarks (Hsu *et al.*2020), in all the models except for portfolio tests. For trademarks, RSD provides brand information for each product. We calculate new brand introduction rate to proxy for the trademark application.[15] In portfolio analysis, we control for trademark factor in Hsu et al (2022) in obtaining alphas.[16]

First, we examine different product introductions' CAR-based value creation measures on future profitability and growth opportunities proxied by ROA and Tobin's Q. We control for common variables used in the literature that affect future profitability and growth opportunities, including log-transformed market equity and firm age, as well as advertising expense, R&D expense, capital expenditure, and M/B ratio. The final dataset for regression has 338 firm and 2,016 firm and year observations.

In the second part of the paper, we conduct portfolio and return predictability analyses. Because our sample size is limited, we sort firms into tercile portfolios based on three product introduction rates to avoid under-diversification. Next, we conduct monthly Fama-MacBeth predictive regression and control for common predictors related to innovation, including size, book to market ratio, momentum, patent scaled by assets, short-term return reversal, asset growth, capital expenditure scaled by assets, R&D to market value of equity, ROA, and a multi-segment firm dummy. The merged sample of return prediction has 347 firms with 20,657 firm months observations.

2.6 Summary Statistics

[15] Here, we assume that when a firm launches a brand, it has already applied for a trademark. This is reasonable as firms will benefit from legal protection from trademark application for their products (Bereskin *et al.*2020, Millot 2009)

[16] We thank Hsu for sharing the data

The general product introduction statistics are in Panel A of Table 1. On average, the abnormal weekly return earned by firms introducing a pioneer product was 12.1%. On the other hand, firms lost 19.4% or 15.1% after they introduced a follower or improver product. For product information, the average product price is $15 while selling quantity is 11 at a given store in a certain week. Sample firms' products on average obtain $5,632 sales per week.

Next, we present means of firm characteristics in (1) the main sample, and (2) splitting the sample by pioneer, follower, and improver rates above or below the H&P industry average. We also calculate the differences of these three groups. We use bold font to indicate differences that are significant at the 5% level.

On average, firms have 3% annual ROA. They have $17 billion in total assets and $18 billion in market value of equity, indicating that they are large firms. The average firm age is 46 years and they apply for 63 patents on average in a particular year. Regarding the subsample analysis, generally firms with product innovations above the industry average have better profitability and lower market value of equity. Interestingly, these firms also have lower R&D expense, but better more patents, patent value and citations (except for improvers). This shows that although industry leaders are smaller than laggards, they are very efficient in innovating new products.

3. How and Why do Product Innovations Differentially Affect Future Performance?

In this section, we address the first part of our research question by investigating the impact of new product introductions on firm operating performance In Section 3.1, we regress next year's ROA and Tobin's Q on standardized CAR-based value creation measures. In Section 3.2, we provide an economic channel between product innovation and future profitability through elasticity of demand. In all tables, we winsorize variables at the 1% and 99% levels and standardize all independent variables to have zero mean and one standard deviation, except for dummies, to avoid outliers and to simplify interpretation.

3.1 How do product Innovations differentially affect Future Performance?

We first regress the next year's ROA and Tobin's Q on current product value creation measures for firm *i* at time *t*. The regress specification is as follows:[17]

$$ROA\ or\ Tobin's\ Q_{i,t+1} = \alpha + \beta_1 Pioneer_{i,t} + \beta_2 Follower_{i,t} + \beta_3 Improver_{i,t} + \lambda' \boldsymbol{X_{i,t}} + \varphi + \gamma + \varepsilon_{i,t}$$

where β_1 to β_3 measure the marginal effects of pioneer/follower/improver product value creation measures on future performance. λ' is a vector of coefficients for control set $\boldsymbol{X_{i,t}}$. We include firm and year fixed effects with φ and γ representing the coefficients of such fixed effects. Furthermore, we repeat the three tests by comparing industry leaders in executing each strategy with industry laggards according to H&P industry classifications based on product similarities.

In accounting for how exploratory and/or exploitative innovations affect profitability and industry competition, we examine firms' manufacturing pioneer, follower and improving products individually and across H&P industry. Because ROA and Tobin's Q represent a firm's performance or growth opportunity as a whole while a firm can have three kinds of product innovation activities at the same time, we include three product innovation measures together to reflect firm-level total innovation strategies that match firm-level profitability measures. We control for common variables described in section 2.5 and also use firm and year fixed effects. We use Newey-West (1986)

[17] We also scale pioneer/follower/improver by total product sales, new product sales, as well as run the specification without industry dummies, the results remain the same. We report all relevant results in online appendix

autocorrelation adjusted heteroscedasticity robust t statistics to derive the significance of the coefficients.

Table 2 shows how different innovation strategies affect firms' future profitability. Models (1)-(3) and (6)-(8) regress future ROA and Tobin's Q on contemporaneous product innovation measures individually, while models (4) and (9) on all product innovation strategies collectively. The coefficient of the pioneer product introduction rate is significantly positive both individually and collectively. Economically, one-standard-deviation increase in pioneer introduction rate is associated with 0.1% increase in ROA next year. Given ROA has a mean of 3%, this is a 3% increase around the mean..

In Models (5) and (10) of Table 2, we regress future profitability on a dummy that equals 1 if the focal firm's product introduction rates are above industry average defined by H&P. The slope thus compares industry leaders with laggards in different product introduction strategies. On average, firms leading the industry in introducing pioneer products are associated with 0.6% greater future ROA than laggards. In sum, pioneers are consistently associated with better future profitability while followers and improvers generally don't experience any improvement.

3.3 Why do Product Innovations Differentially Affect Future Profitability?

In this section, we provide an economic channel through which product innovations affect profitability. With price and quantity sold data for each product, we derive the price elasticities of demand for pioneer, follower and improver as well as other existing products. The price elasticity of demand is the percent change of demand in response to one percent change in price. Intuitively, a product with low price elasticity of demand indicates its demand is inelastic to change in price. Furthermore, firms manufacturing such low elasticity of demand products should keep a high demand or sales with increase in their products' prices, thus maintaining a high profitability.

The economics literature documents a canonical double-log regression whose beta is the price elasticity of demand (Nicholson 1992). For each product *i* at week *t*, we run this pooled OLS regression at product-week level:

$$Ln(Quantity\ Demanded)_{i,t} + = \alpha + \beta_1\ Ln\ (Price)_{i,t} + \varepsilon_{i,t}$$

where β_1 is the price elasticity of demand.

In addition, we design another specification that includes control variables to account for unobservable heterogeneities in firm characteristics that may covary with quantities sold and controls for time trend of new product introduction. These variables include product price standard deviation, quantity demanded standard deviation and total sales as well as firm age, beginning value of total asset, total sales as reported by Compustat and Herfindahl index based on the three-digit SIC code. The specification is as follows:

$$Ln(Quantity\ Demanded)_{i,t} + = \alpha + \beta_2\ Ln\ (Price)_{i,t} + \beta_3{}'Controls_{i,t} + \lambda'\boldsymbol{X}_{i,t} + \ \varepsilon_{i,t}$$

where β_2 is the price elasticity of demand, β_3 is a vector of coefficients of control variables and λ is a vector of coefficients of fixed effects X, including firm and year. We separately run this regression for pioneer, follower and improver products.

Next, we first obtain the β_1 from the canonical double log regression and assign it to corresponding product, thus aggregating it at the product-firm-year level. We regress all the products' absolute value of price elasticity of demand on pioneer, follower and improver dummies with product and firm level controls. To properly track each firm's product innovation strategies, we use multiplicative fixed effects of firm by year and industry by year in this specification:

$$Individual\ product's\ absoulute\ value\ of\ price\ elasticity\ of\ demand_{i,t} = \alpha + \varphi_{1-3}$$

$$Pioneer/Follower/Improver\ Dummies_{i,t} + \varphi_4' Controls_{i,t-1} + \lambda' \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t-1}$$

where φ_1 to φ_3 are coefficients of the three dummy variables. Because the universe of products includes pioneer, follower, improver and existing products, each dummy's coefficient is a comparison of absolute value of price elasticity of demand between pioneer/follower/improver and existing products.

