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**Abstract**

Radical innovation has long dominated academic and industry discussions due to its potential to disrupt markets and establish long-term competitive advantages. However, many dominant firms in R&D-intensive industries increasingly struggle to develop entirely new technologies. In contrast, nondominant firms are turning to incremental innovations as a more feasible and cost-effective strategy. This study explores whether, and under what conditions, incremental innovations can capture market share compared to radical innovations. We use a comprehensive dataset from a major biochemical knowledge-intensive industry, encompassing over 700 brands, 19,000 customers, and spanning 72 months of sales, supplemented with governmental and field data. Our findings indicate that products developed through incremental innovations, particularly those launched by nondominant firms, can effectively capture more market share compared to those based on radical innovations. We also identify that price-adjusted efficacy is associated with higher market share gains for incremental innovations, an effect not found for radical innovations. Additionally, incremental innovations designed in and tailored to local markets are more successful, with informed customers showing a higher propensity to adopt these innovations. We conclude by discussing the strategic implications for nondominant manufacturers' innovation strategies.

*Keywords:* incremental innovation, radical innovation, R&D, product efficacy, nondominant firms.

## Introduction

Innovation is a major topic in the marketing discipline and is essential for the development of new products, enabling firms to enhance their competitive positioning. However, in certain industries—particularly those that are R&D-intensive, such as pharmaceuticals and crop science—the cost of innovation is extraordinarily high. Companies in these sectors often allocate nearly half of their gross earnings to research and development (R&D)[1] efforts aimed at creating new products. Adding to these challenges, the innovation landscape is becoming increasingly complex, characterized by higher risks, longer development timelines, and rising costs (Phillips McDougall 2018, Scannell et al. 2012).

Firms typically adopt one of two approaches to develop new unique products: investing in the creation of entirely new technologies (i.e., radical innovation) or improving existing technologies (i.e., incremental innovation). Radical innovation is a major aspiration for many companies due to its potential to generate entirely new products (Chandy and Tellis 1998), to dramatically improve companies' market positioning (Rubera and Kirca 2012), and to create substantial barriers for competitors (Sorescu et al. 2003). However, despite its advantages, radical innovation is notoriously challenging, costly, and risky to achieve (Wies, Moorman, and Chandy 2023). As such, it typically falls within the realm of dominant firms, which possess the significant resources required to sustain the intensive R&D efforts that such breakthroughs require (Chandy et al. 2003, Chandy and Tellis 2000, Sorescu et al. 2003). For example, in pharmaceuticals and crop science it takes more than 10 years and upwards of tens or hundreds of millions of dollars to create a single new product.

[1] McKinsey (2020), "Building an R&D Strategy for Modern Times," McKinsey Quarterly and Phillips McDougall (2018), "Evolution of the Crop Protection Industry since 1960."

In an increasingly complex innovation landscape, nondominant companies face a difficult decision: whether to allocate their limited resources to expensive and high-risk radical innovations or to focus on existing technologies through incremental innovation. While radical innovations are often portrayed as the gold standard in R&D, numerous academics and practitioners argue that incremental innovations should not be dismissed (e.g., Corstjens 2018, Harvard Business Review 2018, Robertson 2017). Anecdotal evidence from various industries demonstrates that nondominant companies have managed to secure significant market share by leveraging incremental improvements to established technologies.

In the pharmaceutical industry, for example, Abraxis launched Abraxane in 2005, an incremental innovation following Bristol-Myers Squibb's radically new cancer drug, Taxol. By binding Taxol's active ingredient to a known protein, Abraxis achieved significantly improved clinical outcomes. Although Taxol had become the leading patented cancer drug by 2000, it lost patent exclusivity that same year. With the introduction of Abraxane, Taxol suffered. By 2016, Abraxane's annual sales reached US$ 1 billion, becoming the market leader, while Taxol's had plummeted to less than US$ 150 million (Sofias et al. 2017).

Another industry where products developed via incremental innovation are increasingly competing with those based on radical innovations is crop sciences. In crop protection, Indian UPL reformulated an old fungicide active ingredient, mancozeb, by altering its concentration and physical characteristics, and launched it under the brand name Unizeb Gold. Priced 60% higher than generic mancozeb yet half the cost of others, Unizeb Gold achieved the third-largest volume market share by 2019, surpassing market leaders Bayer and Syngenta[2].

[2] This information was given to us during an interview with a senior executive of this industry.

Despite some successful cases, there are also examples of failures. Merck Sharp & Dohme launched Fosavance, an incremental innovation derived from its leading osteoporosis drug, Fosamax, shortly after the patent expired. However, it faced criticism from the medical community for its higher cost and lack of incremental benefits for patients ("New Drugs from Old," 2006). Sales plummeted thereafter.

Previous research has shown that dominant companies, possessing greater resources to develop and market radical innovations, tend to favor and benefit from this approach to innovation (Sorescu et al. 2003). Furthermore, studies have demonstrated circumstances where radical innovation offers a superior competitive advantage (e.g., greater market share) as compared to incremental innovations (Rubera and Kirca 2012). However, the literature has largely overlooked which strategy nondominant companies with limited resources (e.g., money, time, customer base) should adopt to enhance their competitiveness. This paper seeks to address this oversight by posing the following questions: What type of innovation is better at helping nondominant firms gain market share? And what moderates its effectiveness?

Our study examines an R&D-intensive, vertically integrated industry for two reasons. First, innovation is a critical factor of success in such industries. Second, innovation, regardless of the type, needs to manifest itself in some form of product superiority. Yet, many industries are characterized by horizontal product differentiation. As a consequence, superior product benefit is a complex construct to measure due to the many dimensions of quality a product can embody. In vertically differentiated industries, however, it is more feasible to measure the manifestation of innovation by evaluating product effectiveness. The crop protection industry neatly fits these two requirements.

To investigate these questions, we introduce a novel dataset from the crop protection industry, a critical sector that safeguards global crop production against pests, which cause an estimated $300 billion in annual economic losses[3]. Despite its importance, this industry has been relatively underexplored in the marketing literature, with very few notable exceptions (e.g., Zhang et al. 2021). We selected this industry for several reasons. First, crop protection is a highly R&D-intensive and innovation-driven sector, similar to industries like pharmaceuticals, which have been studied more extensively in the context of innovation. Second, product innovation in this industry can be inferred *ex post* through a regulatory framework, e.g., Sorescu et al. (2003). Third, dominant global players—such as Bayer and BASF— and nondominant players are both known to have adopted radical and incremental innovations over time to varying degrees. Lastly, crop protection allows for near-perfect vertical differentiation identification. In other words, differently from some pharmaceutical categories wherein drugs may cause side-effects or be better suited for a segment of customers, in our context product superiority is unidimensional and can be objectively determined via application to crops in field experiments.

The dataset we use, audited by a leading market research company, covers a comprehensive six-year period and includes volume sales, prices, and marketing variables (e.g., price, distribution) of 715 products from 77 companies in the crop protection market. This allows us 97% view of the market by volume. Our analysis also includes the purchase information (transactions and profiles) of 19,000 business customers (i.e., farmers). Additionally, we enrich our analysis with data from independent studies that evaluate the efficacy, in the field, of the top-selling products as well as government regulatory data that unambiguously identify the type of innovation employed to create each product observed in our dataset.

[3] FAO. (2017). The future of food and agriculture: trends and challenges.

To empirically address our research questions, we specify a series of Multiplicative Competitive Interaction (MCI) and log-linear models to estimate the extent to which a particular class of innovation is related to market share gains. We calibrate our models with two specifications. First, we model market share as a function of innovation type (incremental, radical or generic) and manufacturer type (nondominant or dominant), controlling for product marketing mix covariates, category effects and a series of other controls. Second, we assess how product superiority (i.e., product efficacy and price-adjusted product efficacy) moderate innovation type's relationship to market share. Finally, we conduct some post-hoc analyses to shed some light on the types of firms that can benefit most from the launch of incremental innovation, and how customer profiles and preferences moderate the success of this R&D approach.

Our findings suggest that nondominant manufacturers are more successful in gaining market share with incremental innovations than with radical innovations. Incremental innovations show a distinct advantage particularly when they carry a strong (price-adjusted) efficacy. While the latter may seem obvious, the marketing literature is full of examples in which objectively better products do not sell more. In fact, we do not find such an effect for radical innovations. The empirical evidence seems to point to that, for incremental innovation to steal share, "the proof is in the pudding." Whereas for radical innovation, it's not just about product superiority. Collectively, our findings suggest that incremental innovation is a promising strategy for nondominant manufacturers to systematically gain market share in an R&D-intensive, vertically differentiated market.

Additionally, to shed some light on the circumstances correlated with higher success when launching incremental innovations, we conducted a couple of post-hoc empirical analyses. These analyses underscore the importance of being fiscally close to the customer when launching incremental innovation, as the location of product development (local versus global) is closely tied to higher market share gains. Furthermore, highly informed consumers—those with greater knowledge, experience, or access to unbiased information—are more likely to favor substituting incremental innovations for prior products developed with other strategies (generics or radical).

In the next section we review the relevant literature. Then we describe the context, data and empirical strategy employed. We follow with two approaches to handle endogeneity and show the robustness of our parameter estimates of interest. In the sequel, we describe our findings and conclude with main results for nondominant firms employing incremental innovations, and discuss their limitations.

## Research Background and Hypotheses

The challenging nature of researching innovation is that often the type (independent variable) is defined based on looking at the outcome (dependent variable). For instance, a disruptive or breakthrough innovation is one that actually succeeds in stealing large market shares or that creates products that changes an industry, respectively (e.g., Christensen 2016). We thus employ a definition that has been used by other researchers (e.g., Padigar et al. 2022, Sorescu et al. 2003) to greatly alleviate this concern as well as one that we can unambiguously measure in our empirical context.

*Radical innovation* has long been a central focus in marketing literature due to its potential impacts on both customers and companies. Past studies have highlighted its ability to enable companies to dominate markets (Tellis et al. 2009), provide superior benefits (Kleinschmidt and Cooper 1991), and achieve higher customer preference over incremental innovations (Rubera and Kirca 2012). Radical innovation has been defined in various ways (e.g., Chandy et al. 2003, Chandy and Tellis 1998, Garcia and Calantone 2002, Gatignon and Xuereb 1997). One commonality is that radical innovations represent substantially new technologies compared to those already in the market (Gatignon and Xuereb 1997). A highly cited definition in the marketing literature is that of Chandy and Tellis' (1998), which characterizes radical product innovation by two primary criteria: the incorporation of "substantially different technology from existing products" and the ability to "fulfill key customer needs better than existing products."

