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# Zooming in or zooming out: Entrants' product portfolios in the nascent drone industry

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## Abstract

**Research Summary:** Faced with demand uncertainty and heterogeneity in a nascent industry, entrants often consider how many customer segments to serve by tailoring the usage breadth of their product portfolios. Portfolio usage breadth is the extent to which products in a portfolio collectively span distinct customer segments. We suggest that when entrants have use experience in contexts that are potential users of the new product, their portfolios exhibit low usage breadth, due to demand-oriented cognition and knowledge. The relationship is stronger for diversifying entrants relative to startups. The empirical context is the U.S. commercial drone industry, wherein entrants need to adapt their product portfolios for five robust and distinct customer segments of photography, short-distance inspection, long-distance surveying, agriculture, and aerial supply chain management.

**Managerial Summary:** New industries often serve multiple customer segments, each with different preferences. Entrants can either launch products catering to the specific preferences of customers in a small number of segments or launch products targeting numerous segments. Evidence from the U.S commercial drone industry shows that when entrants have experience in one of the customer segments adopting the new industry's product, they tend to introduce products targeting fewer segments. By recognizing the impact of prior experiences on product portfolio development, entrepreneurial

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leaders gain insights to assess whether their cognitive alignment with a customer segment has restricted their broader exploration of the demand environment, or whether their superior demand knowledge about a customer segment has created a competitive advantage.

**KEYWORDS**

entry strategy, nascent industries, pre-entry experience, product portfolio, user innovation

## 1 | INTRODUCTION

Entry strategy in a nascent industry can shape how entrant firms compete and capture value. For entrants in industries faced with heterogeneous demand across various customer segments (Adner & Levinthal, 2001; Klepper & Thompson, 2006), a key component of entry strategy is which customer segments to target with their product portfolios. Entrants can shape their product portfolios' usage breadth so that their products collectively span few or numerous distinct customer segments. Low usage breadth portfolios consist of products that target a single or few customer segments, whereas high usage breadth portfolios consist of products that collectively target numerous segments.

Despite the strategic and performance implications of portfolio usage breadth, the pervasive demand uncertainty in a nascent industry complicates decision-making about product portfolios. To align products with customer preferences, entrants often make costly investments to offer technical designs pertaining to each segment (Baldwin & Clark, 2000; Helfat & Raubitschek, 2000). However, in an uncertain nascent industry, they face insufficient demand knowledge about customers' evolving preferences (von Hippel, 1986). Simultaneously, since value capture hinges on addressing customers' preferences, entrants' revenue is often tied to their portfolio usage breadth (Siggelkow, 2003). Further, entrants' competitive dominance can arise from early commitment to lucrative segments (Sorenson, 2000). Yet, demand uncertainty implies insufficient knowledge about which segments exist and how each segment's commercial viability evolves, thereby making revenue estimations difficult.

Although scholars have examined interrelated aspects of entry strategy such as whether and when to enter (e.g., King & Tucci, 2002; Mitchell, 1989) and technology choices (e.g., Benner & Tripsas, 2012; Eggers, 2012; Kapoor & Furr, 2015; Martin & Mitchell, 1998), antecedents of product portfolio strategies in nascent industries remain understudied. To address this research gap, this article explores entrants' pre-entry experience as an influential antecedent. On the premise that demand uncertainty can complicate decision-making about product portfolios, we suggest that entrants with different experiences can in turn exhibit heterogeneity in their portfolio usage breadth.

One relevant experience is pre-entry "use experience," defined as whether an entrant was a user in a context where the nascent industry's product can fulfill needs. Cognitively, use experience situates an entrant in a demand-oriented context (Baldwin, Hienerth, & Von Hippel, 2006; Shah & Tripsas, 2007), narrowing its cognitive frame in identifying and evaluating customer segments. Further, use experience privileges an entrant with demand knowledge about segments from which it emerges (Gambardella, Raasch, & von Hippel, 2017), thereby impacting knowledge acquisition costs about segments. Overall, due to the interplay between demand-oriented cognition and knowledge, we suggest that entrants with use experience introduce low usage breadth portfolios. On the other hand, entrants without use experience are neither affiliated with a segment-specific cognitive frame nor have access to specialized demand knowledge, which leads to their high usage breadth portfolios.

Another distinction in experience is between diversifying entrants and entrepreneurial startups, which conditions the link between pre-entry use experience and product portfolios. Diversifying entrants and startups often differ in organizational resources and routines (Helfat & Lieberman, 2002; Klepper & Simons, 2000). When these pre-existing resources are coupled with use experience, diversifying entrants become more focused than startups in identifying and evaluating opportunities. Thus, the likelihood of offering a low breadth portfolio strengthens for diversifying entrants.

The empirical context is the U.S. commercial drone manufacturing industry from 2014 to 2016. Distinct customer segments of photography, short-distance inspection, long-distance surveying, agriculture, and aerial supply chain management have adopted commercial drones. During the timeline of the study, the industry faced considerable demand uncertainty, due to limited consensus about which segments would endure and what customers' preferences were. Regulatory requirements in Section 333 of the 2012 Federal Aviation Administration (FAA) Modernization and Reform Act enable comprehensive data collection about drone models and their intended usages.