Last but not least, we aggregate all the individual product's absolute value of price elasticity of demand into firm-year level by value weighting them by their respective annual sales. We then univariately compare firms with and without pioneer, follower and improver products as well as firms that are above the HP industry mean in terms of pioneer/follower/improver introduction.

Table 4 presents the price elasticity of demand results. Panel Aa presents the canonical price elasticity of demand regression at product-weekend level. The pioneer, follower and improver products respectively have -17.9%, -23.1% and -20.2% raw price elasticity of demand. This means that for a pioneer product, its demand on average declines by 17.9% with one percent increase in its price as compared to 23.1% decline for follower and 20.2% for improver, making pioneer the most inelastic new product. Panel Ab shows the regression with controls and fixed effects. The raw price elasticities show the same pattern for three kinds of new products.

Panel B shows the product-firm-year level regression of absolute value of each product on pioneer, follower and improver dummies with controls and firm by(and) year or industry by(and) year fixed effects. Because the pioneer, follower and improver are dummies compared to existing products, the coefficients are the difference. Economically, model (1) for example shows that, on average, a pioneer product's absolute value of price elasticity of demand is 16.9% lower than that of an existing product, controlling for follower and improver product as well as other variables. For followers and improvers, they are 6.3% and 5.1% lower than existing products, thus making pioneers the lowest elasticity of demand among all products. This conclusion is robust to every firm's pioneer products, every year's pioneer products' introduction, and every industry's pioneer products as well as all the pioneers introduced by each firm in each year or each industry in every year.

Panel C presents the univariate compassion of firm level absolute value of elasticity of demand. We report the mean values of firms with or without each product with Satterthwaite T statistics for the difference in mean. We find that only pioneer products show significant difference. For example, on average, pioneer firms' aggregate absolute value of price elasticity of demand is 24 lower than non-pioneer firms.

Taken together, these panels comprehensively analyze how price elasticity of demand explains product innovation success. We first document a fact that pioneer products are most price inelastic. Next, aggregating these absolute price elasticities of demand at product level, we find that pioneers still have lowest price elasticity of demand after controlling for various controls and most importantly this empirical finding is robust to firm by year or industry by year fixed effects. Furthermore, after aggregating all products into a firm level absolute value of price elasticity of demand, we find that pioneer firms are more price inelastic than non-pioneer firm. These findings show that pioneer products can help firms maintain a high quantity sold (demanded) with price increase, which translate into superior operating profitability.

4. How and Why Do Product Innovations Affect Stock Performance?

In this section, we test the second part of our research question on how product innovations differentially affect stock performance. Since we are already using CAR-based measures, we aim to test if the market could correctly value pioneer/follow/improver innovation strategies at the time of their introduction.

4.1 Portfolio Analysis

We run portfolio analysis to test product innovation and firm stock performance. Because of the limited sample size, we use tercile portfolios to avoid portfolio under-diversification. Because we are using a CAR-based measure, we assume the market was already informed at the time the product was launched and sold to the grocery market. Thus, we sort firms into three portfolios based 30^{th} and 70^{th} percentiles of pioneer CARs in each month, and keep balancing this portfolio monthly. We repeat the same process for follower and improver and hold these portfolios for different horizons, from next month to next year. For each group of tercile portfolios, we form a long-short portfolio based on the differences of top 70 and bottom 30 portfolios. Next, we run time-series regressions of each portfolio's excess returns on (1) Fama-French 3 Factors Plus Momentum, Profitability (RMW) and Investment (CMA). In addition, since the new product measures are related to firm innovation efforts, we control for trademark factor, in addition to the Fama French 5 factors plus a momentum. We report all the portfolios' excess returns and alphas.

In Table 5, we show the excess returns for three groups of long short portfolios for holding one month, one quarter, half year and one year. We find that only the pioneer portfolios that hold for one month has significant excess returns at 4.9%. The alphas of this one month long short portfolio range from 5.3 to 5.6%. When holding for longer than one month, no portfolios have significant excess returns and alphas. On the other hand, follower and improver portfolios don't show any significant excess returns and alphas.

In sum, we find that firms with higher CARs around pioneer products' introduction tend to be underpriced only for a month. Forming a monthly balancing portfolio will yield alphas from 5.3 to 5.6%. This indicates that the stock markets underreacted to such product's launch in a short time window. Since the CAR is already a market-based measure, this underreaction doesn't persist long before the market corrects itself. Follower products do not have any significant alphas, meaning that financial analysts can correctly value these products due to there being a precedent. Improver products are still associated with mispricing possibly due to high-tech firms in our sample as these mispricing disappears when adding the innovation efficiency factor that specifically controls for technological innovation efficiency.

4.2 Return Predictability

The portfolio analyses show that pioneer products are undervalued for a short horizon, while follower and improver products tend to be correctly priced. Next, we investigate if the pioneer product CAR-based measure can predict returns in the short horizon.

To this end, we aggregate product information at monthly level to predict next week and a week after next week's returns. Following the innovation literature, we include an extensive set of variables that are found to predict returns. We winsorize all variables at 1% and 99% and standardize all independent variables to have zero mean and one standard deviation to avoid the impact of outliers and make interpretation easy. We also include the industry dummies according to Fama and French (1997) 48 industries and use Newey-West t statistics. We report the time-series average slopes in percentage. The Fama-MacBeth regression model is as follows:

$$Weekly\ Returns_{i,t+1\ or\ t+2} = \alpha + \beta_1 Pioneer\ CARs_i + \beta_2 Follower\ CARs_i + \beta_3 Improver\ CARs_i + \lambda' \boldsymbol{X_{i,t}} + \sum_{f=1}^{48} \varphi_f * Industry_f + \varepsilon_{i,t}$$

Table 6 reports the return prediction results. Only past pioneer product introduction can significantly predict next week's returns after controlling for other known predictors. Specifically, in model (1), one-standard-deviation increase in past pioneer introduction can increase next month return by 0.502%, significant at 5% level. Furthermore, models (5)-(8) show that the return predictive power tends to dissipate in the second week.

Overall, this section finds that using a CAR based measure to proxy for innovation strategies tends to only exhibit underpricing in a very short time window. The market is able to correct its mispricing only on pioneer products in a week.

5. Extension analysis: How does the new products adjust to inflation?

With the product price data, we test how the new products adjusted their prices with abnormal shock to the expected inflation. The inflation shock is calculated as the monthly realized inflation minus the expected inflation from XXX model. For price data, we calculate the weekly and monthly price growth.

We next regress the price growth on standardized inflation shock. We use full sample, pioneer, follower, improver and existing product samples as dependent variables in three set of models, including the models that only include inflation shock, that include multiple fixed effects, and that include controls and fixed effects.

Table 7 reports the results. Panel A, model (1) shows that on a weekly basis, all products would on average increase 0.015% in price on a weekly basis per one unit increase in last month's inflation shock. However, models (2) and (3) show that pioneer and follower products are not sensitive to inflation shock. In other words, their prices are not necessarily increasing with a positive shock to the inflation. Models (4) and (5) confirm that the positive price increase effect is due to the improver and existing products that experienced increase in price following an abnormal increase in inflation. This results are consistent in different model settings and monthly price growth samples. We conclude that exploratory innovation, especially pioneering innovation, is less likely to be influenced by inflation. Perhaps it is because the pioneer products have already been priced high, thus there is little room for its price to increase. We leave this for future research.