On the other hand, *Incremental innovation,* has been defined as products that provide changes in existing technologies (Garcia and Calantone 2002, Sorescu et al. 2003) and offer relatively low customer benefits per dollar (Chandy and Tellis 1998). These authors offer a coherent framework for assessing innovations across various industries. However, as previously recognized, determining whether an innovation is truly radical or incremental is rather challenging (Sorescu et al. 2003).

The literature typically categorizes innovations based on the "newness of technology" and "customer-need fulfillment" into high or low levels. To operationalize these classifications, researchers have primarily relied on surveys and binary categorizations (e.g., Chandy and Tellis 2000, Sorescu et al. 2003, Zhou et al. 2005). While this simplification facilitates the operationalization of certain constructs, it may not accurately capture the complexities of real-world scenarios. For example, in some industries, it may be easier to determine whether a technology is new or old—such as new active ingredients in pharmaceuticals that have never been introduced to the market (e.g. Sorescu et al. 2003). However, measuring customer benefits can be challenging, particularly if drugs have major side-effects. Drawing a clear line based on benefits to classify an innovation as radical or not is often impractical and arbitrary.

Moreover, when developing a product, managers may have a more direct choice over investing in new or existing technologies but not specifically in customer benefits. Therefore, we follow Chandy et al. (2003) by defining radical innovation as a product that requires substantially new technologies, whereas incremental innovations involve relatively minor improvements to existing technologies. Regarding the fulfillment of customer needs criterion, we propose a more objective alternative for its assessment.

***Innovation and Dominance***

The term *dominance* represents the power a company yields in the market. The definition of dominance has been recognized in marketing literature as multi-faceted incorporating several characteristics that enable companies to have higher market power over their competitors. We adopt the same definition of firm dominance as adopted by Chandy et al. (2003), which includes greater market shares, greater investments, and greater resources.

These facets may shape a company's motivation to pursue different types of innovation. While conventional wisdom suggests that dominant companies primarily focus on incremental innovations, this perspective has been challenged by several studies in the marketing literature (e.g., Chandy and Tellis 1998, 2000, Sorescu et al. 2003). The traditional assumption is that because dominant firms rely heavily on significant revenues from existing products, they will be less motivated to invest in entirely new technologies. However, Chandy and Tellis (2000) demonstrate that dominant companies actually introduce more radical innovations than their nondominant counterparts.  The reason is that they possess greater economic resources to manage the substantial investments, time, and risks involved in developing new technologies, while also facing pressure from various stakeholders to consistently introduce radical innovations (e.g., Christensen et al., 2017).

In R&D-intensive industries, dominant firms are not only more inclined to focus on radical innovations—since new technologies are crucial for the industry's sustainability—but they are also more successful in marketing them. The reason is that radical innovations, which are technically unprecedent, increase product-related uncertainty for customers (Jing 2015, Padigar et al. 2022). This uncertainty creates a significant challenge for firms, as they must persuade consumers to invest considerable effort in engaging with the advertising content, understanding the new concept, and assessing their needs in relation to an unproven product (Lu and Shin 2018). Therefore, due to superior market-based and marketing capabilities (Chandy and Tellis, 2000; Padigar et al., 2022), dominant firms are better equipped to market these innovations compared to nondominant firms. Moreover, consumers may perceive these radical innovations as less risky when they are introduced by dominant manufacturers, owing to higher brand equity, which increases their likelihood of adoption (Dowling and Staelin 1994).

On the other hand, nondominant companies often face limitations in their capacity for innovation and suffer from disadvantages in marketing them. These firms typically have fewer financial and technical resources, making it challenging to sustain the necessary investments and risks associated with radical innovations. Therefore, these companies tend to focus their resources on key products (Sorescu et al. 2003). One less costly approach (Rubera and Kirca 2012) might be to develop incremental innovations that can create price or functional benefits for users (Banbury and Mitchell 1995, Henderson and Clark 1990).

Although previous research has emphasized that radical innovations are generally superior to incremental innovations, and that dominant firms are more effective in marketing radical innovations and achieving better outcomes with them, prior literature suggests a different perspective for non-dominant companies. Given their disadvantages in resource allocation, incremental innovations may serve as a more effective strategy for these firms. Thus, we propose the following hypothesis:

H1. Incremental innovations introduced by nondominant manufacturers capture more market share as compared to radical innovations.

### *Moderators of Innovation Success*

As discussed previously, one key dimension of innovation is its ability to meet customer needs better than existing products. Chandy and Tellis (1998) describe this as the customer benefit fulfillment per dollar. However, measuring "benefits" can be complex. In R&D-intensive industries with functional benefits such as  in the pharmaceutical industry, this translates into efficacy in treating a disease. Although, incorporating drug side-effects may complicate things. In our research setting, crop protection, efficacy is simply and objectively measured by the percentage of pests killed.

While higher efficacy products are expected to gain more market share, this is not always the case. Dominant firms may often distort demand through various mechanisms, for instance, asset specificity, channel relationships, brand equity and advertising spending (Datta et al. 2017, Hoeffler and Keller 2003).  For example, research has shown that patients rely on brand reputation and product prominence in stores as indicators of efficacy, especially in the face of negative medical news (e.g., Hermosilla & Ching, 2023).

In contrast, we conjecture that nondominant firms lack the market power to significantly distort demand in this way. Therefore, for their incremental innovations to succeed, we argue that these firms must demonstrate significantly higher product efficacy to overcome their competitive disadvantages. Moreover, considering the price-quality trade-off perceived by customers, price-adjusted efficacy becomes a crucial predictor of a product's success in the market. We conjecture that (price-adjusted) efficacy is particularly important for incremental innovations. Formally:

H2: Product efficacy (H2a) and price-adjusted efficacy (H2b) have a stronger moderating effect on the incremental innovation's ability to capture market share gains compared to radical innovations.

Figure 1 presents an overview of our model framework and hypothesis.

**Insert Figure 1 here.**

## Study Context

The ideal context to test our hypotheses requires a mature and R&D-intensive industry consisting of products that can be neatly categorized in different types of innovation. The crop protection sector, in our view, satisfies these conditions. At US$79 billion in annual sales,[4] the world's leading manufacturers of crop protection products invest tens of millions of dollars annually into new product R&D. This investment is significant and proportionally similar to what pharmaceutical companies spend (i.e., approximately 40% of Ebitda). Moreover, in this industry, the journey from the initial synthesis of ingredients to the first sale of a new product often spans more than 10 years (Phillips McDougall 2018), reflecting the substantial time and resources necessary for developing and introducing new crop protection products.

The crop protection sector involves the development and sale of products to safeguard crops from pests, diseases, and other threats. Around 47% of global sales of crop protection are for herbicide control, with 50% being equally split by fungicides and insecticides. The small remaining fraction corresponds to ancillary products and services. In many ways, the development of these products follows a similar pattern to the pharmaceutical industry's development of drugs to protect and improve human health. Both industries invest heavily in R&D to create new products. And both industries must navigate regulatory frameworks and ethical considerations to ensure that their products are both safe and effective for their customers. Therefore, findings from the crop protection research should have implications for other R&D-intensive industries.

In this context, industry reports, investor presentations, and our discussions with industry executives point to an upward trend in the use of incremental innovations. Market-level data

[4] S&P Global. (2023). Crop Science Market Insight and Forecast

indicate that the crop science market is dynamic with average brand market shares decreasing year over year while the number of products in the market is increasing. Prices have remained relatively stable (see Figure 2).

**Insert Figure 2 here.**

***Available Data***

To investigate this phenomenon, we introduce a novel database provided by a leading market research and audit company in agribusiness. Our dataset comprises six years (2014 to 2019) of monthly nationwide sales data sold from crop protection manufacturers to customers (farmers) in Brazil. As one of the world's largest food producers—the leading global producer of many crops such as coffee, sugarcane, and citrus, and the second largest producer of soy—Brazil is a strategic market for global manufacturers of crop protection and offers an ideal research setting for a few reasons. All major chemical companies operate in this market. Among them are Bayer (Germany), BASF (Germany), Corteva (US), Syngenta (Switzerland), FMC (US), and UPL (India). And differently from large agricultural powerhouses such as the US, Germany, and India, virtually all major players are foreign-born companies. As such, we feel that Brazil is a "neutral battleground" where chemical companies do not have a home-field advantage. In this market, competition is fierce, and innovation driven. Our dataset includes all primary categories of crop protection products, namely fungicides, insecticides, and herbicides (97% of the market). These products are instrumental in boosting crop yields and account for nearly 40% of a farmer's total production cost in a season. So, customers are keenly aware of prices, product efficacy, and new product launches.

Our data consists of sales and marketing-mix information, explained subsequently, spanning 72 months. This dataset is considered the industry standard for assessing manufacturer and product marketing performance across different regions, channel formats, and customers. Collected by Spark, a market research company, it is often equated with the Nielsen Scan Track of agriculture.

Our dataset comprises 715 brand products from 77 manufacturers, including all meaningful products and companies in the market. This dataset includes information on the volume purchased, price paid, and retail channels where the product was bought. And because the market research is exhaustive across products, from volume sold, we can reliably compute market shares.

Upon doing so, we observe that five manufacturers accounted for more than 80% of the market share in 2014. But they have been steadily losing market share since then. See Figure 3 for an analysis of industry concentration and Figure 4 for changes in market shares from 2014 to 2019 across tiers.

Differently from sales tracking in consumer-packaged goods, the data in the crop protection industry is gathered directly from customers (i.e., farmers). They disclose their purchases for each crop season in a highly granular format. Over the course of the six-year period, over 19,000 structured audits were conducted based on a geographically representative sample to build the available dataset. One of the unique features of our data is that it includes demographic information about each customer and specific details about every crop defense transaction during the timespan of the collection period. This includes payment methods and whether advice was sought before making a purchase. Further, to ensure the accuracy of the data, the collected information is counter-audited through purchase documents and fact-checking with retail channels. The research company even drills down to the level of each individual farm plot to gather micro-area data, as most professionalized farmers keep a detailed log of purchases and usages of crop defense in their farms for accounting purposes. Such detailed information offers reliable insights into purchasing trends and consumer behavior in this market, which we use as controls in the empirical analysis. It is also the primary source by which manufacturers benchmark against competitors.

**Insert Figure 3 and Figure 4 here.**

### *Inferring Dominance*

We adopt the definition of firm dominance as outlined by Chandy et al. (2003). According to this definition, a manufacturer is considered dominant if it holds a large market share and possesses substantial investments and resources relative to its competitors. To measure dominance, we use four indicators: global market share, local market share, global R&D investments as a percentage of the manufacturer's EBITDA[5], and total assets.