Statistical results under different specifications corroborate our hypotheses. Supplement analyses illuminate key mechanisms. First, consistent with the mechanism that use experience directs entrants' cognition and knowledge, we demonstrate the link between entrants' background in a particular segment and whether their products are used only in that segment. Entrants' reaction to competition and market size signals further indicates the cognition and knowledge link: instead of entry deterrence due to competition or entry inducement due to increasing market size, entrants' experience in a segment continues to underpin their entry. Second, in line with the mechanism that use experience privileges entrants with demand knowledge, we find that when entrants with use experience offer products targeted at their past segment, they generally outperform in segment-specific market share.

This article provides novel theoretical contributions. First, usage breadth of an entrant's product portfolio is an important and understudied aspect of entry strategy. By integrating user innovation and entry strategy research streams, we unpack pre-entry antecedents of portfolio usage breadth. Second, we shed light on entrants' strategic decision making in the face of demand uncertainty pervading a nascent industry. Low usage breadth portfolios of entrants with use experience stem from experience-based narrow framing of the decision space, possibly at the expense of bypassing uncertain unknown opportunities. However, broader exploration in absence of use experience links to a more systemic tackling of knowledge shortage in many uncertain unfamiliar segments. Taken together, diversity in approaches can aggregate to a collective knowledge base and reduce industry-wide uncertainty, despite various firm-level targeted customer segments, portfolio usage breadth, and resultant performance.

# 2 | CONCEPTUAL BACKGROUND

## 2.1 | Demand heterogeneity across customer segments

The demand environment for a product refers to customers' preferences for different functional attributes, maximum willingness to pay for each attribute, and minimum performance threshold. Demand heterogeneity exists when customers vary in the relative importance that they assign to each attribute, implying differential willingness to pay and performance thresholds (Adner & Levinthal, 2001). Demand heterogeneity leads to persistent distinct customer segments, across which customers' functional and price preferences differ (Klepper & Thompson, 2006). For example, laser customer segments span industrial processes, medical imaging, surgery, and fiber optics. Each laser customer segment prefers different light emission wavelengths, power, and portability (Conti, Gambardella, & Novelli, 2019). Similarly, customer segments in the software security industry diverge in preferences for network security, data protection, and antivirus features (Gambardella & Giarratana, 2013).

## 2.2 | Product portfolio usage breadth

Faced with heterogeneous demand across customer segments, entrants' product portfolios can differ in their usage breadth. Usage breadth is the extent to which products in a portfolio collectively span distinct customer segments. With low usage breadth portfolios, entrants target a single or small number of customer segments via one or few constituent products that closely overlap in the small number of targeted segments. With high usage breadth portfolios, entrants target multiple distinct customer segments, although high portfolio breadth can be achieved in two ways. On the one hand, a high breadth portfolio can comprise one or multiple products overlapping in the many targeted segments. On the other hand, these portfolios can include multiple products that each span fewer segments and exhibit less overlap. As an illustration, a portfolio targeting four customer segments can consist of one product targeting four segments, or four products each targeting one distinct segment. Both portfolios have the same high usage breadth but approach it differently at the product-level.

## 2.3 | Constructing a product portfolio from individual products

Since a product portfolio consists of one or more products, product-level choices aggregate to construct portfolios with varying levels of usage breadth. At the product level, to offer functional features and performance thresholds that meet customer preferences, entrants can adapt a product's technical design. A technical design refers to how embedded or modular components are linked in an architecture and form a product (Baldwin & Clark, 2000). For example, laser firms can change lasing material to meet preferences across segments. Semiconductors enable long laser wavelength in fiber optics, whereas $CO_2$ provides low power in laser surgical applications (Klepper & Thompson, 2006). Similarly, in semiconductors, technical designs of analog, discrete, memory, and logic chips address different preferences across data processing, storage, and consumer devices segments (Uzunca, 2018).

Thus, for each product, the number of targeted segments is intertwined with the extent to which its technical design is tailored to specific segments.[1] The fewer the targeted segments in a product, the more specialized the product's technical design is to the preferences of those

[1]Two assumptions precede the link between a product's technical design and its targeted segments. First, although it may be possible to use a product designed for a specific segment in another segment, the specialized components and

segments. Tailoring a product's technical design to a segment requires access to demand knowledge of customer preferences in that segment (Baldwin & Clark, 2000). Hence, when a product targets a small number of segments, entrants need specialized demand knowledge about each segment. This demand knowledge can guide a search for technical knowledge about how to embed customers' preferred attributes in a product's design. By contrast, when a product targets several segments, its design is often above the performance threshold for those segments but may not necessarily reflect idiosyncratic preferences in any one segment. Entrants are then unlikely to require deep demand knowledge specific to multiple segments.

Overall, to alter usage breadth at the portfolio-level, the considerations at the technology-demand nexus aggregate across constituent products. For example, to offer a low usage breadth portfolio, entrants need demand and technical knowledge specific to the targeted segments. However, to offer a high usage breadth portfolio in which products' technical designs are largely agnostic to customer preferences in any segment, entrants are unlikely to draw on specialized knowledge for any segment.

## 2.4 | Product portfolios and uncertain demand in a nascent industry

Past studies have approximated the decision-making process about product portfolios with the following steps.[2] First, entrants often identify a list of customer segments that they perceive may adopt a new product (Gruber, MacMillan, & Thompson, 2008). Next, entrants apply their desired evaluation criteria and compare alternative product portfolios based on the identified segments (Baron & Ensley, 2006). Evaluation criteria can assess the costs of product development and knowledge acquisition for introducing the technical designs that meet preferences for their selected segments (Baldwin & Clark, 2000). Further, the evaluation criteria can consider the revenue generation potential (Siggelkow, 2003).