6. Conclusion

In this paper, we study how and why firms' explorative and/or exploitative innovation strategies differentially affect corporate operating and stock performance. We find that when firms focus on exploration over exploitation in introducing pioneer products, they can earn higher profitability and enjoy better growth opportunities. However, a following or improving strategy is unable to create value. We then provide an economic channel of why pioneer outperform based on price elasticity of demand. For stock performance, investors are able to correctly price followers and improver products, while taking approximately a week to fully value the pioneering product.

Our paper has highlighted the benefits of original and pioneering product introduction. If firms are lacking such ideas, they should focus on improving their existing business lines, which can bring in steady profitability.

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Figure 1: Coverage of Patent and/or Trademarks by the Sample Firms

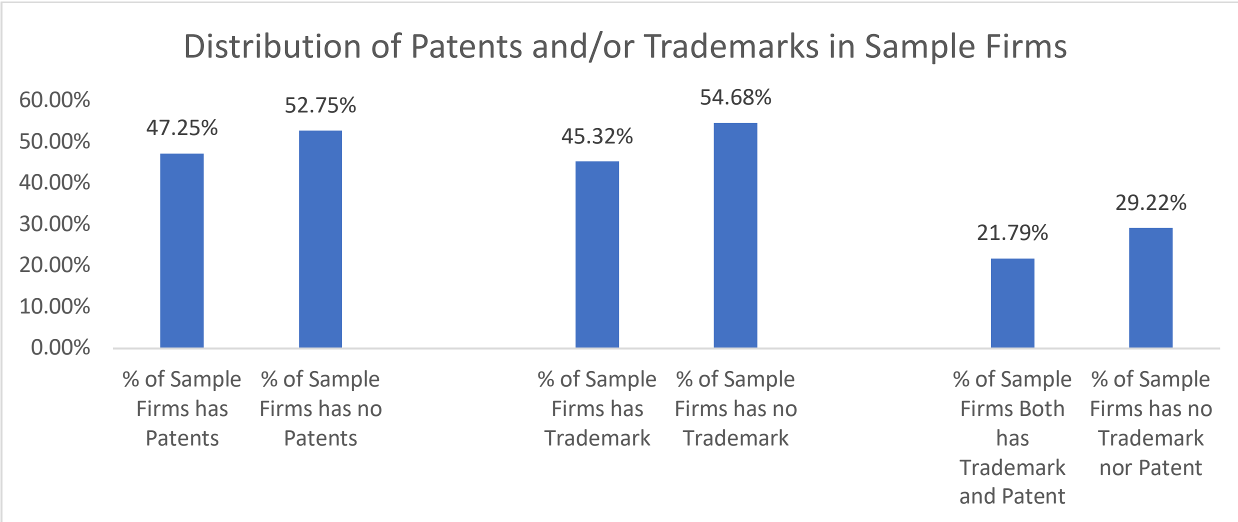


Figure 2: Univariate Comparison of Three Product Innovation Strategies Between Industry Leaders and Laggards

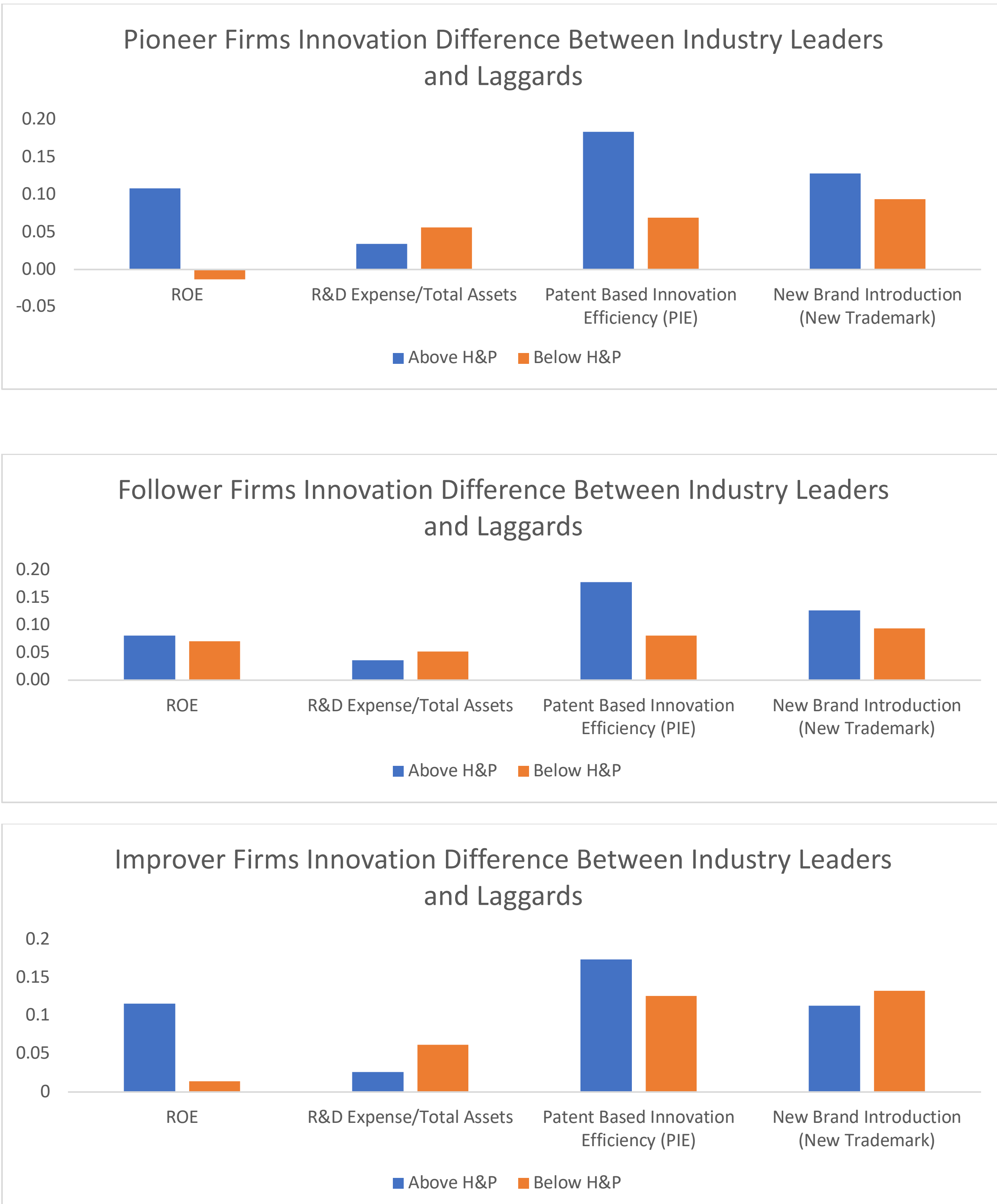


Figure 3: RSD U.S. Market Penetration. Source: https://slideplayer.com/slide/5736272/