Our analysis reveals that eight manufacturers account for approximately 80% of the global market, all of which are publicly listed companies. Global market share data were obtained from publicly available sources[6]; local market share data were provided by a market research company; R&D investment figures were sourced from investor relations materials; and total assets were drawn from FactSet. All the information is from 2017, which is positioned in the middle of the dataset. Table 1 summarizes the characteristics of these manufacturers.

We applied k-means clustering with two clusters, categorizing the companies as either dominant or nondominant. Four companies were classified as dominant, while the other four were classified as nondominant. The dominant companies collectively account for 55% of the global market share, 67% of the local market share, an average R&D spending equivalent to 47% of EBITDA, and an average of $81 million in assets. In contrast, the four nondominant companies collectively hold 20% of the global market share, 24% of the local market share, an average R&D spending equivalent to 28% of EBITDA, and an average of $11 million in assets. Although we lack information for the rest of the market, it is reasonable to classify other manufacturers as nondominant.

**Insert Table 1 here.**

[5] We choose EBITDA instead of revenues because EBITDA helps normalize differences in capital structure, tax environments, and non-cash accounting items across companies.
[6] Huang, Longjian (2023), "Ranking List of Global Top 20 Agrochemical Enterprises for FY22," AgroPages.

### *Inferring Type of Innovation*

To define the type of innovation for the 715 products in our data we use the government regulatory framework similar to Sorescu et al. (2003). Regulatory bodies in Brazil, like the Food and Drug Administration (FDA) in the US, provide data for each product approved for sale. This data includes their approval date, trade name, manufacturer, active ingredients, and dosage form.

Crop protection products in Brazil are classified in a manner akin to the US FDA's system[7] for pharmaceutical products, and they fall into three categories: new products with new active ingredients, new products with existing active ingredients, or generic products. We define radical innovations as new products that incorporate new active ingredients not previously introduced to the market. As previously discussed, discovering and developing these ingredients often takes years and demands significant R&D investment. To safeguard their intellectual property, manufacturers typically patent these active ingredients upon discovery. While the patent is in effect, no competitor can launch a product containing the same active ingredient. However, the patent owner may release different versions of their patented products during this period. This approach is also used by manufacturers to extend patent protection (Hitchings et al. 2012). Since the main active ingredient remains unchanged, we follow the extant literature and classify these new versions also as radical innovations, as each represents a product with no equivalent active ingredient at the time of launch.

Incremental innovation refers to products that introduce new formulations of active ingredients that have gone off-patent (i.e., new products based on existing ingredients). These products are commonly referred to within the industry as formulation innovations or "reformulations"[8]. In contrast, generic products are identical copies of previously approved products. We determine this by comparing them to earlier-released products containing the same

[7] FDA. (2023, October 13). Orange Book: Approved Drug Products with Therapeutic Equivalence Evaluations
[8] Adama (2024), "Summary Earning Call 2023."

active ingredient, dosage and formulation. It is important to note that these classifications remain fixed over the six-year period covered by our data, as they reflect the innovation status at the time of launch rather than the product's current state in a specific year. This approach allows us to capture the nature of the product introductions and the types of innovations pursued at the time of their release. However, we identify the specific year when radical innovations lose their patent protection to control for the entry of direct substitutes[9]. Based on this classification, we identified 715 products in total: 481 generics, 176 radical innovations, and 58 incremental innovations.

To ensure our classification aligns with industry standards, we validated it through two key steps. First, we analyzed how some companies present their products in investor relations materials, gaining insights into prevailing industry narratives and ensuring our categories reflect common industry practices. Second, we collaborated with one of the largest manufacturers in our dataset to cross-check our classifications against their internal system. We engaged their Global Innovation Director, a seasoned expert with over thirty years of product development experience, who had no prior exposure to our methodology. We had this director to independently classify his company's products based on the literature's definitions of radical innovation, incremental innovation, and generics. His classifications aligned perfectly with ours, which were derived from regulatory government agency data. This strong alignment across multiple internal and external validation steps underscores the validity and reliability of our classification system.

***Measuring Product Efficacy***

To test our second hypothesis, we continue using the original dataset while supplementing it with an additional dataset on product efficacy. Measuring product efficacy in crop protection is often a significant undertaking as it requires conducting real-world field experiments with various

[9] We infer patent expiration from the date the first competing product, with same active ingredient, is registered in the market.

products under near identical environments. Herbicides, insecticides, and fungicides are used for the purpose of reducing weeds, insects, and fungi, respectively. An objective measure of a product's efficacy, thus, requires a field experiment where the same crop field in a proximate region is divided into sections. Each section is sprayed with a different product, and the remaining live weeds, insects, and fungi after a period are counted.

The cost of conducting these trials is often high and manufacturers may be reluctant to share their own findings. As a result, this kind of data is only available when large institutions invest in these types of trials and choose to make the results public. Understanding product efficacy is essential to test our second hypothesis. Therefore, we sought to gather and analyze the most comprehensive and reliable data available to help shed light on this important issue. We were able to procure two such studies conducted by an independent and reputable institution. These studies analyzed the comparative performance of fungicide and insecticide products using field experiments, comparing product performance[10] with control areas without treatment. The study was conducted in 2017, overlapping our data period, and took place in the same geographical regions as our data.

Not all products in the original dataset were tested[11]. For both the insecticides and fungicides categories, the products tested in the field trials represent a significant portion of the category's volume sales, accounting for 85% and 66%, respectively. By using these studies, we can supplement our own dataset with external unbiased data on product efficacy, devoid of the influence of manufacturers. While this approach is not without limitations, namely the variation of efficacy

[10] Fungicides and insecticides studies funded and carried out by developed by Fundação MS. Unfortunately, we could not find data for the herbicides category.
[11] It's likely unrealistic for an institution to test every product available in the market. Thus, they would need to make a selection, presumably focusing on the most popular products, as these would have the most widespread impact.

across time and the incomplete assessment of all products in the market, it allows us to gain a more comprehensive understanding of observable product performance in the field.

Efficacy comparisons are only valid within a category[12]. Therefore, we transformed the original product efficacy measures into percentiles. That way, an 80th percentile score indicates that the product performed better than 80% of the other products in its category. We also calculate an analogous price-adjusted performance measure. We recognize that product performance may not be the only factor driving sales. Customers may choose to purchase lower-performing products if they are considerably cheaper. We operationalize price-adjusted efficacy by weighing efficacy by the total price of the product. This is achieved by dividing the efficacy metric by the price per unit area of the product. This ratio represents the efficacy ranking obtained by dollar spent, allowing us to assess the impact of price on customer behavior in relation to product performance.

Lastly, it is important to consider that product efficacy may diminish over time as pests and diseases develop resistance (Phillips McDougall 2018). To control for this effect in our six-year timespan, we collected data on the number of years the products are on the market. This information was obtained from official government sources and is calculated based on the date that the product was first registered with the Ministry of Agriculture.

***Main Variables Description***

At the most disaggregated level, the data available to us is by customer-product-purchase occasion. There are 535,612 such occasions. To explore our first hypothesis, we aggregate the data to the product level, broken down by geographical state and month of purchase. This enables us to

[12] Product performance is delimited slightly differently for each category. For insecticides, the effectiveness metric is in percentage of control. This metric is created by considering the percent of insects living in the control area (X) and the percent living in the treated plant (Y). Then, Y is subtracted from X to determine the percentage of insects killed by the treatment. This percentage is divided by the percent living in the control area (X) to obtain the percentage of control. For fungicides, it is measured by the area under the disease progress curve. The calculation is based on multiple assessments of disease severity in the plant over time, providing a single value by computing the area below the disease progress curve. Consider X to be the area under the disease progress curve (AUDPC) of the control plant and Y to be the AUDPC of the treated plant. The effectiveness is then computed as X minus Y divided by X.

assess the impact of various innovations on sales. Next, we detail the key variables used in our empirical model.

**Dominant Manufacturer** Manufacturers were categorized as either dominant or nondominant according to the level of market share and R&D investments, as previously outlined. This is represented by a single dummy variable, where 1 indicates a dominant manufacturer and 0 denotes a nondominant one. Over the six-year span of our dataset, there were no significant entries or exits of manufacturers. Consequently, we can confidently assume that the classification of dominant manufacturers remains static throughout the study period.

**Type of Innovation** Each product is assigned to one of three categories, represented by two dummy variables: radical innovation or not, incremental innovation or not. Generic is coded as (0,0). This classification reflects the type at the product introduction. Notably, each product receives a unique and stable classification over time.

**Efficacy/Price-Adjusted Efficacy** Product efficacy measures the percentage of pests eliminated during control trials. Efficacy has been standardized on a scale of 0 to 100, reflecting the product's percentile rank within its category. Price-Adjusted Efficacy is then calculated by dividing the efficacy score by the product's price. While not a perfect measure, this approach aligns with the concept of "customer needs fulfillment per dollar," as outlined by Chandy and Tellis (1998).

**Sales** Product sales data in the crop protection industry are presented in two formats. Sales volume is informed in metric tons of product. However, products in this market with the same use case (herbicides, insecticides, or fungicides) may require different volume amounts per area due to product-specific properties (i.e., dose). To compare across products, manufacturers in the crop protection industry normalize volume data using an index metric that is the product of the volume (in kilograms or pounds) by the rate amount to treat a single hectare[13] (ha). The result is known as the "potential treated area."[14] We use both sales in metric tons and potential treated area to investigate our hypotheses.

**Price** Similar to sales, prices are also reported in two formats: prices paid per kilogram of product and the price per treated hectare (ha). In our analysis, we operationalize price using both formats depending on whether the dependent variable is sales (or share) in metric tons or sales in treated hectares.

**Distribution** We include distribution as a control in our model because of its importance from the marketing-mix perspective, as reported in previous studies (Ataman et al. 2010, Sharma et al. 2019). Indeed, Wilbur & Farris (2014) describe that distribution is a major issue in improving new products' market share. More points of sale to distribute a brand are generally associated with higher sales. We operationalize distribution as the number of sales outlets the product was sold per state per year.

## Empirical Analysis

### *Model for Testing Innovations' Market Share Gains (H1)*

We provide preliminary evidence of H1 by plotting the sales of incremental innovations over time, along with the sales of radical innovations and generic products in Figure 5. Additionally, we present the descriptive summary of our variables in Table 2 From the aggregate data perspective, Figure 5 shows that, as a group, all incremental innovation-based products have increasing sales. However, it remains unclear whether these incremental innovations are capturing market share from each other, from radical innovations, or from generics, and whether this is a phenomenon driven by a few highly successful incremental innovations or it is a systematic pattern.