However, a nascent industry exhibits demand uncertainty, which implies partial knowledge about explicit and latent, functional and price preferences of current and emerging customer segments. Two aspects of demand uncertainty can complicate the above decision-making process. First, the nature and size of customer segments are often not fully known. Inventors may not foresee all the customer segments that a novel product ultimately targets (Rosenberg, 1982). It is after firms' diverse product offerings that new customer segments gradually emerge (Agarwal & Bayus, 2002). Thus, in addition to insufficient information to identify a complete list of customer segments, entrants need to assess whether a product portfolio can withstand fluctuations in the size of segments. Second, complete knowledge of customer preferences is often lacking. Due to limited interactions with the new product, customers cannot initially articulate their specific preferences (von Hippel, 1986). Thus, entrants find it difficult to ascertain which products' technical designs meet latent preferences in each segment.

In strategic decision making under uncertainty, the roles of experience-based cognitive frames (e.g., Gavetti & Levinthal, 2000) and knowledge (e.g., Helfat, 1997) are often

architecture make it inefficient for use in other segments. Second, despite generic products lacking segment-specific designs, there are customers who purchase them due to lower prices or preference to use add-on modifications.

[2]We acknowledge that this stylized decision-making process may be deliberate or implicit, pursued fully or partially. Further, at extreme uncertainty, gathering sufficient information about alternative trajectories may require commitment to one trajectory (Gans, Stern, & Wu, 2019). At other times, customer segments may not exist unless actors engage in imaginative formation of the opportunity landscape (Alvarez & Porac, 2020).

accentuated. Thus, within an uncertain demand environment that impedes complete optimization about product portfolios, our hypotheses link entrants' experiences to their decision-making process.

# 3 | HYPOTHESES

## 3.1 | The role of pre-entry use experience

Our primary focus is on pre-entry "use experience," defined as whether an entrant was a user in a context where a new product can fulfill needs. Before entering an industry, actors can accumulate use experience from activity in contexts that become potential users of a new product, regardless of a history of direct interaction with a new product. For instance, farming is a context in which drones are used to spray and monitor agricultural fields. Any farmer, regardless of their personal drone use, has use experience in crop spraying and field assessment. Similarly, an agricultural firm, regardless of its adoption of a drone, has use experience in farming tasks and understands farmers' needs.

Past studies have noted how pre-entry use experience shapes cognition and knowledge, which we use as building blocks for our logic. Because cognition is partly situated by the context around decision makers (Ocasio, 1997), use experience may shape a demand-oriented cognitive frame congruent with the segment from which an entrant emerged (e.g., Baldwin et al., 2006). For knowledge, use experience can facilitate accrual of demand knowledge, as "learning by using" suggests that "there are essential aspects of learning that are a function not of the experience involved in producing the product but of its utilization by the final user" (Rosenberg, 1982, p. 122). In entrants' product portfolio decision-making, the interplay of demand-oriented cognition and knowledge can condition the steps of identifying potential customer segments and then evaluating cost and revenue potential criteria.

In the first step, when identifying a list of customer segments under uncertainty, entrants tend to rely on cognitive interpretations of the demand environment (Grégoire & Shepherd, 2012). Each entrant's unique cognitive frame may then lead to identifying different market opportunities (Shane, 2000). Thus, due to their narrow demand-oriented cognition, entrants with use experience can be inattentive to all potential segments and identify fewer segments as the starting point of the process. For example, the range of identified customer segments can vary if entrants view drones as "flying robots," compared to a narrow cognitive interpretation as "flying cameras." The latter cognitive frame can filter out customer segments that draw on non-camera drone capabilities.

In the second step, when entrants assess alternative customer segments, diverging cognitive frames can lead to assigning different weights to evaluation criteria (Baron & Ensley, 2006). For example, managerial background favors profitability as an evaluation criterion, whereas engineers value scientific novelty (Gruber, Kim, & Brinckmann, 2015). Specific to entrants with use experience, demand-oriented cognition can lead to asymmetric emphasis on positive aspects of the few familiar customer segments. Cognitively, they may then overlook the revenue potential of other segments or downplay competition and uncertain viability of their selected segment.

Cost considerations reinforce the favorable evaluation of few segments. Access to resources and knowledge matching a customer segment's profile generally reduces pre-entry adjustment costs (e.g., Silverman, 1999). For example, surgeons know about health issues treated by lasers, surgical standards, and their peers' preferences, which may aid in adapting laser systems for surgical needs but no other segment (Katila, Thatchenkery, Christensen, & Zenios, 2017). Thus, due to access to demand knowledge, entrants with use experience are likely to evaluate the familiar segment as attainable, while appraising demand knowledge acquisition for numerous other segments as costly. Together, these steps direct entrants with use experience to identification and favorable evaluation of few segments, implying lower portfolio usage breadth.