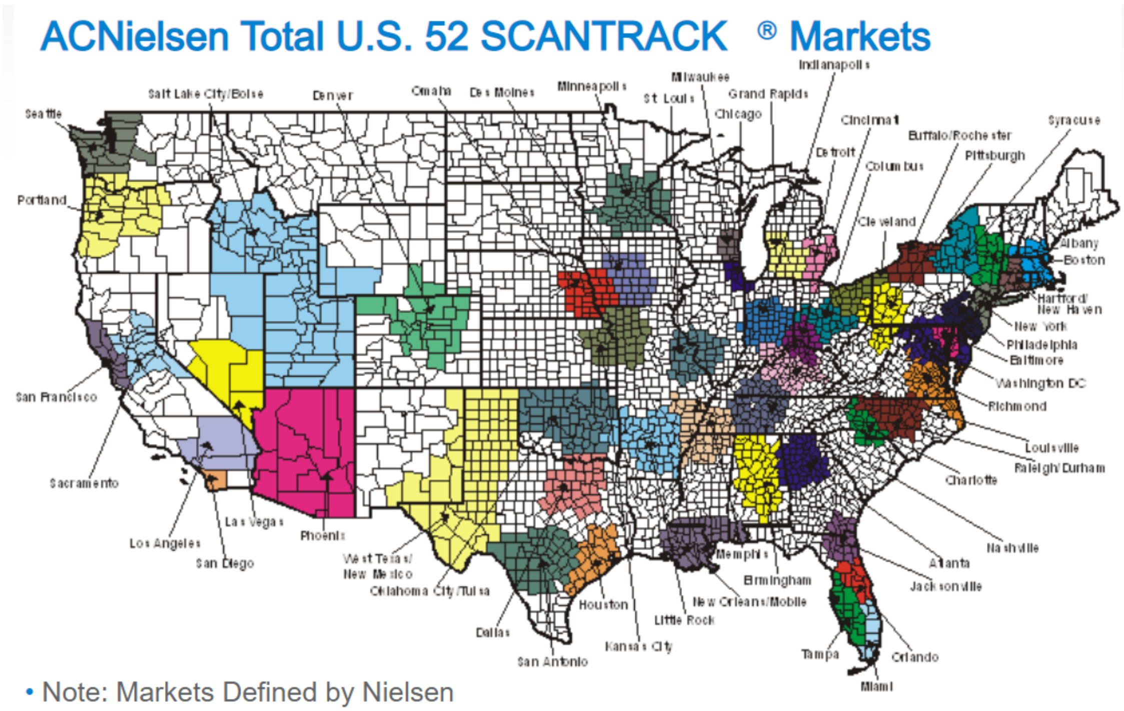


Figure 4: Examples of GS1 Company Prefix and UPC code

This figure shows two common UPC codes' composition. One is applied by the firm with six digit firm prefix and other with nine digit firm prefix. Source: https://www.gs1-us.info/gs1-company-prefix/

Table 1: Summary Statistics

This table shows two sets of summary statistics. **Panel A** shows the general product by firm-year characteristics. **Panel B** shows the firm-year means in general sample, and samples split by pioneer, follower and improvers. Within each new product group, we divide the sample into industry leaders (above H&P) and laggards (below H&P) and calculate the differences. We bold the difference if they are significant at or above 5% level. For brevity, we only report the main firm-year sample that convers

Panel A: Product Characteristics

	Mean	Std Dev	p25	Median	P75
Pioneer Product CAR	0.121	0.029	-0.015	0.263	0.940
Follower Product CAR	-0.194	0.030	-0.017	0.006	1.108
Improver Product CAR Rate	-0.151	0.02	-0.01	0.004	0.97
Total Products	290.56	895.95	3	21	138
Firm Average Weekly Product Price (in dollars)	14.76	35.35	3.6	6.96	14.31
Firm Average Weekly Product Quantities Sold	11.36	128.58	1.42	2.23	4.98
Firm Average Weekly Product Sales (In dollars)	5652.34	11248.5	97.22	897.87	5525.89

Panel B: Firm Characteristics Based on 2,016 Firm-Year Observations or 338 Unique Firms	Sample Mean	Sample Median	Pioneer Means			Follower Means			Improver Means		
			Above H&P	Below H&P	Difference	Above H&P	Below H&P	Difference	Above H&P	Below H&P	Difference
ROA	0.03	0.05	0.03	0.01	**0.02**	0.03	0.02	0.01	0.04	0.01	**0.03**
Tobin's Q	1.58	1.12	1.97	0.70	**1.27**	0.41	0.40	0.01	1.58	1.22	**0.36**
Market Value of Equity (ME)	18289.88	1765.03	16688.30	23465.25	**-6776.95**	16739.80	23710.97	**-6971.17**	18448.69	18009.58	439.11
Firm Age	45.74	46.90	45.66	45.98	-0.32	45.90	45.20	0.70	47.34	42.95	**4.39**
Advertising Expense/Total Assets	0.03	0.01	0.03	0.03	0.00	0.03	0.03	**0.00**	0.03	0.03	0.00
R&D Expense/Total Assets	0.03	0.01	0.03	0.05	**-0.02**	0.03	0.04	**-0.01**	0.03	0.05	**-0.02**
Capital Expenditure / Total Assets	0.04	0.03	0.04	0.04	0.00	0.04	0.04	**0.00**	0.04	0.04	0.00
Market to Book Ratio	3.49	2.59	3.42	3.69	-0.27	3.50	3.45	0.05	3.54	3.39	0.15
Number of Patents	63.38	0.00	68.53	46.94	**21.59**	64.68	58.87	5.81	66.62	57.74	8.88
Ln(TSM)	0.01	0.00	0.01	0.00	**0.01**	0.01	0.00	**0.01**	0.01	0.01	0.00
Ln(TCW)	0.03	0.00	0.13	0.09	**0.04**	0.13	0.09	**0.04**	0.11	0.13	**-0.02**

Table 2: Profitability Tests

This table shows profitability tests for product innovation measures. We use Fama-MacBeth (1973) predictive regression of future ROA and contemporaneous Tobin Q on the Cumulative Abnormal Returns in models (1) - (4) and (6) – (9). We then regress ROA and Tobin Q on a dummy that equals 1 if the firm's pioneer or follower or improver CAR is above H&P industry mean in models (2), (4) and (6). In all models, we report average slopes and Newey-West (1987) autocorrelation-adjusted heteroscedastic robust standard errors in parentheses from annual Fama and MacBeth (1973) cross-sectional regressions. We include industry fixed effect in models (1), (3) and (5). *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variables			ROA T+1					Tobin Q		
Standardized Pioneer CARs	0.001**			0.001**		0.010**			0.010**	
	(0.001)			(0.001)		(0.005)			(0.004)	
Standardized Follower CARs		0.000		0.001			-0.008		-0.007	
		(0.000)		(0.001)			(0.012)		(0.012)	
Standardized Improver Cars			0.001	0.001				-0.001	-0.001	
			(0.001)	(0.001)				(0.009)	(0.010)	
Pioneer CAR above H&P Average					0.006***					0.064***
					(0.001)					(0.009)
Follower CAR above H&P Average					0.002					0.015
					(0.001)					(0.015)
Improver CAR above H&P Average					-0.000					0.010
					(0.002)					(0.009)
Number of New Products	0.009	0.009	0.010	0.010	0.010	0.844***	0.843***	0.843***	0.843***	0.894***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.100)	(0.100)	(0.101)	(0.101)	(0.090)
Ln (Market Value of Equity (ME))	0.000	0.000	0.000	0.000	-0.000	0.019**	0.019**	0.019**	0.019**	0.020**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Ln(Firm Age)	0.067	0.067	0.067	0.067	0.043	-1.25***	-1.25***	-1.25***	-1.25***	-0.637**
	(0.053)	(0.053)	(0.053)	(0.053)	(0.049)	(0.381)	(0.380)	(0.380)	(0.381)	(0.250)
ROA	0.24***	0.24***	0.24***	0.24***	0.164***	0.995***	0.994***	0.994***	0.994***	0.899***
	(0.061)	(0.061)	(0.061)	(0.061)	(0.058)	(0.274)	(0.274)	(0.274)	(0.274)	(0.267)
Advertising Expenditure	-0.061	-0.061	-0.061	-0.061	-0.152	7.168**	7.168**	7.172**	7.166**	6.651**
	(0.278)	(0.278)	(0.278)	(0.278)	(0.129)	(2.991)	(2.992)	(2.991)	(2.993)	(2.958)
R&D Expense	0.264	0.264	0.265	0.266	0.220	6.234**	6.227**	6.229**	6.230**	6.315**
	(0.311)	(0.311)	(0.311)	(0.311)	(0.266)	(2.671)	(2.671)	(2.671)	(2.674)	(2.800)
Capital Expenditure	0.188	0.188	0.187	0.187	0.214	2.074*	2.075*	2.073*	2.077*	1.908*
	(0.137)	(0.137)	(0.137)	(0.137)	(0.137)	(1.176)	(1.176)	(1.177)	(1.178)	(1.147)
Ln(Patent)	0.006	0.007	0.007	0.006	0.006	0.031	0.032	0.033	0.031	0.096
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.070)	(0.070)	(0.070)	(0.070)	(0.061)
Ln(TSM)	0.000	0.000	0.000	0.000	0.001	0.032	0.031	0.031	0.032	0.023
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)
Ln(TCW)	-0.004	-0.004	-0.004	-0.004	-0.004	-0.052	-0.052	-0.052	-0.052	-0.11***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.040)	(0.040)	(0.040)	(0.040)	(0.035)
Trademark	0.001	0.001	0.001	0.001	0.001	-0.059**	-0.060**	-0.060**	-0.059**	-0.077**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.027)	(0.027)	(0.027)	(0.027)	(0.025)
Constant	-0.296*	-0.294	-0.295	-0.296*	-0.283	-1.204	-1.193	-1.190	-1.204	-4.458***
	(0.179)	(0.179)	(0.179)	(0.179)	(0.185)	(1.542)	(1.541)	(1.542)	(1.544)	(1.043)
Observations	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016
R-squared	0.627	0.627	0.627	0.627	0.633	0.796	0.796	0.796	0.796	0.792
F statistics	3.223	2.999	2.943	2.868	25.707	10.252	9.989	10.161	9.001	24.347
Firm and Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Robust Std Errs at Firm Level	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 3: Elasticity of Demand Tests