[13] Hectare is a unit of land area used in the imperial and US customary systems.
[14] Although the name might indicate so, “treated area” does not mean the area available in the farm. Product rate is calculated using several other variables, such as the number of applications, number of products and other technical factors which are not discussed in this paper.

Therefore, we specify and estimate a regression model to rigorously test our first hypothesis while controlling for other significant factors known to affect sales and shares over time.

**Insert Figure 5 here and Table 2 here.**

In Hypothesis 1, we aim to capture the competitive dynamics between different types of innovation and the dominance of their manufacturers, measured by product sales and market share, while controlling for marketing mix variables. To examine this, we use a log-liner specification that captures the underlying relationships between covariates in our dataset and sales, along with normal i.i.d. errors. As for estimation, we use a generalized least square (GLS) estimator for efficiency (Swamy and Arora 1972). Equation 1 describes the model specification for sales.

$$\begin{aligned}\log(\mathrm{SALES}_{ijt}) = {} & \beta_0 + \beta_1 \mathrm{INC}_i + \beta_2 \mathrm{RAD}_{\,i} + \beta_3 \mathrm{NDOM}_m + \beta_4 \mathrm{NDOM}_m \times \mathrm{INC}_i \\ & + \beta_5 \mathrm{NDOM}_m \times \mathrm{RAD}_i + \beta_6 \log(\mathrm{PRICE}_{ijt}) + \beta_7 \log(\mathrm{DIST}_{ijt}) \\ & + \beta_8 \log(\mathrm{AGE}_{ik}) + \beta_9 \mathrm{CLIFF}_{ik} + \beta_{10} \mathrm{FUNG}_i + \beta_{11} \mathrm{INSEC}_i \\ & + \beta_{12} \log(\mathrm{SALES}_{ijt-1}) + \varepsilon_{ijt}\end{aligned} \quad (1)$$

Where:

| | |
|---|---|
| $\log(\mathrm{SALES}_{ijt})$ | Log of volume sales in metric tons for product *i* in state *j* in month *t* |
| $\mathrm{INC}_i$ | Dummy variable that equals 1 if product *i* is an incremental innovation product and 0 otherwise |
| $\mathrm{RAD}_i$ | Dummy variable equals 1 if product *i* is a radical innovation product and 0 otherwise |
| $\mathrm{NDOM}_m$ | Dummy variable equals 1 if manufacturer *m* is nondominant and 0 otherwise |
| $\log(\mathrm{PRICE}_{ijt})$ | Log of price per kilogram of product *i* in state *j* in month *t* |
| $\log(\mathrm{DIST}_{ijt})$ | Number of outlets the product *i* was sold in state *j* in month *t* |
| $\log(\mathrm{AGE}_{ik})$ | Number of years product *i* has been in the market in year *k* |
| $\mathrm{CLIFF}_{ik}$ | Dummy variable equals 1 if product *i* has lost its patent before or on year *k* |
| $\mathrm{FUNG}_i$ | Dummy variable that equals 1 if product *i* is an herbicide and 0 otherwise |
| $\mathrm{INSEC}_i$ | Dummy variable equals 1 if product *i* is a fungicide and 0 otherwise |
| $\log(\mathrm{SALES}_{ijt-1})$ | Log of sales for product *i* in state *j* in month *t-1* |
| $\varepsilon_{ijt}$ | Normally and independently distributed random error term |

To account for other potential marketing-mix effects, we include price and distribution variables as controls in our regression analysis. We also control for the number of years the product has been on the market and introduce a dummy variable indicating when patented radical innovations lost their patent (i.e., patent cliff). Lastly, we partially account for potential unobserved endogeneity in our model by using lagged product sales as an instrument. We have no measures of promotion. We feel that this omitted variable is not a major cause for concern as the crop defense industry historically sets advertising budgets in proportion to prior sales. This being the case, the inclusion of lagged sales partially captures the correlation with promotional support for each product.

Following the description of our model using absolute sales volume, we proceed to describe our model in relative terms (i.e., market share). This provides us with a more nuanced understanding of the relationship between our covariates and sales. In this fast-growing market, using market shares helps us assess the competitive dynamics of the market and the role of product development strategy, abstracting away market growth.

To model market shares under the constraints that they must be positive and collectively sum up to one, we use a Multiplicative Competitive Interaction (MCI) model, estimated with GLS as per Nakanishi & Cooper (1974). Further it is shown to be the aggregate data analog to a multinomial logit (Cooper and Nakanishi 1997).

This method relies on log-centering transformations, also known as centered log-ratio (CLR). This process entails computing the logarithmic ratio of each share, $S_{ij}$, to the geometric mean of all shares at the observation point $j$, denoted as $\tilde{S}_j$. We describe this model specification in Equation 2.

$$\log\left(\frac{\mathrm{SHARE_{ijt}}}{\widetilde{\mathrm{SHARE}}_{\mathrm{jt}}}\right) \tag{2}$$

$$= \gamma_0 + \gamma_1\mathrm{INC_i} + \gamma_2\mathrm{RAD_i} + \gamma_3\mathrm{DOM_m} + \gamma_4\mathrm{DOM_m}\times\mathrm{INC_i} + \gamma_5\mathrm{DOM_m}\times\mathrm{RAD_i}$$

$$+ \gamma_6\log\left(\frac{\mathrm{PRICE_{ijt}}}{\widetilde{\mathrm{PRICE}}_{\mathrm{jt}}}\right) + \gamma_7\log\left(\frac{\mathrm{DIST_{ijt}}}{\widetilde{\mathrm{DIST}}_{\mathrm{jt}}}\right) + \gamma_8\log\left(\frac{\mathrm{AGE_{ik}}}{\widetilde{\mathrm{AGE}}_{\mathrm{k}}}\right) + \gamma_9\mathrm{CLIFF_{ik}}$$

$$+ \gamma_{10}\mathrm{FUNG_i} + \gamma_{11}\mathrm{INSEC_i} + \gamma_{12}\log\left(\frac{\mathrm{SHARE_{ijt-1}}}{\widetilde{\mathrm{SHARE}}_{\mathrm{jt-1}}}\right) + \varepsilon^*_{\mathrm{ijt}}$$

Where:

| | |
|---|---|
| $\log\left(\mathrm{SHARE_{ijt}}/\widetilde{\mathrm{SHARE}}_{\mathrm{jt}}\right)$ | CLR of volume share in potential area treated for product *i* in state *j* in month *t* |
| $\log\left(\mathrm{PRICE_{ijt}}/\widetilde{\mathrm{PRICE}}_{\mathrm{jt}}\right)$ | CLR of price per hectare of product *i* in state *j* in month *t* |
| $\log\left(\mathrm{DIST_{ijt}}/\widetilde{\mathrm{DIST}}_{\mathrm{jt}}\right)$ | CLR of number of outlets the product *i* was sold in state *j* in month *t* |
| $\log\left(\mathrm{AGE_{ik}}/\widetilde{\mathrm{AGE}}_{\mathrm{k}}\right)$ | CLR of number of years product *i* has been in the market in year *k* |
| $\log\left(\mathrm{SHARE_{ijt}}/\widetilde{\mathrm{SHARE}}_{\mathrm{jt-1}}\right)$ | CLR of volume share for product *i* in state *j* in month *t-1* |
| $\varepsilon^*_{ijt} = (\varepsilon_{ijt} - \bar{\varepsilon}_{\mathrm{jt}})$ | Normally and independently distributed random error term |

***Model for Efficacy Role on Innovations Market Share (H2)***

Table 3 presents summary statistics for the subset of products with available efficacy data. On average, radical innovation products have an efficacy percentile of 45, incremental innovations average 50, and generics score 19. While incremental innovations show slightly higher efficacy than radical innovations, the difference is not statistically significant. However, when adjusting prices, incremental innovations demonstrate a higher efficacy-to-price ratio, offering a particularly compelling value proposition for customers. In contrast, the efficacy-to-price ratios for radical innovations and generic products are nearly identical.

Average sales (by volume) per product show a similar pattern, namely, incremental innovations have, on average, higher sales than radical innovations and generics, with the latter two being similar to each other. While these numbers provide some evidence of the second hypothesis, these described differences do not appear to be significant as both efficacy and sales measures possess large standard deviations. As described before, we employ a similar statistical approach to test H2, adding structure to the comparison set and duly accounting for the role of available marketing variables.

**Insert Table 3 here.**

In our subsequent analysis, the second model delves deeper into the intricate relationship between product efficacy and type of innovation as they relate to sales. As discussed in the research background section, a long list of prior research has shown that higher performance does not always lead to higher sales as branding, marketing and retail convenience can distort demand.

We present our model in Equation 3 and 4. It employs similar specifications as in our first model, with appropriate modifications to include measures of product efficacy. We operationalize efficacy from both an absolute (equation 3) and a relative price-adjusted sense (equation 4). For the latter, we exclude price from our model to avoid collinearity issues with price-adjusted efficacy.

$$\begin{aligned}
\log\left(\frac{\text{SHARE}_{ijt}}{\widehat{SHARE}_{jt}}\right)
&= \alpha_0 + \beta_1 \text{INC}_i + \alpha_2 RAD_i + \alpha_3 \log\left(\frac{\text{EFFIC}_i}{\widehat{\text{EFFIC}}}\right) + \alpha_4 \log\left(\frac{\text{EFFIC}_i}{\widehat{\text{EFFIC}}}\right) \times \text{INC}_i \\
&+ \alpha_5 \log\left(\frac{\text{EFFIC}_i}{\widehat{\text{EFFIC}}}\right) \times \text{RAD}_i + \alpha_6 \log\left(\frac{\text{PRICE}_{ijt}}{\widehat{PRICE}_{jt}}\right) + \alpha_7 \log\left(\frac{\text{PRICE}_{ijt}}{\widehat{PRICE}_{jt}}\right) \times \text{INC}_i \\
&+ \alpha_8 \log\left(\frac{\text{PRICE}_{ijt}}{\widehat{PRICE}_{jt}}\right) \times \text{RAD}_i + \alpha_9 \log\left(\frac{\text{DIST}_{ijt}}{\widehat{DIST}_{jt}}\right) + \alpha_{10} \log\left(\frac{AGE_{il}}{\widehat{AGE}_l}\right) \\
&+ \alpha_{11} DOM_m + \alpha_{12} CLIFF_i + \alpha_{13} INSEC_i + \alpha_{14} \log\left(\frac{\text{SHARE}_{ijt-1}}{\widehat{SHARE}_{jt-1}}\right) + \varepsilon^*_{ijt}
\end{aligned} \tag{3}$$

$$\log\left(\frac{\text{SHARE}_{ijt}}{\widetilde{SHARE}_{jt}}\right) \tag{4}$$

$$= \delta_0 + \beta_1 \text{PPR}_i + \delta_2 PAT_i + \delta_3 \log\left(\frac{\text{PAE}_{ijt}}{\widetilde{\text{PAE}}_{jt}}\right) + \delta_4 \log\left(\frac{\text{PAE}_{ijt}}{\text{PAE}_{jt}}\right) \times \text{PPR}_i$$

$$+ \delta_5 \log\left(\frac{\text{PAE}_{ijt}}{\widetilde{\text{PAE}}_{jt}}\right) \times \text{PAT}_i + \alpha_9 \log\left(\frac{\text{DIST}_{ijt}}{\widetilde{DIST}_{jt}}\right) + \alpha_{10} \log\left(\frac{AGE_{il}}{\widetilde{AGE}_l}\right)$$

$$+ \alpha_{11} DOM_m + \alpha_{12} CLIFF_i + \alpha_{13} INSEC_i + \alpha_{14} \log\left(\frac{\text{SHARE}_{ijt-1}}{\widetilde{SHARE}_{jt-1}}\right) + \varepsilon^*_{ijt}$$