The decision-making steps can unfold differently for entrants without use experience, due to their lack of demand-oriented cognitive frames or knowledge. First, when listing customer segments, these entrants may recognize demand heterogeneity, but do not privilege specific segments. Alternatively, demand-agnostic cognition may make them unaware of customer segmentation. In either case, they appear to consider numerous segments. In the second step, their evaluation criteria is often impartial. They can notice that targeting multiple segments may increase total revenue (Siggelkow, 2003), secure access to growing segments and compensate for shrinking ones (Eggers, 2012), or act as testing beds for customer feedback (Sorenson, 2000). Further, cost considerations may not deter high breadth, given entrants' two options in constructing portfolios. The less costly option involves products that do not cater to unique preferences in each segment, whereas the costly option of demand knowledge acquisition for targeted segments yields multiple products addressing preferences in segments.

**Hypothesis (H1).** *Entrants with pre-entry use experience are likely to introduce product portfolios with lower usage breadth.*

## 3.2 | The moderating role of diversifying entrants versus startups

We next examine the moderating role of whether entrants are diversifying entrants or startups. Diversifying entrants come from other industries to a nascent industry, utilizing firm-level experiences from user industries (Adams, Fontana, & Malerba, 2013). Startups draw on founder-level experiences as end users (Baldwin et al., 2006; Shah & Tripsas, 2007) or employees in user industries (Adams, Fontana, & Malerba, 2015). When immersed in user contexts, both exhibit demand-oriented cognitive frames and knowledge, yielding a low usage breadth portfolio, per H1. However, differences in organizational routines and resources can shift their decision-making about product portfolios.

When identifying potential customer segments, organizational routines of diversifying entrants may restrict opportunity cognition. Diversifying entrants often have communication and information processing routines that can inhibit the flow of unplanned information (Henderson & Clark, 1990; Joseph & Ocasio, 2012). Since these routines largely sustain preexisting operations, user diversifying entrants may pay less attention to the full range of possible segments. Compared to user startups that initially lack such routines, user diversifying entrants are likely to identify a shorter list of segments.

In evaluating identified customer segments, user diversifying entrants persist in considering a small number of segments. Cognitively, diversifying entrants typically have inelastic managerial beliefs about sources of value creation (Tripsas & Gavetti, 2000), resulting in a more favorable evaluation of a few familiar segments. By contrast, startups commonly face cognitive pressure to build a novel identity tied to the nascent industry (Santos & Eisenhardt, 2009) and its technological frontier (Khessina & Carroll, 2008). Thus, their evaluation criteria may at times favor novel segments.

Cost considerations also reflect differences in pre-existing resources of diversifying entrants and startups. In general, diversifying entrants have complementary resources in production, marketing, and distribution (Mitchell, 1989). For user diversifying entrants, these resources are often specialized to one customer segment, limiting fungibility and value to other segments (Levinthal & Wu, 2010). For example, the brand of an agriculture firm is valuable for selling agricultural drones but foreign for selling photography drones. Thus, although complementary resources and demand knowledge reduce adjustment costs of entry into few familiar segments, they do not foster increased breadth. By contrast, startups' limited firm-level resources are unlikely to shift the evaluative calculus.

Together, the mechanisms suggest a reinforced process of identifying a small number of customer segments and applying strict evaluation criteria for user diversifying entrants, relative to user startups.

> **Hypothesis (H2).** *Relative to startups with use experience, the likelihood of introducing lower usage breadth product portfolios is stronger for diversifying entrants with use experience.*

Without use experience that ties their cognition or knowledge to specific segments, entrants are likely to offer higher usage breadth portfolios, per H1. Targeting several customer segments can be attained via two types of portfolio configuration, which differ in cost. We suggest that the diversifying entrant versus startup dichotomy can be a contingency in shaping the composition of products in a high breadth portfolio, as these firms differ in tendencies to incur product development costs.

One type of high usage breadth portfolio comprises one or multiple products that are largely agnostic to customer preferences in any segment. Because products in this portfolio typically have features acceptable to, but not tailored for specific segments, entrants are unlikely to need specialized demand knowledge about any segment. Thus, in evaluating cost as a decision criterion, this portfolio enables avoiding a costly search to acquire demand knowledge about several segments. Compared to diversifying entrants, startups typically face resource constraints (Helfat & Lieberman, 2002). Not only do they lack ample financial capital, but also their inadequate initial resources and network access often restrict their subsequent knowledge accumulation and acquisition (Clough, Fang, Vissa, & Wu, 2019). Thus, non-user startups may be more inclined to offer the less costly product portfolio that does not require substantial commitment to acquiring demand knowledge about several segments.

> **Hypothesis (H3).** *Relative to diversifying entrants without use experience, the likelihood of introducing higher usage breadth portfolios (consisting of products agnostic to customer preferences in targeted segments) is stronger for startups without use experience.*

The other type of high usage breadth portfolio includes multiple products, each catering to customer preferences in respective segments. Here, the overall portfolio covers a broad range, whereas each product spans fewer less-overlapping segments. Increased usage breadth in this portfolio expands the number of segments for which demand knowledge is needed, so that customers' preferences can be embedded in each product's technical design. Arranging interdependent design, production, and distribution tasks for multiple products also increases costs. Overall, in entrants' evaluative calculus, the cost of demand knowledge acquisition and product development for this portfolio is high.