In this table, we present elasticity of demand tests. **Panel Aa** presents the pooled OLS regression that calculates the elasticity of demand in this specification: Ln (Demand) = β*Ln (Price) + α where the β is the original price elasticity of demand. In **Panel Ab**, we control for more variables at both product level and firm level. We also use firm and year fixed effects. In **Panel B**, we first run Ln (Demand) = β*Ln (Price) + α for each product and collect β. Next, we value weight the βs of all products by sales at firm level to generate a firm-level aggregated elasticity of demand measure. For interpretation convenience, we present the absolute values. In Panel C, we regress all the βs of all products on pioneer, follower and improver dummies to allow for more controls and fixed effects, including firm and(by) year as well as industry and(by) year.

Panel Aa: Pooled OLS Regression, Product-Weekend Level			
Dependent Variable	Ln (Quantity Demanded Each Weekend)		
	Pioneer Products	Follower Products	Improver Products
Ln (Price)	-0.179***	-0.231***	-0.202***
	(0.002)	(0.002)	(0.000)
Constant	1.475***	1.570***	1.526***
	(0.004)	(0.004)	(0.001)
Observations	91,064	123,803	4,514,052
R-squared	0.091	0.084	0.096

Panel Ab: Regression with Controls and Fixed Effects, Product-Weekend Level			
Dependent Variable	Ln (Quantity Demanded Each Weekend)		
	Pioneer Products	Follower Products	Improver Products
Ln (Price)	-0.165***	-0.234***	-0.185***
	(0.003)	(0.001)	(0.000)
Price Std	-0.000	-0.012***	-0.004***
	(0.001)	(0.001)	(0.000)
Ln (Product Annual Sales)	0.163***	0.176***	0.204***
	(0.006)	(0.002)	(0.000)
Quantity Demanded Std	0.014***	0.002***	0.023***
	(0.000)	(0.000)	(0.000)
Firm Level Industry Competition	-0.480***	-0.009	0.007***
	(0.021)	(0.009)	(0.001)
Ln (Firm Age)	0.004***	-0.001***	0.002***
	(0.000)	(0.000)	(0.000)
Ln (Total Asset)	-0.076***	-0.020***	-0.007***
	(0.005)	(0.002)	(0.000)
Ln (Firm Total Sale)	0.065***	0.016***	0.030***
	(0.005)	(0.002)	(0.000)
Constant	0.914***	1.119***	0.588***
	(0.016)	(0.006)	(0.001)
Year Fixed Effect	Y	Y	Y
Firm fixed effect	Y	Y	Y
Observations	91,064	123,803	4,514,052
R-squared	0.277	0.191	0.353

Panel B: Regression Analysis, Product-Firm-Year Level				
Dependent Variable	Absolute Value of Price Elasticity of Demand of Each Product			
Pioneer Dummy	-0.169***	-0.185***	-0.157***	-0.169***
	(0.038)	(0.040)	(0.039)	(0.042)
Follower Dummy	-0.063***	-0.075***	-0.054**	-0.075***
	(0.024)	(0.025)	(0.025)	(0.026)
Improver Dummy	-0.051***	-0.049***	-0.048***	-0.050***
	(0.004)	(0.004)	(0.004)	(0.004)
Quantity Demanded Std	-0.169***	-0.185***	-0.157***	-0.169***
	(0.038)	(0.040)	(0.039)	(0.042)
Ln (Product Annual Sales)	-0.028***	-0.029***	-0.027***	-0.029***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Level Industry Competition	0.083***	0.172***	0.184***	0.185***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln (Firm Age)	-0.090***	-	-0.107***	-9.361***
	(0.016)		(0.016)	(0.386)
Ln (Total Asset)	0.006	-	0.016*	1.558***
	(0.008)		(0.009)	(0.536)
Ln (Firm Total Sale)	-0.007	-	-0.015*	-2.469***
	(0.009)		(0.009)	(0.586)
Constant	-0.486***	-0.902***	-0.531***	-0.934***
	(0.072)	(0.002)	(0.074)	(0.002)
Observations	612,891	612,891	575,588	575,588
R-squared	0.291	0.308	0.298	0.305
P Value of F Test between Pioneer and Follower	0.03	0.02	0.03	0.06
P Value of F Test between Pioneer and Improver	0.01	0.00	0.01	0.00
P Value of F Test between Follower and Improver	0.79	0.30	0.79	035
Fixed Effects	Firm and Year	Firm by Year	Industry and Year	Industry by Year

Panel C: Univariate Analysis, Firm-Year Level	Absolute Value of Price Elasticity of Demand (%) of Each Firm			
	Yes	No	Difference	Satterthwaite T Statistics
Pioneer Firms	48%	49%	-21%	-2.73
Follower Firms	58%	65%	-7%	-0.63
Improver Firms	-55%	69%	15%	-1.74
Pioneer Above HP Industry Average	46%	68%	-22%	-1.83
Follower Above HP Industry Average	53%	44%	10%	0.72
Improver Above HP Industry Average	54%	46%	9%	0.79

Table 5: Portfolio Analysis

In **Panel A**, we report portfolio excess returns and alphas. For each month, we sort firms into three portfolios based 30th and 70th percentiles of CARs around pioneer product's entry. We repeat the same process for follower and improver and hold these portfolios for different horizons, including one month, one quarter, half year and one year and calculate their average monthly excess returns. For each group of tercile portfolios, we form a long-short portfolio (L-S) based on the differences of top 70 and bottom 30 portfolios. Next, we run time-series regressions of each portfolio's excess returns on Fama-French 3 Factors plus Profitability (RMW), Investment (CMA) and Momentum factors. In addition, since the new product measures are related to firm innovation efforts, we control for Trademark Factor. We report average monthly excess returns for L-S portfolio and alphas against above mentioned two asset pricing models. ***, **, and * present 1%, 5%, and 10% significance level, respectively.