Where:

| | |
|---|---|
| $\log\left(\text{EFFIC}_i / \widetilde{\text{EFFIC}}\right)$ | CLR of efficacy of product *i* |
| $\log\left(\text{PAE}_{ijt} / \widetilde{\text{PAE}}_{jt}\right)$ | CLR of price-adjusted efficacy of product *i* in state *j* in month *t* |
| $\log\left(\text{AGE}_{il} / \widetilde{\text{AGE}}_l\right)$ | CLR of product *i*'s age in year $l$ since its initial registration |

## Results

### *On innovation type and company type*

Table 4 provides the parameter estimates for two dependent variables, sales by volume and by market shares. Regarding manufacturer dominance, the results align with previous research, showing that products from nondominant manufacturers capture significantly less sales ($\beta 3 = -.259$, $p < .01$) and market share ($\gamma 3 = -.123$, $p < .01$) than dominant firms. Moreover, the results reveal a statistically significant relationship between the type of innovation and sales. Incremental innovations achieve significantly higher sales compared to generics ($\beta_1 = .150$, $p < .05$), and radical innovations also outperform generics ($\beta_2 = .122$, $p < .01$), also as expected.

Corroborating our hypothesis, we find that incremental innovations from nondominant manufacturers perform better, capturing significantly more sales ($\beta_4 = .254$, $p < .01$) and market share ($\gamma_4 = .238$, $p < .01$) as compared to their use of radical innovations, which garner significantly less sales ($\beta_5$ = .141, p < .01) but not market share. These findings support our first hypothesis from both an absolute (sales) and relative (market share) market success perspectives. This suggests that for nondominant firms, incremental innovations are a more effective strategy for market share growth, whereas radical innovations do not offer the same outcomes.

Regarding the control variables, as expected, price is negatively associated with sales volume ($\beta_6$ = -.795, p < .01), as expected. However, it has a positive but only marginally significant coefficient in the market share model. In both models, the effect of distribution is positive and significant, indicating that greater product availability at points of sale is linked to increased sales. The introduction of the patent cliff dummy yields negative and significant coefficients, as anticipated. The loss of market exclusivity due to the patent cliff enables new competitors to enter, resulting in a decline in market share. Additionally, the number of years a product has been on the market shows a significant negative effect on both sales volume and market share. Category dummies are also significant in most cases, and both models exhibit a notable lag effect of past sales or market share.

In summary, these results confirm Hypothesis 1 as incremental innovations by nondominant manufacturers are more effective at capturing market share than their use of radical innovations.

**Insert Table 4 here.**

***On the role of product efficacy***

Table 5 presents the estimates used to test the second hypothesis. Using a smaller dataset, we find that higher product efficacy generally leads to increased market share ($\alpha_3$ = .105, p < .01). This effect is also present for incremental innovations albeit marginally so ($\alpha_4$ = .106, p < .1). As for radical innovations, the result in inverted ($\alpha_5$ = -.073, p < .01). We hypothesized that efficiency would be a stronger determinant of success for incremental innovations than for radical innovations but not to the point of flipping the direction of the relationship. We thus confirm that efficacy has a greater impact on the market share of incremental innovations than for radical innovations, partially supporting H2a.

**Insert Table 5 here.**

Regarding the impact of price-adjusted efficacy on competitive dynamics, qualitatively, the same results as above hold. Products with higher price-adjusted efficacy capture significantly more market share ($\delta_3 = .101$, $p < .01$). Incremental innovations with higher price-adjusted efficacy capture even more market share ($\delta 4 = .129$, $p < .05$). However, for radical innovations, the effect is negative and statistically significant ($\delta 6 = -.099$, $p < .01$), collectively supporting Hypothesis 2b. This suggests that both efficacy and price are more crucial for the success of incremental innovations than for radical innovations, as hypothesized.

In both models, distribution levels are positive and significant, while product age is not statistically significant. Additionally, the interaction effects between price and innovation type reveal that incremental innovations are the most sensitive to price changes ($\alpha 8 = -.262$, $p < .01$), while the effect for radical innovations is not statistically significant. The dummy variable for the patent cliff remains negative and statistically significant. The category dummy is not significant, but lagged sales continue to be significant and positive, indicating the persistence of past performance on current outcomes.

***Addressing endogeneity concerns***

One concern permeating all our empirical models is that of endogenous simultaneity. We conjecture that the choice of innovation type, e.g., incremental innovation (versus generics), has an impact on future market shares of the products launched based on those innovations. It is theoretically possible that executives making these decisions will look at the shares of their current products in the market, thus generating a reverse causality concern.

We first attempted to gage whether this theoretical possibility is indeed plausible in this market in practice. We interviewed the CEO of the company that collects much of the data that we used for this paper. He knows all the major players and has had an extensive career in marketing and innovation, having worked for global firms such as BASF, Syngenta and Novartis. According to him, while it is true that senior managers and executives tend to look at general market shares when making future R&D investments decisions, it is less common that they will look at precise product market share changes over time (our DV of interest when lags are used) as a basis to select future innovation types (our IVs of interest). As such, we opted to add lags as controls and have reported the findings based on this model specification.

We still opted to take the conservative approach of finding appropriate instruments for type of innovation. The number of patents filed by each firm prior to each product's launch tends to be correlated with the type of innovation. Firms employing more radical innovations tend to have more patents than firms employing more incremental innovations. Yet, due to their inherent nature, patent grants tend to not be driven by market shares of other products. We collect this data for each firm by writing a Python script to scrape data from INPI, the Brazilian patent granting agency. This script searches for patents associated with all active ingredients and manufacturers in our dataset, covering the period from 1970 to 2024. We then matched these patents to the relevant products. Two variables were collected in this manner: number of patents filed by the firm prior to product launch and number of patents on the active ingredient prior to product launch. Since we are using as instruments the overall number of patents of a company (not the patents for a specific product), this measure reflects the innovation type without being directly impacted by market shares. In addition, these patent counts precede the market effects and thus shape the innovation approach rather than the market performance itself. To complement, we also collect R&D spending by firm as a percentage of Ebitda.[15] We assume that while higher spending may shift the likelihood toward more incremental or radical innovations, its level is not based on the shares of products in the market that were often launched many years prior.

To address potential endogeneity concerns, we apply instrumental variable (IV) techniques using two-stage least squares (2SLS) estimation. Specifically, we employ Amemiya and MaCurdy (1986) transformation for IV estimation within our model. This approach enhances the reliability and consistency of our estimates by accounting for endogeneity in the predictors, particularly addressing issues of simultaneity and reverse causality between innovation types and market shares.

As Table 6 shows, the parameter estimates using the model with lags and with the instruments for type of innovation result in qualitatively similar results. Significant parameters of interest (hypothesized) are of the same sign and have comparable significance levels. The only exception is in the volume sales model whereby the coefficient for incremental innovation goes from being significant to marginally significant (Table 6, line 1). This gives us confidence that the bulk of any outstanding driver of endogeneity, to the extent that it is observable by us, has been taken care of. Given the robustness of the results, we take the parsimonious decision to report and discuss estimates with the simpler lag model as it generates parameters that have smaller standard errors, are simpler to interpret, and don’t rely on extra assumptions.

**Insert Table 6 here.**

## Post-Hoc Analysis

Our study reveals that nondominant companies are more successful when they introduce products based on incremental innovation than when using radical innovation. While this finding is

[15] This data was gathered from two sources. R&D Spending came from materials published on investor relations websites. This data covers eight firms responsible for 80% of the market share. The remaining 69 manufacturers are private companies and R&D spending information for them is unavailable. To address this, we used the average R&D-to-EBITDA ratio of non-dominant manufacturers as an estimate.

interesting and novel to nondominant firms, it also raises further questions about how best to develop incremental innovations. To gain deeper insights, and *after* having identified the above results, we examined investor relations materials, conducted interviews with C-level executives of dominant and non-dominant manufacturers, and gathered news articles to identify factors that might further contribute to the success of this class of innovations.

We found three measurable features. Firstly, manufacturers often emphasize the importance of leveraging knowledge from customers and utilizing local development facilities to create products that meet specific local demands[16]. Secondly, they note that being "active ingredient agnostic" allows them to creatively combine existing technologies, providing flexibility in developing new solutions without being constrained by proprietary active ingredients, what the innovation industry has termed the “not invented here syndrome”[17]. And thirdly, successful incremental innovators mentioned the importance of market timing whereby ingredients that recently went off patent were quickly innovated upon.

Existing literature underscores the importance of local information in new product development, particularly in fostering creativity and speed (Ganesan 1994), and indicates that customer-related local information is difficult to transfer across regions (von Hippel 1998).  For instance, Siemens’ competitive advantage has remained in its business units' deep vertical know-how about their customers, rather than relying solely on faraway centralized global R&D centers for innovation (Collis and Junker 2021).

We collected data to determine the markets for which each incremental innovation was developed. By analyzing publicly available information and press coverage about product launches,

[16] UPL (2021), “Capital Markets Day 2021.”
[17] Yuan, Grace (2024), “Adama Focusing on Value Innovation and Advanced Proprietary Formulation Technologies, Delivering More Effective, Sustainable and Differentiated Products,” AgroPages, (accessed September 22, 2024), [available at https://news.agropages.com/News/Detail-50228.htm].

we classified each product launch with a dummy variable indicating whether it was designed in and specifically for the local market or whether the R&D was done remotely (e.g., at a global R&D facility). We also added variables pertaining to the original patent holder of the radical innovation and the age of the most recent active ingredient. We then applied a model akin to Equation 2, incorporating these three additional factors. This model was applied to a subset of the original dataset containing only incremental innovations since the interest here was to find catalysts of additional success within this generally successful approach.