Lacking use experience, although entrants are unlikely to have internal demand knowledge about any specific segment, they may fill their demand knowledge gap from customers (Chatterji & Fabrizio, 2014), user communities (Jeppesen & Frederiksen, 2006), or more formal external sources (Capron & Mitchell, 2009). In contrast to startups, diversifying entrants have superior capital, complementary resources (Ganco & Agarwal, 2009; Klepper & Simons, 2000), and integrative product development capabilities (Helfat & Raubitschek, 2000; Moeen, 2017). Thus, non-user diversifying entrants may be more inclined to apply their greater resources to obtain demand knowledge specific to multiple customer segments, as they may find the costs more manageable.

> **Hypothesis (H4).** *Relative to startups without use experience, the likelihood of introducing higher usage breadth portfolios (consisting of multiple products each catering to customer preferences in targeted segments) is stronger for diversifying entrants without use experience.*

## 4 | DATA AND METHODS

### 4.1 | Industry description

The context is the U.S. commercial uncrewed aerial vehicles or drones manufacturing industry. Drones are heavier-than-air powered aerial vehicles that do not have a human operator onboard and have a sufficient degree of autonomy for the intended functionality (Clarke, 2014). Primitive pilotless aircrafts have been around for decades, originally in the military. After Nikola Tesla's 1898 patent for a remote-controlled (RC) device, RC planes became popular toys. Recently, advanced drones have entered civilian airspace for commercial uses that are neither weapons nor toys. The FAA notes 863,895 registered drones and 256,138 certified remote pilots in the United States in December 2021.

Two factors have led to the takeoff of commercial drones. First, the past decade has experienced major drone design and manufacturing advancements. Autonomous flight technology has benefitted from modern communication and navigation systems. Miniaturization of electronic components, spurred by the proliferation of smartphones and portable electronics, has fostered drone design. Availability of off-the-shelf electronic components and open-source drone communities have led to knowledge diffusion. Additive and computer-aided manufacturing have enabled rapid production.

Second, the sociopolitical aspects in the United States have become clearer. Although initially perceived as a weapon, proposals to use drones after Hurricane Katrina or for Amazon Prime air delivery have improved social perceptions. Further, collective action by firms, associations, public agencies such as NASA and DARPA, universities, and state and federal governments has resulted in regulations and infrastructure for safe flying of drones in the national airspace (Palubinskas & Minniti, 2020).

The commercial drone manufacturing industry is an appropriate setting to study usage breadth. First, diverse commercial segments such as filmography, inspection, geo-surveying, agriculture, and package delivery have employed drones (McKinsey, 2017; PwC, 2016). The contrasting customers' preferences and performed tasks across segments require adjustments in the technical design of drones. Thus, there could be drones that cater specifically to a subset of customers, in addition to drones that offer acceptable functions across a wide span of customers.

Second, for each segment, customers' preferences and drones' integration into the task workflow were initially unknown. The co-founder of Aeryon Labs, a drone startup, described the uncertainty as: "we saw that there were a lot of potential uses for UAVs, but we didn't know which ones would engage with the market" (Pachner, 2015). This uncertainty is reflected in diverging forecasts of industry experts about the market size, often ranging between \$12 billion and \$127 billion by 2021–2025 with different sub-estimates for segments (BI Intelligence, 2016; McKinsey, 2017; PwC, 2016).

## 4.2 | Sample of drone manufacturers

In 2012, U.S. Congress passed the FAA Modernization and Reform Act that mandated guidelines for the integration of drones into the U.S. airspace. Previously, flying a drone required an airworthiness certificate or a certificate of authorization, which involved a sporadic, lengthy, and costly review that was originally enacted for airplanes. Section 333 of the Act allowed customers to petition the FAA for exemptions from airworthiness certificates. Under the new law, customers seeking to commercially fly drones, referred to as petitioners, had to petition for drone models they intended to use and the intended usages, which the FAA reviewed and exempted.[3] Even if a previous exemption had been granted for a particular drone model, each petitioner had to file a new petition for that same model. Petitioners could also file amendments. In 2016, this process was replaced with "Part 107 Small UAS Rule," a blanket exemption for the commercial operation of any drone that met certain criteria.

Via the Section 333 process, the FAA authorized 5,543 exemptions and 863 amendments. The first petition was filed in January 2014 and exemptions were granted until August 2016. The regulatory documents enable comprehensive data collection about manufacturers whose drones were used commercially in the United States between 2014 and 2016. We use Section 333 exemption documents available to the public on the FAA website and construct a sample of drone models, manufacturers, and their associated uses. Online Appendix A1 contains three annotated Section 333 exemptions. From these exemptions, we have first extracted a complete list of drone models. We used industry reports, firm websites, and other public sources to identify the respective manufacturer of each model. Universities, the U.S. Army, and not-for-profit or government entities were excluded.

The sample consists of 230 manufacturers of 431 drone models.[4] Although the sample is based on FAA exemptions in the United States, firms are global. Specifically, 31.7% of sample firms are headquartered outside of the United States, such as in China (e.g., DJI) and Europe (e.g., Parrot, senseFly).

[3]While Section 333 applied to commercial drones, FAA implementation of the regulation had another component for recreational drones. Section 336 established the "Special Rule for Model Unmanned Aircrafts," which permitted individuals to fly "recreational" drones within certain physical dimensions without a special exemption.

[4]These numbers are slightly lower than the list of drones in the Section 333 exemptions. First, we dropped firms without verifiable founder history. Second, we dropped drone models for which the exemptions were not specific.