Pioneer CAR Sorted Portfolios	*Long Short Portfolio (L-S)*	*L-S Against FF5+Mom Factors*	*L-S Against FF5+Mom+Trademark Factors*
		Holding for One Month	
Average Return or Alphas	4.964**	5.291**	5.607*
	(2.016)	(2.209)	(2.879)
		Holding for One Quarter	
Average Return or Alphas	2.245	1.191	0.810
	(1.552)	(1.711)	(1.700)
		Holding for Half Year	
Average Return or Alphas	-0.133	0.124	-0.442
	(1.219)	(1.342)	(1.269)
		Holding for One Year	
Average Return or Alphas	0.090	0.034	0.257
	(0.437)	(0.443)	(0.370)

Follower CAR Sorted Portfolios	*Long Short Portfolio (L-S)*	*L-S Against FF5+Mom Factors*	*L-S Against FF5+Mom+Trademark Factors*
		Holding for One Month	
Average Return or Alphas	0.306	-0.662	-0.243
	(0.780)	(0.664)	(0.815)
		Holding for One Quarter	
Average Return or Alphas	0.168	0.002	-0.070
	(0.364)	(0.415)	(0.418)
		Holding for Half Year	
Average Return or Alphas	-0.167	-0.260	-0.393
	(0.293)	(0.328)	(0.316)
		Holding for One Year	
Average Return or Alphas	-0.167	-0.094	0.038
	(0.240)	(0.242)	(0.226)

Improver CAR Sorted Portfolios	*Long Short Portfolio (L-S)*	*L-S Against FF5+Mom Factors*	*L-S Against FF5+Mom+Trademark Factors*
		Holding for One Month	
Average Return or Alphas	0.245	0.183	-0.243
	(0.577)	(0.361)	(0.815)
		Holding for One Quarter	
Average Return or Alphas	0.343	0.075	-0.070
	(0.301)	(0.318)	(0.418)
		Holding for Half Year	
Average Return or Alphas	0.343	0.075	-0.070
	(0.301)	(0.318)	(0.418)
		Holding for One Year	
Average Return or Alphas	-0.335*	-0.174	0.038
	(0.177)	(0.180)	(0.226)

Table 6: Return Predictability

This table reports return predictability results. we regress the returns of next week and the second week, excluding the previous week on contemporaneous monthly cumulative CARs that is a sum of past CARs associated with different kinds of new product introduction over the past 12 months. We report average slopes (in %) and standard errors from Fama and MacBeth cross-sectional regressions. Industry dummies are included in each model but not reported to save space. ***, **, and * present 1%, 5%, and 10% significance level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES		Next Week Return				Second Week Return		
Pioneer CARs	0.502**			0.471*	0.163			0.519
	(0.248)			(0.271)	(0.259)			(0.402)
Follower CARs		0.018		0.055		0.044		0.063
		(0.038)		(0.049)		(0.103)		(0.077)
Improver CARs			0.003	0.078			0.060	-0.040
			(0.056)	(0.058)			(0.084)	(0.068)
Number of New Product	0.001	0.000	0.000	0.041	0.000	0.000*	0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.057)	(0.000)	(0.000)	(0.000)	(0.001)
Size	0.009	0.008	0.009	0.030	-0.082*	-0.081*	-0.082*	-0.001
	(0.041)	(0.041)	(0.041)	(0.037)	(0.047)	(0.047)	(0.048)	(0.068)
Book-to-Market	0.004	0.004	0.005	0.005	-0.055**	-0.057**	-0.055**	-0.032*
	(0.010)	(0.010)	(0.010)	(0.011)	(0.026)	(0.028)	(0.026)	(0.017)
Momentum	-2.097	-2.106	-2.049	-1.695	-8.202**	-8.121**	-8.120**	-8.930*
	(2.952)	(2.995)	(2.969)	(2.974)	(3.360)	(3.361)	(3.298)	(4.754)
Patent/Asset	3.490	3.373	3.691	3.466	6.482	6.522	6.239	1.761
	(5.066)	(5.119)	(5.136)	(5.334)	(6.445)	(6.490)	(6.455)	(6.623)
Reversal	12.281***	12.257***	12.240***	12.372***	0.018	0.008	-0.043	-0.181
	(1.192)	(1.190)	(1.178)	(1.137)	(0.843)	(0.844)	(0.848)	(1.568)
Asset Growth	0.371	0.385	0.389	0.443	0.812	0.817	0.814	1.034**
	(0.305)	(0.309)	(0.309)	(0.303)	(0.521)	(0.526)	(0.518)	(0.432)
Investment	1.059	1.056	1.015	1.399	5.035	5.115	4.989	0.957
	(1.573)	(1.552)	(1.560)	(1.627)	(4.408)	(4.420)	(4.442)	(3.391)
Rd/ME	21.500	22.810	21.930	13.040	15.87	18.19	16.05	46.13***
	(37.09)	(36.77)	(36.56)	(25.13)	(51.38)	(51.65)	(51.38)	(17.29)
ROA	-0.593	-0.642	-0.656	-0.636	3.985***	4.021***	4.000***	2.826**
	(0.908)	(0.907)	(0.906)	(0.798)	(1.312)	(1.324)	(1.316)	(1.116)
Number of Business Segments	-0.089	-0.094	-0.095	-0.124	0.014	0.006	0.010	-0.050
	(0.092)	(0.095)	(0.093)	(0.092)	(0.119)	(0.123)	(0.118)	(0.151)
Innovation Efficiency	0.048	0.065	0.050	0.074	-0.071	-0.073	-0.064	-0.091
	(0.067)	(0.069)	(0.070)	(0.079)	(0.057)	(0.058)	(0.059)	(0.094)
TSM	-0.056	-0.066	-0.058	-0.075	0.010	0.011	0.009	0.065
	(0.039)	(0.040)	(0.040)	(0.045)	(0.029)	(0.027)	(0.029)	(0.066)
Citation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trademark	0.206	0.140	0.241	0.251	-0.101	-0.046	-0.158	-0.322
	(0.704)	(0.703)	(0.675)	(0.759)	(0.785)	(0.812)	(0.788)	(0.401)
Constant	0.053	0.112	0.026	-0.194	0.775	0.718	0.818	-0.032
	(0.689)	(0.687)	(0.674)	(0.673)	(0.564)	(0.571)	(0.565)	(0.603)
Observations	20,657	20,657	20,657	20,657	20,657	20,657	20,657	20,657
R-squared	0.314	0.313	0.313	0.323	0.256	0.257	0.258	0.520
F statistics	3.596	3.500	3.473	3.833	1.656	1.680	1.659	1.771

Table 7: Inflation Shock

This table reports the inflation shock to different kinds of products, including all products in the full sample, pioneer, follower, improver and existing products. The inflation shock is defined as the difference between the actual inflation and expected inflation. For product, we create two datasets in which one records each product's weekly average price, another shows monthly price. We create product weekly and monthly price growth measures and regress them on the inflation shock in models (1)-(5). Then we add product (UPC), year and month fixed effect as well as cluster standard errors at UPC level in models (6)-(10). In addition, we control for product total weekly sale, firm annual product sale and number of stores this product was sold as control variables in models (11) – (15). ***, **, and * present 1%, 5%, and 10% significance level, respectively.