Table 7 presents the results of our exploratory analysis. As one would expect, we find that nondominant manufacturers garner lower shares than their dominant counterparts ($\beta = -0.757$, $p < .01$). Likewise, locally developed innovations also garner less shares than their competitors that are produced at a global R&D facility ($\beta = -0.563$, $p < .01$), a luxury afforded only by the largest global manufacturers. However, and this is the interesting finding, the positive and significant interaction between locally developed products and nondominant manufacturers ($\beta = 0.832$, $p < .01$) reveals that, when it comes to developing and launching incremental innovations, being close to the customer increases the nondominant firm's chances of market success. A possible reason behind this, we speculate, is that innovating incrementally close to the customer may result in better addressing specific market needs than attempting to do so from far away.

As for the role of the active ingredient creator, it is not statistically significant, nor is its interaction with nondominant manufacturers. These null effects are actually quite noteworthy. They provide valuable insights for would-be incremental innovators. The lack of a significant advantage for owning the technology of which the radical innovation was originally based upon suggests that firms that possess the original proprietary active ingredients do not necessarily accrue a market edge versus their competitors when both are attempting to identify incremental innovations from the same source. When it comes to incremental innovation, the “not invented here” syndrome might be an unwarranted bias that needs to be overcome.

Finally, the results show that products with newer active ingredients tend to achieve higher market share ($\beta = .711$, $p < .01$), supporting the notion that innovations incorporating the latest technologies are more effective and appealing to consumers.

**Insert Table 7 here.**

***On the role of customer knowledge.***

In the second half of the Results section, we confirmed that product efficacy (m.s.) and price-efficacy (sig.) are—in contrast to radical innovations—determinants of market share gains for incremental innovations. We used objective field experiment data on product efficacy available to us to show this. However, customers in this market are unlikely to possess this knowledge even for a small subset of the 140 to 180 products in the market for each one of the three crop defense categories that we studied. In this section we aim to explore whether better knowledge of products (price and efficacy being two key dimensions) based on incremental innovations, in a vertically differentiated industry, are associated with higher sales. As before, we continue comparing the results with those for products using a radical innovation approach.

## Theoretical Basis

Complex products such as crop protection require the ability and willingness of customers to acquire and interpret comparative information regarding product effectiveness. However, prior studies have indicated that some customers do not possess adequate knowledge to make optimal decisions or may perceive the cost of acquiring this knowledge as too high (Hortacsu and Syverson 2004, Kim et al. 2010). Moreover, as cognitive gaps can result in suboptimal choices by customers (Chioveanu and Zhou 2013, Matějka and McKay 2015), they may often exhibit excessive inertia and avoid deviating from their established purchasing patterns even when it is in their best interest to do so (Bronnenberg et al. 2012).

Hortacsu et al. (2017) provide evidence that demographic factors such as income, education, and age can be associated with the notion of how customers deal with information and product choice. The authors demonstrate that households with lower income, less education, and a higher proportion of senior citizens exhibit greater inertia. On the other hand, Bronnenberg et al. (2015) found in a multi-category study that well-informed consumers are more likely to switch products to avoid paying a premium for branded items with the same efficacy as generics. Meanwhile, Johnson & Rehavi (2016) demonstrate that in markets with complex choice decisions (e.g., patients deciding on a C-section) experts can significantly influence the choices of less informed consumers.

This line of research suggests that the success of incremental innovations may be closely related to the presence in the market of customers who are knowledgeable about new product launches, have the ability or motivation to collect product effectiveness from unbiased sources and are more willing to switch usage based on engaging in cost-efficacy analysis. Prior research has also shown that certain observable customer characteristics are correlated with their interest and ability to acquire and interpret comparative product efficacy. And when it's the case, they choose more effective incremental innovations over alternatives.

**Empirical Method**

Since we do not directly observe customer-specific knowledge levels of products in this category, we are left with using indirect measures. We employ a linear model to estimate the effect of various proxies for customer knowledge available to us (farm size, customer age, schooling, source of product recommendation, source of financing) both as main effects and interacting with the two types of innovation (radical or incremental, versus generics) on market shares, controlling for the set of controls in the prior models. Contrary to the prior models, the unit of observation is a product purchase by region by year by farmer profile. This results in 46,077 observations. In the Web Appendix, we provide details on (a) the precise definition of each proxy for knowledge along with our expectation of the result, (b) the structure of this new customer-view of the data (as opposed to the product-view utilized up to now), and (c) the model specification.

**Results**

**Table 8** shows the results by initially presenting each customer knowledge proxy variable separately (column 1 to 5) and subsequently aggregating all the factors (column 6) into one single measure added as percentiles. We find that in this specification price coefficients are positive suggesting endogeneity. Therefore, we estimate this model using a 2SLS approach using the global pesticides price index as an instrument for price. Next, we discuss the parameter estimates of customer knowledge variables.

**Farm Size (column 1)** Larger farms have larger share of incremental innovations ($\beta_4^{(1)}$ = .051, $p < .01$) than smaller farms. A smaller positive correlation is also observed for radical innovations ($\beta_5^{(1)}$ = .037, $p < .01$). Our contention is that larger farms are professionally operated by customers with more financial incentives and resources to inform themselves.

**Customer's Age (column 2)** We find that younger farmers, more open to novelty, purchase more incremental innovations ($\beta_4^{(2)}$ = .150 $p < .05$) compared to generics, but not radical innovations.

**Educational Background (column 3)** More educated farmers are significantly more likely to purchase radical innovations ($\beta_5^{(3)}$ = .116, $p < .01$), and there is also a marginally significant tendency for them to buy incremental innovations ($\beta_4^{(3)}$ = .119, $p < .1$). This suggests that education leads farmers to learn the advantages of innovative products versus generics.

**Recommendation Sources (column 4)** The coefficients for independent recommendations are not statistically significant for either incremental or radical innovations.

**Independent Financing (column 5)** Farmers who use independent financing are more likely to purchase products ($\beta_3^{(5)}$= .150, p < .01), but not necessarily innovations.

**Composite Index (column 6)** Constructed by adding percentiles (see Web Appendix), we choose to include all factors irrespective of their piecewise statistical significance to ensure comprehensive representation and to mitigate a potential variable selection bias. The final column of Table 8 showcases the outcome of our model when incorporating this composite index. Notably, we find that more knowledgeable farmers, based on five proxies, are associated with higher purchases of incremental innovations ($\beta_4^{(6)}$ = .083, p < .01). And this relationship is considerably larger than for radical innovations ($\beta_5^{(6)}$ = .058, p < .01). Taken together, we find partial evidence for more knowledgeable customers, based on observable proxies, purchasing more incremental innovations, arguably, because they can better judge product (price) efficacy.

Insert Table 8 here.

## Conclusion, Caveats, and Future Research

Research and development of new products is a critically important marketing function. However, in many mature R&D-intensive industries, market share outcomes often fail to sustain the financial returns required from high R&D investments in pursuing completely new technologies. This situation strains firms and incentivizes them to find alternative paths rather than attempting to create the next blockbuster product. This paper is intended to study the alternative to this approach, namely incremental innovations, particularly for nondominant firms who are the ones most affected by the diminishing returns of major R&D investments towards radical innovations. It's important to note that we did not intend to compare the success of radical innovations versus incremental innovation in general, regardless of the type of firm . Using a unique dataset in the crop science industry, covering multiple firms, multiple innovation strategies, multiple product launches in 6 years, we empirically estimate multiple models to explain the drivers of sales and market share gains.

First, we confirm that incremental innovations by nondominant manufacturers systematically capture more market share than when they employ radical innovations. We borrow from the relevant literature to argue that this result is at least in part due to the higher bar necessary to, not just create radical innovations, but also market them. Nondominant companies often don't have the resources that dominant companies have in order to successfully launch radical innovations. This finding is significant because the R&D investments and development time required for incremental innovations are considerably lower than those for patented products, yet they still produce differentiated products compared to generics (e.g., Pushpakom et al., 2019). Second, using field data we find that incremental innovations capture market share to the extent that they are observably more (cost) effective. This might seem like an obvious finding, but the marketing literature is full of examples where this is not the case. Interestingly, we find that radical innovations don't show the same relationship with efficacy. This is in line with past research (e.g., Bronnenberg et al., 2015; Hermosilla & Ching, 2023) as demand can be skewed by the market assets of dominant companies (Sorescu et al. 2003). The lesson here is that incremental innovations are not a ubiquitous solution. To sustain growth in a competitive environment, these innovations should be objectively more effective as a way to overcome their lower market assets (e.g., distribution, brand equity) compared to radical innovations often launched by well-known and resourceful companies.

After obtaining these results, we studied factors that could catalyze the success of incremental innovations by nondominant firms. Our post-hoc analysis reveals several factors related to the success of incremental innovations in the context we investigated. We find that innovations gaining more market share are associated with research done in close proximity to customers, and that being the developer of the active ingredient does not result in any measurable advantage. This suggests that successful incremental innovations are those where managers tailor their products to meet specific local market needs rather than relying on proprietary active ingredients. Investing

Finally, we observe various characteristics of a sample of 19,000 business customers (farmers) as well as their purchases over the course of six years. Prior research has highlighted the role of customer knowledge in the choice between branded and generic products, demonstrating that more informed customers tend to make optimal choices (Bronnenberg et al. 2015, Hortacsu et al. 2017). Our findings reveal that the more informed the customer—e.g., being younger, and managing larger farms—the more likely they are to purchase incremental innovations.

***Generalization***

While our research is focused on the crop protection market, the insights we have uncovered are applicable to several other R&D-intensive industries. One such industry with significant similarities in product development, regulatory aspects, and marketing is the pharmaceutical industry. Like our context, pharmaceutical companies face challenges regarding diminishing R&D returns and the complexities of new product development. The implications drawn from our research can be almost directly translated to pharmaceuticals. In fact, there is a substantial body of research in pharmaceutical literature discussing incremental innovations and their integral role in manufacturers' strategies (Chandon 2004, Murteira et al. 2013, Pushpakom et al. 2019). However, to the best of our knowledge, our study is the first to compare these kinds of innovations in a closed setting, examining the complete market landscape.