## 4.3 | Drone usage classification

Section 333 exemption documents specify how each petitioner intended to use each drone model, from which we extract information about usages associated with drone models. Three features of the Section 333 process point to the reliability of the data. First, petitioners were unlikely to misrepresent their intended usages or request usages incompatible with a drone. The purchase of commercial drones is capital-intensive (on average $18,000), and securing an exemption was critical to petitioners as it constituted the only legal means of commercial drone flight. Second, the FAA neither automatically approved all requested usages for a drone nor automatically approved every usage in which the drone could be employed.[5] Rather, the FAA based its decisions on technical manuals provided by petitioners. Third, petitioner-filed exemptions enable a "wisdom of the crowds" assumption, whereby multiple exemptions for each drone can increase the accuracy of our inference for each drone's usages.

Our classification follows four steps: (a) define usage segments, (b) map exemptions to usage segments, (c) aggregate exemption-level usage segments, and (d) validate the classification.

### 4.3.1 | Defining usage segments

We started with a complete list of industries adopting drones, shown in Column 2 of Table 1. Next, we classified these industries into five usage segments: photography and videography, short-distance inspection, long-distance surveying, precision agriculture, and aerial supply chain management, as listed in column 1 of Table 1. Two conditions enable classifying these diverse industries into five segments: common tasks performed by drones for multiple industries, and differences in technical specifications required to effectively perform those tasks.

First, drones perform common tasks across subsets of these industries. For example, videography for newsgathering, sport events, closed-set movies, and real estate promotions share common tasks. Tasks in insurance assessment and wind turbine and powerplant monitoring involve short-distance or vertical travel, whereas tasks in mapping mining sites, exploring oil & gas sites, and monitoring railroads involve long-distance travel. To identify common tasks, we relied on information from the FAA, the Association for Unmanned Vehicle Systems International (AUVSI), the Center for Study of Drones at Bard College, and industry reports (BI Intelligence, 2016; McKinsey, 2017; PwC, 2016).

Second, there are often technical specifications that make drones suitable for each task. A drone's flying range, cruise and max speed, endurance, flight altitude, autonomous capability, and weight-carrying capacity influence the types of tasks it can effectively perform. These attributes typically arise from design choices such as airframe architecture (fixed wing, multirotor), takeoff mode (vertical, runway), power (battery capacity and configuration), or navigation (autopilot, RC, GPS). Further, drones often differ in pre-installed and compatible payloads, such as cameras or sensors. Column 3 of Table 1 lists technical specifications and payload options utilized and preferred in each segment.

For example, drones utilized for photography typically move slowly to capture more detail. For inspection, drones often reach high altitudes and stay still in the air for steady observation.

[5]To verify this, we retrieved the original petitions for 100 random exemptions from regulations.gov, which is the document repository for U.S. Federal government agencies. Inspecting original communications between petitioners and FAA reveals 88% match between petitioners' requested usages and FAA's authorized usages in exemptions.

**TABLE 1** Drone usage segments

| Usage segment | Common applications/ industries | Common drone features/specifications | Sample keywords in dictionary |
|---|---|---|---|
| Professional photography and videography | Movie production<br>Events and sport<br>News and media<br>Nature and landscapes<br>Movie special effects<br>Real estate promotion | *Architecture*:<br>• Multi-rotor airframe<br>*Performance metrics*:<br>• Shorter endurance, range<br>• Ability to hover in place<br>*Valuable payloads*:<br>• High resolution cameras<br>• Image stabilizing gimbals | closed-set filming<br>film production<br>feature films<br>photojournalism<br>real estate<br>real property |
| Long-distance surveying | Pipeline inspection<br>Railroad inspection<br>Search and rescue<br>Security surveillance<br>Mining<br>Mapping<br>Oil and gas exploration<br>Wildlife and ecological monitoring | *Architecture*:<br>• Fixed-wing airframe<br>*Performance metrics*:<br>• Longer endurance, range<br>• Beyond visual line of sight (BVLOS)<br>*Valuable payloads*:<br>• LiDAR, laser-based systems<br>• Thermal and infrared sensors | pipeline<br>railroad<br>casualty site<br>reconnaissance<br>mining<br>land survey<br>forestry<br>solar farms<br>archeological |
| Short-distance inspection | Utilities inspection<br>Insurance assessment<br>Bridge inspection<br>Turbines<br>Gas and electric<br>Wind turbine<br>Flare stack<br>Petrochemical plants | *Architecture*:<br>• Rotary-wing airframe<br>*Performance metrics*:<br>• Shorter range<br>• Ability to hover in place<br>*Valuable payloads*:<br>• Thermal and infrared sensors<br>• Gas sensing and leakage sensors | turbine<br>building inspection<br>power plant<br>telecom tower<br>construction<br>property damage<br>structure inspection<br>flare stack |
| Precision agriculture | Field monitoring<br>Crop health assessment<br>Crop dusting and spraying | *Architecture*:<br>• Fixed wing airframe<br>*Performance metrics*:<br>• Longer endurance, range<br>• Faster max speed<br>*Valuable payloads*:<br>• Hyper- and multi-spectral sensors<br>• Liquid sprayers | agriculture<br>crop<br>farm |
| Aerial supply chain management | Retail parcel delivery<br>Inventory management | *Architecture*:<br>• Hybrid airframes<br>*Performance metrics*:<br>• Longer range<br>• Faster max speed<br>• Beyond visual line of sight (BVLOS)<br>*Valuable payloads*:<br>• Ability to lift and drop | delivery<br>inventory management<br>stockpile inventory |