Panel A: Weekly Level	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
						Product Weekly Price Growth %									
	Full Sample	Pioneer	Follower	Improver	Existing Product	Full Sample	Pioneer	Follower	Improver	Existing Product	Full Sample	Pioneer	Follower	Improver	Existing Product
Standardized Inflation Shock	0.015***	-0.049	-0.010	0.041***	0.015***	0.010***	-0.165	0.052	0.006	0.008***	0.005*	-0.124	0.074	0.014*	0.005*
	(0.002)	(0.067)	(0.044)	(0.008)	(0.003)	(0.003)	(0.191)	(0.047)	(0.009)	(0.003)	(0.002)	(0.086)	(0.046)	(0.008)	(0.003)
Log (Total Weekly Sale)											-0.466***	-0.36***	-0.45***	-0.44***	-0.465***
											(0.001)	(0.023)	(0.020)	(0.003)	(0.001)
Log (Firm Level Annual Sale)											0.000***	0.000	-0.000	0.000***	0.000***
											(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Stores Sold											0.000***	0.000***	0.001***	0.000***	0.000***
											(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.186***	0.777***	0.414***	0.540***	1.243***	1.186***	0.779***	0.409***	0.539***	1.242***	3.929***	2.610***	2.771***	3.215***	3.976***
	(0.002)	(0.054)	(0.041)	(0.007)	(0.003)	(0.000)	(0.003)	(0.001)	(0.000)	(0.000)	(0.010)	(0.141)	(0.118)	(0.023)	(0.011)
Observations	55,605,725	88,627	117,254	4,310,210	51,089,634	55,596,671	88,589	116,958	4,300,736	51,078,833	55,605,725	88,627	117,254	4,310,210	51,089,634
R-squared	0.000	0.000	0.000	0.000	0.000	0.013	0.026	0.032	0.030	0.014	0.005	0.004	0.005	0.005	0.005
F Statistics	37.700	0.540	0.050	27.727	32.277	15.511	3.284	1.223	0.519	10.137	32.594	67.89	128.9	44.688	30.599
Upc, year, month fixed effects	N	N	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Robust Std Err Clustered at UPC	N	N	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: Monthly Level	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	Product Monthly Price Growth %														
	Full Sample	Pioneer	Follower	Improver	Existing Product	Full Sample	Pioneer	Follower	Improver	Existing Product	Full Sample	Pioneer	Follower	Improver	Existing Product
Standardized Inflation Shock	0.152**	0.000	0.000	-0.003	0.160*	0.015***	0.000	0.000	-0.000	0.022***	0.021***	0.000	0.000	-0.000	0.023***
	(0.077)	(0.000)	(0.000)	(0.007)	(0.082)	(0.002)	(0.000)	(0.000)	(0.000)	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)	(0.003)
Log (Total Weekly Sale)											0.001***	0.000	-0.000	-0.000***	0.001***
											(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (Firm Level Annual Sale)											0.000**	-0.000*	0.000	-0.000	0.000***
											(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Stores Sold											-0.000***	-0.000	0.000	0.000	-0.000***
											(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.881***	0.000	0.000***	7.774***	0.949***	-0.003***	0.000***	0.000***	0.000***	-0.003***	-0.009***	0.000	0.000**	0.000***	-0.006***
	(0.077)	(0.000)	(0.000)	(0.006)	(0.083)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14,607,976	21,797	27,725	1,211,246	13,551,050	14,596,419	21,732	27,054	990,580	13,537,596	14,607,976	21,797	27,725	1,007,404	13,537,596
R-squared	0.000	0.000	0.000	0.000	0.000	0.072	1.000	1.000	1.000	0.078	0.032	0.006	0.003	0.001	0.079
F Statistics	18.899	0.132	1.123	0.199	24.377	39.888	0.235	0.247	0.357	73.385	140.440	1.708	0.180	14.038	88.000
Upc, year, month fixed effects	N	N	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Robust Std Err Clustered at UPC	N	N	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Appendix 1: Variable Definitions

Firm Year Level Tests	
Number of Pioneer Products	Total number of pioneer products introduced in year T
Number of Follower Products	Total number of follower products introduced in year T
Number of Improver Products	Total number of improver products introduced in year T
Total New Products	Total new products introduced in year T
Pioneer Product Introduction Rate	Sales of pioneer products/total new product sales
Follower Product Introduction Rate	Sales of follower products/total new products
Improver Product Introduction Rate	Sales of improver products/total new products
Size	Total Assets (AT)
Sale	Total Sales (SALE)
Firm age	Firm Age using Founding Date (Field and Ritter)
Innovation Efficiency	Patents scaled by past 5-year cumulative R&D expense assuming 20% depreciation rate
New Trademark Introduction	New brands introduced in year T scaled by total brands owned in year t
ROE	Net Income (NI)/Shareholder's Equity Total (SEQ t-1)
ROA	Earnings Before Interest (EBITDA)/Total Assets (AT t-1)
COP	Revenue (REVT)-Cost of Goods Sold (COGS)-Administrative Expenses (XSGA-XRD)-Δ(Accounts Receivable (RECT))-Δ(Inventory (INVT))-Δ(Prepaid Expenses (XPP))+Δ(Deferred Revenue (DRC+DRLT))+ Δ(Trade Accounts Payable (AP))+Δ(Accrued Expenses (XACC))
Advertising Expense/Total Assets	Advertising Expense (XAD)/Total Assets (AT t-1)
R&D Expense / Total Assets	Research and Development Expense (XRD)/ Total Assets (AT t-1)
Capital Expenditure / Total Assets	Capital Expenditures (CAPX)/ Total Assets (AT t-1)
Market to Book Ratio	(Common Share Outstanding* Price Close (CSHO * PRCC_F) / Common Equity (CEQ)
Market Value of Equity	Common Share Outstanding* Price Close (CSHO * PRCC_F)
Firm-Month Predictability Tests	
Size	Total Assets (AT)
Momentum	Past 11 month returns
Patents/Assets	Number of Patents (t-1) / Total Assets (AT t-1)
Short-Term Return Reversal	Monthly return in the previous month
Asset Growth	Total Assets (AT)/AT (T-1)-1
Capx/Assets	Capital Expenditure (CAPX)/ Total Assets (AT t-1)
R&D/Market Equity	[Research and Development Expense (XRD)/ Common Share Outstanding* Price Close (CSHO * PRCC_F t-1)
Multi-Segment Firm	More than one business segment

Appendix 2: Detailed Examples of How Pioneer, Follower and Improver Products are Assigned based on Modules

Pioneer Example (1):
In year 2013, Nielsen added three modules: "ELECTRONIC CIGARETTES – SMOKING; ELECTRONIC CIGARS – SMOKING; ELECTRONIC REM ACCESSORY – SMOKING". Anecdotally, 2013 and 2014 saw the start of mass commercialization and sales of E-Cigarette, especially favored by teenagers, which caused a big concern to the policy makers. Since the entry of these products was so new that Nielsen had to add three modules, all the products that belong to these three modules are regarded as pioneers.