Additionally, the insights from our research can also be translated to other knowledge-intensive and innovation-based industries, as described by Sorescu et al. (2003). Our study highlights that a critical factor for product success is the value brought to the customer—specifically, cost-effectiveness—rather than the magnitude of investment in R&D. Although the process of creating incremental innovations is beyond the scope of our study, we suspect that the main source of innovation may lie in how marketing collaborates with R&D to create these products. While developing new technologies often involves a strenuous process of trial and error, an exclusive focus on technological advancement can lead companies to lose sight of the value being generated for the customer. In contrast, when companies aim to create new products using already available technologies, they must prioritize customer needs over the technology itself.

***Implications for Marketing Practice***

For nondominant manufacturers, our research highlights substantial opportunities to leverage incremental innovations as a means to gain market share from both generics and radical innovations. Nondominant firms can benefit from looking beyond their existing portfolios to develop new products using available technologies. This requires building broader capabilities to identify and modify active ingredients, experimenting with new mixtures, and altering molecules to create innovative products that offer superior cost-effectiveness to customers.

However, success is not guaranteed by merely reformulating existing products; it necessitates delivering higher price-efficacy to customers. Nondominant firms must focus on understanding customer needs and preferences, ensuring that their innovations provide tangible value by being both more effective and less costly. On that note, being physically close helps. By prioritizing customer value over technological advancement alone, nondominant firms can overcome challenges related to lower brand recognition and compete more effectively against dominant manufacturers. This customer-centric approach allows them to be more agile and responsive to market needs, reducing reliance on extensive R&D investments and lengthy development timelines associated with radical innovations.

***Limitations and Future Research***

Our research methodology has certain limitations that warrant acknowledgment. Specifically, we do not examine internal factors within firms (e.g., portfolio strategy, budget allocation) that could influence the choice of innovation adopted.

Additionally, our dataset is primarily focused on a single R&D-intensive industry. While we are confident that our results are applicable to adjacent industries with similar characteristics, we cannot claim that our findings are generalizable to industries that are less R&D-intensive or significantly different in nature. Future research should aim to broaden the scope by including other industries to evaluate the generalizability of these findings.

Moreover, the backdrop of our research is set in an industry currently facing diminishing returns from R&D investments. This scenario raises questions about the viability of incremental innovation at different phases of industry maturity. Indeed, we believe that the effectiveness of incremental innovations may vary depending on the technological maturity of the market (Banbury and Mitchell 1995). We advocate for future research to explore these aspects, aiming to provide a more nuanced understanding of the benefits and drawbacks of incremental innovations.

In conclusion, when it comes to innovation in high R&D-intensive industries, radical innovation may not be the only viable strategy. Incremental innovations can, under the right circumstances, be a valuable addition to a firm's new product development portfolio.

# Tables

**Table 1: Manufacturers Characteristics**

| Manufacturers | Global Market Share (%) | Local Market Share (%) | R&D Investments (% of Ebitda) | Total Assets (Million USD) | Categorization accordingly to Chandy et al. (2003) |
|---|---|---|---|---|---|
| Syngenta | 17% | 21% | 36% | 20,680 | Dominant |
| Bayer | 14% | 27% | 43% | 92,245 | Dominant |
| BASF | 12% | 10% | 63% | 97,588 | Dominant |
| Corteva | 11% | 9% | 46% | 112,964 | Dominant |
| Adama | 6% | 5% | 13% | 4,883 | Nondominant |
| Sumitomo | 5% | 4% | 66% | 25,830 | Nondominant |
| FMC | 5% | 5% | 23% | 9,206 | Nondominant |
| UPL | 4% | 10% | 11% | 3,139 | Nondominant |
| Rest of the market | 26% | 9% | N/A | N/A | Nondominant |

**Table 2: Descriptive Statistics of the Dataset**

| | Incremental Innovations | | | | Radical Innovations | | | | Generic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min. | Max. | Mean | Std. Dev. | Min. | Max. | Mean | Std. Dev. | Min. | Max. |
| Sales (Metric Tons) | 60.41 | 166.76 | .01 | 3334.84 | 32.74 | 128.30 | .01 | 7125.97 | 45.40 | 130.35 | .01 | 2579.45 |
| Sales (Area Treated) | 65.05 | 132.88 | .06 | 2434.45 | 70.82 | 166.93 | .06 | 4531.30 | 41.76 | 83.92 | .06 | 2169.00 |
| Price (per kg) | 26.22 | 25.30 | 2.66 | 146.44 | 56.02 | 69.44 | 2.39 | 688.84 | 18.49 | 33.87 | 1.72 | 497.68 |
| Price (per ha) | 11.56 | 6.37 | .30 | 43.93 | 12.08 | 7.37 | .68 | 81.04 | 7.23 | 5.20 | .27 | 97.65 |
| Outlets | 3.16 | 3.92 | 1.00 | 58.00 | 3.44 | 4.70 | 1.00 | 81.00 | 2.38 | 2.97 | 1.00 | 45.00 |
| Products | 58 | | | | 176 | | | | 481 | | | |

*Note: Volumes are in millions*

**Table 3: Descriptive Statistics Efficacy Dataset**

| | Incremental Innovations | | | | Radical Innovations | | | | Generics | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min. | Max. | Mean | Std. Dev. | Min. | Max. | Mean | Std. Dev. | Min. | Max. |
| Efficacy (Percentile) | 49.86 | 29.41 | 2.60 | 100.00 | 44.68 | 33.78 | .00 | 100.00 | 19.10 | 19.11 | .00 | 55.11 |
| Price-Adjusted Efficacy | 6.47 | 3.31 | .55 | 47.12 | 5.26 | 3.39 | .50 | 40.35 | 5.28 | 3.84 | .13 | 28.56 |
| Product Age | 4.85 | 2.60 | .00 | 11.00 | 7.96 | 3.26 | .00 | 14.00 | 7.88 | 3.28 | 1.00 | 14.00 |
| Sales in Metric Tons | 61.21 | 184.87 | .01 | 3334.84 | 32.96 | 77.11 | .01 | 1830.60 | 34.44 | 118.40 | .00 | 1785.28 |
| Sales in Area Treated | 86.16 | 166.97 | .06 | 2434.45 | 95.11 | 196.54 | .07 | 4531.30 | 63.56 | 142.24 | .13 | 2169.00 |
| Price per kg | 34.32 | 28.48 | 4.57 | 146.44 | 54.63 | 47.83 | 3.17 | 300.43 | 27.53 | 20.36 | 4.76 | 130.52 |
| Price per ha | 11.53 | 5.10 | 1.35 | 43.93 | 12.87 | 7.50 | 1.05 | 50.60 | 6.30 | 2.69 | 1.53 | 34.73 |
| Number of outlets | 3.85 | 4.69 | 1.00 | 58.00 | 4.37 | 5.56 | 1.00 | 81.00 | 3.08 | 3.75 | 1.00 | 34.00 |
| Number of products | 11 | | | | 31 | | | | 7 | | | |

*Note: Product Age is 0 when the product was sold the same year it was registered.*

**Table 4: Effect of Type of Innovation on Sales and Market Share**

| | *Dependent variable:* | |
|---|---|---|
| | Volume Sales † | Market Share †† |
| | (1) | (2) |
| Incremental Innovation | .150$^{**}$ | -.098$^{**}$ |
| | (.063) | (.044) |
| Radical Innovation | .122$^{***}$ | -.049$^{**}$ |
| | (.035) | (.024) |
| Nondominant Manufacturer | -.259$^{***}$ | -.123$^{***}$ |
| | (.030) | (.022) |
| Nondominant Manufacturer x Incremental Innovation | .254$^{***}$ | .238$^{***}$ |
| | (.070) | (.049) |
| Nondominant Manufacturer x Radical Innovation | .141$^{***}$ | -.014 |
| | (.044) | (.032) |
| Price † | -.795$^{***}$ | |
| | (.011) | |
| Price †† | | .019$^{*}$ |
| | | (.011) |
| Distribution † | 1.249$^{***}$ | |
| | (.008) | |
| Distribution †† | | .985$^{***}$ |
| | | (.007) |
| Product Age † | -.299$^{***}$ | |
| | (.014) | |
| Product Age †† | | -.001 |
| | | (.011) |
| Patent Cliff | -.198$^{***}$ | -.057$^{***}$ |
| | (.026) | (.020) |
| Fungicide | .198$^{***}$ | -.022 |
| | (.027) | (.019) |
| Insecticide | -.174$^{***}$ | .021 |
| | (.023) | (.016) |
| Lagged Volume Sales † | .162$^{***}$ | |
| | (.004) | |
| Lagged Market Share †† | | .124$^{***}$ |
| | | (.005) |
| Constant | 4.055$^{***}$ | .113$^{***}$ |
| | (.060) | (.027) |
| Observations | 24,614 | 24,614 |
| $R^2$ | .635 | .550 |

*Note 1:* $^{*}$p<.1; $^{**}$p<.05; $^{***}$p<.01
*Note 2:* † Variables are log-transformed
*Note 3*: † † Variables are centered log ratio

**Table 5: Type of Innovation and Efficacy Impact on Product Market Share**

| | *Dependent variable:* | |
|---|---|---|
| | Market Share † | |
| | (1) | (2) |
| Incremental Innovation | .020 | -.027 |
| | (.045) | (.040) |
| Radical Innovation | -.081** | -.059* |
| | (.038) | (.034) |
| Efficacy † | .105*** | |
| | (.030) | |
| Efficacy † x Incremental Innovation | .106* | |
| | (.055) | |
| Efficacy † x Radical Innovation | -.073** | |
| | (.036) | |
| Price-Adjusted Efficacy † | | .101*** |
| | | (.030) |
| Price-Adjusted Efficacy † x Incremental Innovation | | .129** |
| | | (.051) |
| Price-Adjusted Efficacy † x Radical Innovation | | -.099*** |
| | | (.036) |
| Price † | -.047 | |
| | (.070) | |
| Price † x Incremental Innovation | -.262*** | |
| | (.085) | |
| Price † x Radical Innovation | .037 | |
| | (.075) | |
| Distribution † | .990*** | .986*** |
| | (.009) | (.009) |
| Product Age † | .023 | .030 |
| | (.021) | (.019) |
| Patent Cliff | -.092*** | -.105*** |
| | (.023) | (.023) |
| Fungicide | .019 | .029 |
| | (.021) | (.020) |
| Lagged Market Share † | .116*** | .117*** |
| | (.007) | (.007) |
| Constant | .214*** | .193*** |
| | (.041) | (.037) |
| Observations | 9,795 | 9,795 |
| $R^2$ | .601 | .600 |