Here, a multi-rotor airframe architecture enables hovering in place and quick elevation, while short-distance flight within a pilot's line of sight does not demand long battery life and autonomous navigation. By contrast, for long-distance surveying and agriculture, drones that can speedily scout large areas are suitable. Technically, drones with a fixed-wing airframe architecture are faster, while longer battery life and autonomous navigation can help with flying beyond visual line of pilot's sight. Supply chain and aerial delivery tasks typically require the ability to hover in place and fly long distances. Because multi-rotor and fixed wing airframes trade off vertical for horizontal flight, hybrid drones with multiple rotors mounted on the fixed wing airframes that blend both airframes are favored for supply chain.

Other examples relate to payloads. High-definition cameras, target tracking sensors, and image stabilization systems are valued in photography and videography. Inspection and surveying can benefit from thermal and infrared sensors that not only enable low visibility and night vision, but also identify overheating, electrical issues, or energy leakage. For some inspection tasks, chemical detection sensors can be useful. Many surveying tasks involve area mapping and 3D visualization, for which geo-tagged imagery or LiDAR is needed. Although thermal sensors are acceptable in precision agriculture, multi- or hyper-spectral sensors provide more accurate vegetation data. Payloads vary in weight, position, and signal interference with the navigation system, which need to be specifically accounted for in a drone's design. Overall, these examples show the importance of appropriately matching technical specifications of a drone to the nature of the task to efficiently meet customer preferences.

#### 4.3.2 | Mapping exemptions to usage segments

In the second step, we map the authorized uses in each Section 333 exemption document to our five usage segments. Exemption documents often list one or few specific authorized uses such as "aerial videography for closed-set filming," "aerial data for precision agricultural surveys," "conduct oil and gas platform inspections on land and over water," or "aerial photography for real estate, construction, insurance, utilities, and ecological preservation."

To link authorized uses to our five segments, we created a keyword dictionary. As an exploratory endeavor, we applied text analysis tools of topic models, n-gram, and text mining indices. We then manually inspected a random set of exemptions to revise the dictionary. Column 4 in Table 1 and Online Appendix A2 list the keywords. If an exemption has any of the keywords, the drone listed in the exemption is marked as used in that segment. We did not use exemptions that did not specify how usages related to many drones or listed general uses such as "aerial data collection" or "aerial imaging."

#### 4.3.3 | Aggregating exemption-level usage segments

As the third step, we aggregate the exemption-level segments. The usage mapping in step 2 is at the exemption level, whereas our interest is in usages across all exemptions for drones in a firm's portfolio. 39% of firms had one exemption, from which their usage is inferred. In a few cases where a drone received one exemption with an unspecific usage description, we manually searched its petitioner's business and assigned it to a segment. Other firms received 70 exemptions on average. In these cases, we compute a firm-level frequency of exemptions that a firm's drones received in each segment. We also compute a similar drone-level frequency.

### 4.3.4 | Validating our classification

Last, we empirically verify whether a drone classified into a given usage segment exhibits technical features that meet task requirements and customer preferences for that segment. Here, our ability to assemble a systematic dataset of technical features for every drone is constrained by public data availability. We started with preliminary technical specifications available in the AUVSI Unmanned Systems and Robotics Database, and extensively expanded the information with hand-collected data from public sources such as firms' or retailers' websites, press releases, advertisements, and user communities. Out of our sample of 431 drones, we were able to find reliable technical specification data for 105 to 363 drones, depending on the specification.

Tables 2a and 2b reports linear probability model estimations of the likelihood that a drone exhibits a particular technical feature. The explanatory variables are five binary variables that equal one if a drone is classified as being used specifically in any one of the five segments.

Models 1–3 of Table 2a focus on airframe architecture. Drones classified in photography and inspection are likely to have rotary airframes, drones in surveying and agriculture have fixed-wing airframes, and drones in supply chain have hybrid airframes. Models 4–7 of Table 2a relate to a drone's performance. Drones classified in surveying and agriculture are likely to be able to fly for longer duration and at higher speeds, whereas drones classified in photography and inspection with no long-distance task have shorter flight range. Drones classified in inspection are likely to be able to fly at higher altitudes, consistent with the need to inspect hard to reach and tall infrastructure.

Models 1-7 of Table 2b look at the type of payloads carried by a drone. In line with the need to live-stream or record high-quality pictures and videos without capturing the drone's mechanical vibration, drones classified in photography are likely to have anti-vibration systems, real-time data transmission, and high-quality cameras. Drones classified in inspection are likely to have high-quality cameras, plus thermal and infrared sensors, which help with inspection tasks. Drones classified in surveying are likely to carry thermal or infrared sensors, geo-tagging systems, and multi- or hyper-spectral sensors, all of which allow for photogrammetry and visualization of a landscape. In line with the need to monitor vegetation patterns, drones classified in agriculture are likely to have multi- or hyper-spectral sensors.

Two additional points are noteworthy. First, Tables 2a and 2b show that drones classified into other usage segments are often unlikely to exhibit technical features that are not specific to their tasks, as indicated by negative coefficients. Second, we could collect technical features for only four drones classified in supply chain. All four of them had the ability to carry and drop off packages.