Picture credit: https://images.app.goo.gl/JwKinovXKoDbqaYs9

Picture credit: https://images.app.goo.gl/JwKinovXKoDbqaYs9

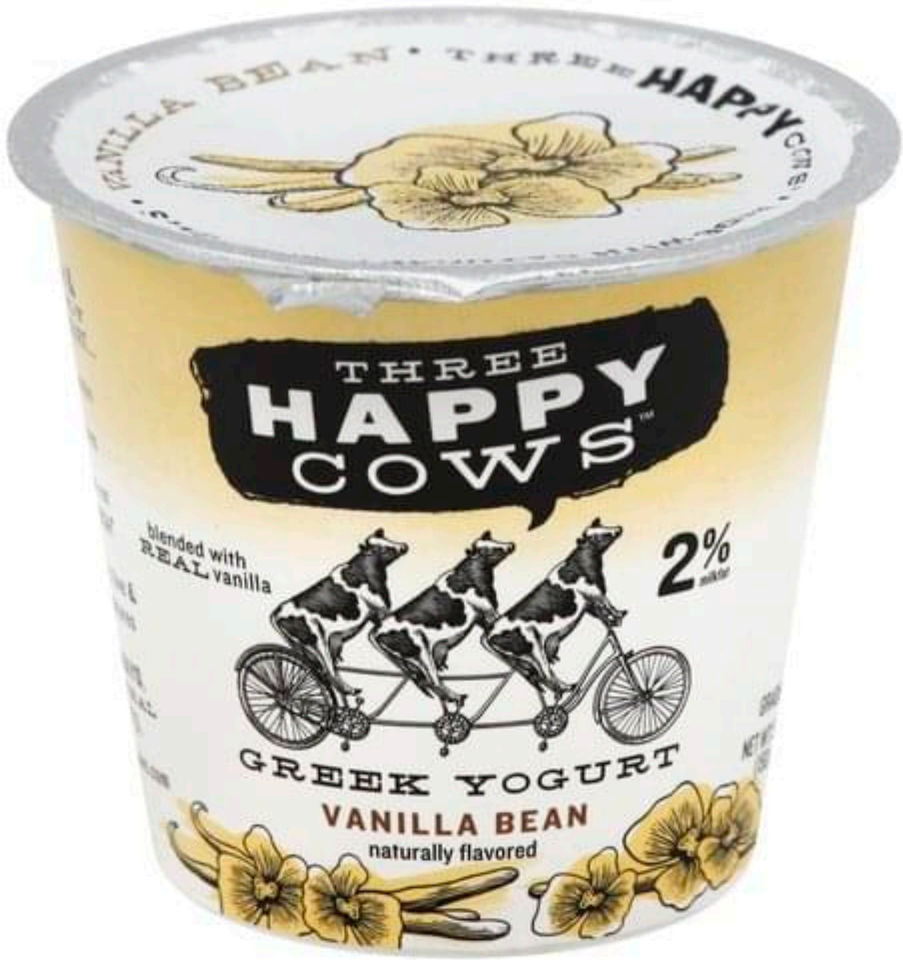
Pioneer Example (2):
In 2014, Nielsen added a new module “RBC BLENDER APPLIANCE”, which accounts for a high-performance blender series. This kind of blender seeks to provide the best flavor of smoothies while maintaining the nutrients contained in the fruits or vegetables through a technology of “pulverization”, which can chop and pulverize the nutrition in skins and seeds and other parts into a very smooth and drinkable manner.

Picture credit: https://images.app.goo.gl/RBMXtWVgZKcCzU698

Pioneer Example (3):
In year 2013, Nielsen added a specific module named "PAIN RELIEVING DEVICE". All the products in this module are regarded as Pioneers. For example, the product "Icy Hot SmartRelief TENS Therapy", which based on our limited knowledge integrates a key technology, Transcutaneous Electrical Nerve Stimulation (TENS), it into a non-prescription, low cost, portable over-the-counter machine.

Picture credit: https://images.app.goo.gl/qkdk2CHmVkTapXfJ6

Follower Product Example (1)
Tyson Foods, a company primarily specializing in prepared meats, acquired the brand "Three Happy Cow" in 2014, announcing its entry into the yogurt market. Nielsen categorizes it as "YOGURT-REFRIGERATED". However, Tyson discontinued the operation in 2015 and according to a report, an insider believed that "*Tyson obviously don't know or understand the dairy business…or especially organic or Non-GMO food.*" Source: https://www.foodnavigator-usa.com/Article/2015/02/11/Production-ceases-at-Greek-Yogurt-brand-Three-Happy-Cows



Picture credit: https://www.innit.com/nutrition/three-happy-cows-greek-vanilla-yogurt/p/00043038000116

Follower Product Example (2)
Anheuser Busch Inbev introduced the Margrita spiked tea beverage and made its entry into the sweet tea market. Nielsen categorizes it into module "TEA – LIQUID"

Picture credit: https://images.app.goo.gl/RiufgiVGba8ieXsy7

Follower Product Example (3)

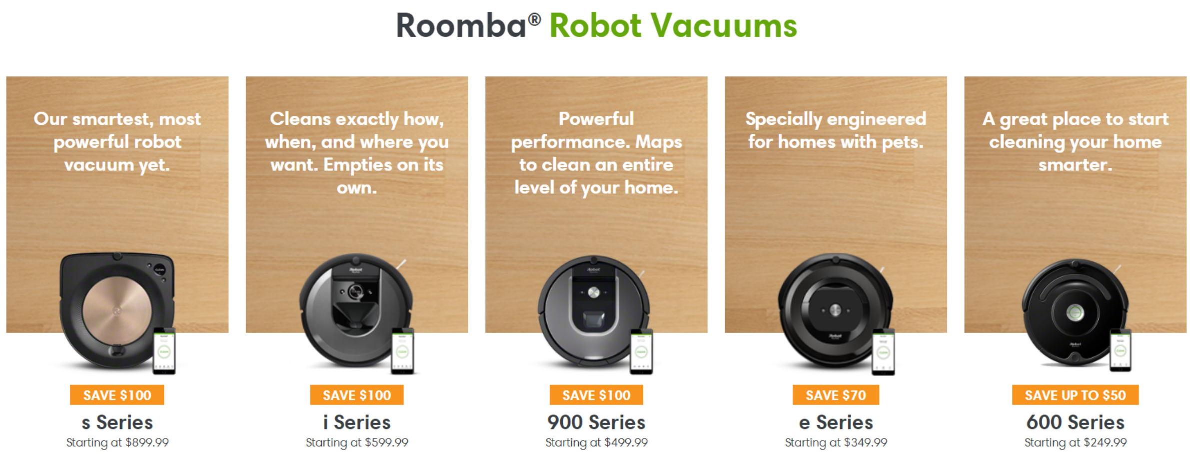
Starbucks, a firm focusing on coffee, introduced Teavana brand that entered into tea drink market, including both packaged (and freshly brewed) tea products. Nielsen categories it as "TEA – PACKAGED"

Picture credit: http://www.fitfoodiemegha.com/2017/03/Teavana-new-tea-menu-starbucks-india-kothrud-reviewed.html

Improver Example (1)
Apple keeps introducing new versions of iPhone every year. The module's name is "CELLULAR PHONE". Picture credit: https://techcrunch.com/2017/09/12/this-is-how-much-the-new-iphones-will-cost/

Improver Example (2)
Anheuser Busch Inbev expands its product lines based on successful models. For example, it introduced Lime flavored beer named Bud Light Lime. The name of module is "BEER". Picture credit: https://images.app.goo.gl/qYZj2f7oXnfFsnDT7

Improver Example (3)
IROBOT CORP has a variety of vacuum products that suit for different households. The module is named "VACUUM AND CARPET CLE" Picture credit: https://www.irobot.com/roomba



Appendix 2a: A Cross-sectional Comparison Among Pioneer, Follower and Improver

Readers might be interested in how pioneer, follower and improver products are in the same business line. Here are some examples:

Example 1:
Pioneer: iPhone: https://en.wikipedia.org/wiki/IPhone_(1st_generation)

Follower: Google Pixel:
https://en.wikipedia.org/wiki/Pixel_(1st_generation)#:~:text=They%20were%20announced%20during%20a,the%20Pixel%204%20in%202019.

Improver: Other Generations of iPhones

Example 2:
Pioneer: Altra's MarkTEN

Follower: Viporesso
https://www.directvapor.com/vaporesso-xros-16w-vape-pod-starter-kit/

Improver: MarkTEN Elite
https://www.cspdailynews.com/tobacco/altria-introducing-closed-vapor-system

Example 3:

Pioneer: Vitamix
https://www.vitamix.com/us/en_us/Shop/5200-Getting-Started?skuId=001372-1093#overview

Follower: Oster Blender
https://www.amazon.com/Oster-Blender-24-Ounce-Smoothie-Brushed/dp/B00XHXN54K

Improver: More Advanced Vitamix Models
https://www.vitamix.com/us/en_us/shop/classic-blenders