*Note 1:* *p<.1; **p<.05; ***p<.01
*Note 2:* † Variables are centered log ratio

**Table 6: Comparison between Parameters of Interest in Models with Lags and with IVs**

| | **Lag controls** | | **2SLS + IV** | |
|---|---|---|---|---|
| **Variable of interest** | Coef. | Std. Er. | Coef. | Std. Er. |
| H1 - *Dependent Variable:* Volume Sales | | | | |
| Incremental Innovation | .150** | (.063) | .159* | (.090) |
| Nondominant Manufacturer | -.259*** | (.030) | -.306*** | (.039) |
| Nondominant Manufacturer × Incremental Innovation | .254*** | (.070) | .513*** | (.102) |
| Price | -.795*** | (.011) | -.825*** | (.012) |
| H1 - *Dependent Variable:* Market Share | | | | |
| Incremental Innovation | -.098** | (.044) | -.171** | (.067) |
| Nondominant Manufacturer | -.123*** | (.022) | -.154*** | (.029) |
| Nondominant Manufacturer × Incremental Innovation | .238*** | (.049) | .447*** | (.075) |
| Price | .019* | (.011) | .012 | (.011) |
| H2 - *Dependent Variable:* Market Share | | | | |
| Incremental Innovation | .020 | (.045) | -.035 | (.050) |
| Efficacy | .105*** | (.030) | .104*** | (.035) |
| Efficacy × Incremental Innovation | .106* | (.055) | .146** | (.059) |
| Price | -.047 | (.070) | .076 | (.112) |
| Price × Incremental Innovation | -.262*** | (.085) | -.482*** | (.135) |
| H2 - *Dependent Variable:* Market Share | | | | |
| Incremental Innovation | -.027 | (.040) | -.027 | (.043) |
| Price-Adjusted Efficacy | .101*** | (.030) | .093*** | (.033) |
| Price-Adjusted Efficacy × Incremental Innovation | .129** | (.051) | .170*** | (.058) |

**Table 7: Purchase Characteristics by Customer Profile**

| | *Dependent variable:* |
|---|---|
| | Market Share † |
| Nondominant Manufacturer | -.757*** |
| | (.276) |
| Local Product | -.563*** |
| | (.186) |
| Local Product × Nondominant Manufacturer | .832*** |
| | (.198) |
| Active Ingredient Creator | .114 |
| | (.218) |
| Active Ingredient Creator × Nondominant Manufacturer | -.273 |
| | (.227) |
| Active Ingredient Age † | .711*** |
| | (.215) |
| Active Ingredient Age † × Nondominant Manufacturer | .346 |
| | (.285) |
| Price † | -.083** |
| | (.038) |
| Distribution † | .977*** |
| | (.018) |
| Fungicide | -.325*** |
| | (.068) |
| Insecticide | -.031 |
| | (.057) |
| Lagged Market Share † | .132*** |
| | (.013) |
| Constant | .677** |
| | (.270) |
| Observations | 2,835 |
| $R^2$ | .598 |

*Note 1:* *p<.1; **p<.05; ***p<.01
*Note 2:* † Variables are centered log ratio.

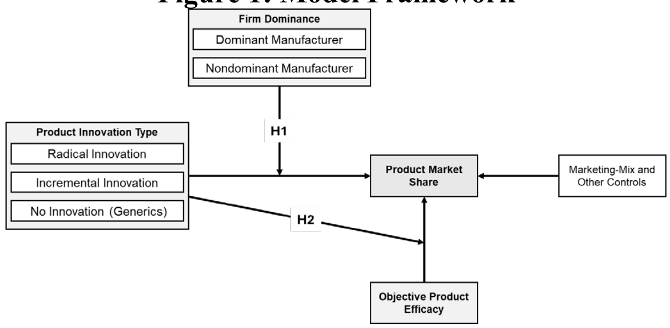
## Table 8: Product Strategy and Customer Profile Effect on Product Sales

| | *Dependent variable:* Market Share † | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | |
| | Estimates | Std. Errors | Estimates | Std. Errors | Estimates | Std. Errors | Estimates | Std. Errors | Estimates | Std. Errors | Estimates | Std. Errors |
| Incremental Innovation | .334*** | (.023) | .336*** | (.023) | .345*** | (.023) | .341*** | (.024) | .358*** | (.038) | .340*** | (.023) |
| Radical Innovation | .313*** | (.024) | .319*** | (.024) | .327*** | (.024) | .323*** | (.024) | .327*** | (.032) | .322*** | (.024) |
| Farm Size † | .004 | (.006) | | | | | | | | | | |
| Farm Size † × Incremental Innovation | .051*** | (.011) | | | | | | | | | | |
| Farm Size † × Radical Innovation | .037*** | (.007) | | | | | | | | | | |
| Customer Age Inverted † | | | .064* | (.033) | | | | | | | | |
| Customer Age Inverted † × Incremental Innovation | | | .150** | (.061) | | | | | | | | |
| Customer Age Inverted † × Radical Innovation | | | .044 | (.041) | | | | | | | | |
| Schooling † | | | | | -.025 | (.036) | | | | | | |
| Schooling † × Incremental Innovation | | | | | .119* | (.065) | | | | | | |
| Schooling † × Radical Innovation | | | | | .116*** | (.044) | | | | | | |
| Independent Recommendation † | | | | | | | -.035 | (.024) | | | | |
| Independent Recommendation † × Incremental Innovation | | | | | | | .036 | (.043) | | | | |
| Independent Recommendation † × Radical Innovation | | | | | | | .024 | (.030) | | | | |
| Independent Financing † | | | | | | | | | .150*** | (.020) | | |
| Independent Financing † × Incremental Innovation | | | | | | | | | -.022 | (.037) | | |
| Independent Financing † × Radical Innovation | | | | | | | | | -.009 | (.025) | | |
| Composite Index † | | | | | | | | | | | .021 | (.015) |
| Composite Index † × Incremental Innovation | | | | | | | | | | | .083*** | (.027) |
| Composite Index † × Radical Innovation | | | | | | | | | | | .058*** | (.018) |
| Dominant Manufacturer | -.137*** | (.014) | -.137*** | (.014) | -.139*** | (.014) | -.139*** | (.014) | -.137*** | (.014) | -.139*** | (.014) |
| Price † | -2.317*** | (.117) | -2.315*** | (.117) | -2.338*** | (.117) | -2.333*** | (.117) | -2.299*** | (.117) | -2.330*** | (.117) |
| Distribution † | .516*** | (.009) | .512*** | (.009) | .510*** | (.009) | .509*** | (.009) | .516*** | (.009) | .514*** | (.009) |
| Product Age † | -.500*** | (.026) | -.501*** | (.026) | -.508*** | (.026) | -.507*** | (.026) | -.498*** | (.026) | -.504*** | (.026) |
| Patent Cliff | -.209*** | (.015) | -.210*** | (.015) | -.212*** | (.015) | -.213*** | (.015) | -.212*** | (.015) | -.210*** | (.015) |
| Fungicide | -.577*** | (.027) | -.582*** | (.027) | -.587*** | (.027) | -.588*** | (.027) | -.581*** | (.027) | -.583*** | (.027) |
| Insecticide | -.087*** | (.013) | -.085*** | (.013) | -.086*** | (.013) | -.086*** | (.013) | -.085*** | (.013) | -.086*** | (.013) |
| Lagged Market Share † | .142*** | (.005) | .143*** | (.005) | .144*** | (.005) | .144*** | (.005) | .142*** | (.005) | .143*** | (.005) |
| Constant | .283*** | (.019) | .284*** | (.019) | .288*** | (.019) | .294*** | (.019) | .167*** | (.024) | .284*** | (.019) |
| Observations | 46,077 | | 46,077 | | 46,077 | | 46,077 | | 46,077 | | 46,077 | |
| $R^2$ | .123 | | .121 | | .121 | | .121 | | .123 | | .122 | |

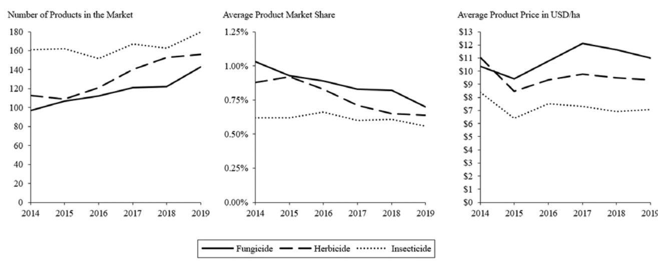
*Note 1:* *p<.1; **p<.05; ***p<.01
*Note 2:* † Variables are centered log ratio

# Figures

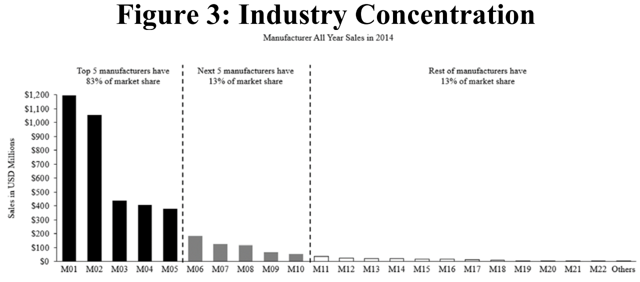
## Figure 1: Model Framework



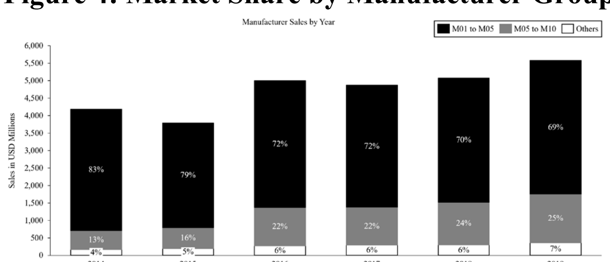

## Figure 2: Sector Trends at Product Level



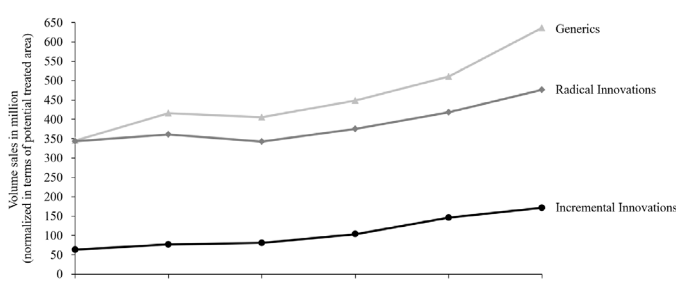

## Figure 3: Industry Concentration




## Figure 4: Market Share by Manufacturer Group




## Figure 5: Sales Volume Growth by Product Development Strategy



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