Overall, patterns in Tables 2a and 2b suggest that our classification appropriately mapped drones with expected technical architectures, performance features, and payloads into the five usage segments, validating our use of Section 333 exemptions to capture meaningful differences in drones' usages.

## 4.4 | Dependent variable: Portfolio usage breadth

We capture the variety of product portfolios by jointly measuring two dimensions of breadth and overlap. Figure 1 is a stylized depiction of three types of product portfolios, resulting from various levels of breadth and overlap. Independently, usage breadth shows the total number of customer segments targeted by all products in a firm's portfolio, separating low breadth (Quadrant 1) from high breadth (Quadrants 2 and 3). To unpack the composition of products in portfolios targeting multiple segments, we include usage overlap. It is defined as the extent to

**TABLE 2a** Validation of drone usage segment classification based on airframe and performance metrics

| (a) | Airframe (1) Multi-rotor | (2) Fixed-wing | (3) Hybrid | Performance metrics (4) Endurance (min) | (5) Speed (mph, max) | (6) Range (miles, max) | (7) Altitude (ft, max) |
|---|---|---|---|---|---|---|---|
| Photo-specific drone = 1 | **0.206** | −0.222 | 0.014 | −0.407 | 0.037 | **−0.776** | −1.139 |
| | **(.000)** | (.000) | (.545) | (.046) | (.767) | **(.005)** | (.177) |
| Inspection-specific drone = 1 | **0.193** | −0.244 | −0.008 | −0.071 | 0.132 | **−0.845** | **0.664** |
| | **(.055)** | (.000) | (.160) | (.702) | (.532) | **(.026)** | **(.000)** |
| Surveying-specific drone = 1 | −0.174 | **0.112** | 0.014 | **0.67** | **0.154** | 0.676 | 0.122 |
| | (.031) | **(.148)** | (.539) | **(.002)** | **(.132)** | (.128) | (.755) |
| Agriculture-specific drone = 1 | −0.400 | **0.371** | −0.008 | **1.267** | **0.572** | 0.506 | 0.915 |
| | (.003) | **(.008)** | (.160) | **(.038)** | **(.000)** | (.387) | (.000) |
| Supply chain-specific drone = 1 | −0.374 | −0.244 | **0.659** | −0.127 | 0.177 | 1.169 | |
| | (.176) | (.000) | **(.017)** | (.047) | (.000) | (.000) | |
| Constant | 0.707 | 0.244 | 0.008 | 3.561 | 3.75 | 1.603 | 8.531 |
| | (.000) | (.000) | (.160) | (.000) | (.000) | (.000) | (.000) |
| Number of observations | 363 | 363 | 363 | 276 | 142 | 135 | 105 |
| *R*-squared | 0.08 | 0.08 | 0.22 | 0.10 | 0.05 | 0.07 | 0.05 |

*Note*: (a) *p*-values in parentheses, robust standard errors; (b) bolded values show coefficients of interest; (c) estimation technique: linear probability model; (d) analysis at the drone-level; (e) the reference category are drones that are classified into multiple usages.

**TABLE 2b** Validation of drone usage segment classification based on payloads

| (b) | Payloads (1) Anti-vibration system | (2) Real-time video | (3) High-quality camera | (4) Thermal or infrared sensor | (5) Geo-tagged imagery | (6) LiDAR | (7) Multi- or hyper-spectral sensor |
|---|---|---|---|---|---|---|---|
| Photo-specific drone = 1 | **0.536** | **0.204** | **0.353** | −0.212 | −0.051 | 0.107 | −0.098 |
| | **(.000)** | **(.042)** | **(.003)** | (.029) | (.395) | (.238) | (.112) |
| Inspection-specific drone = 1 | −0.130 | −0.018 | **0.686** | **0.621** | −0.107 | 0.441 | −0.154 |
| | (.000) | (.086) | **(.000)** | **(.000)** | (.000) | (.221) | (.000) |
| Surveying-specific drone = 1 | −0.019 | 0.019 | −0.202 | **0.214** | **0.190** | **0.015** | **0.179** |
| | (.775) | (.615) | (.005) | **(.039)** | **(.041)** | **(.784)** | **(.063)** |
| Agriculture-specific drone = 1 | −0.130 | −0.018 | −0.314 | 0.121 | −0.107 | 0.084 | **0.392** |
| | (.000) | (.086) | (.000) | (.565) | (.000) | (.537) | **(.012)** |
| Supply chain-specific drone = 1 | −0.130 | −0.018 | −0.314 | −0.045 | −0.107 | −0.059 | −0.154 |
| | (.000) | (.086) | (.000) | (.871) | (.000) | (.001) | (.000) |
| Constant | 0.130 | 0.018 | 0.314 | 0.379 | 0.107 | 0.059 | 0.154 |
| | (.000) | (.086) | (.000) | (.000) | (.000) | (.001) | (.000) |
| Number of observations | 224 | 224 | 224 | 229 | 224 | 226 | 229 |
| *R*-squared | 0.17 | 0.09 | 0.10 | 0.08 | 0.05 | 0.04 | 0.08 |

*Note*: (a) *p*-values in parentheses, robust standard errors; (b) bolded values show coefficients of interest; (c) estimation technique: linear probability model; (d) analysis at the drone-level; (e) the reference category are drones that are classified into multiple usages.

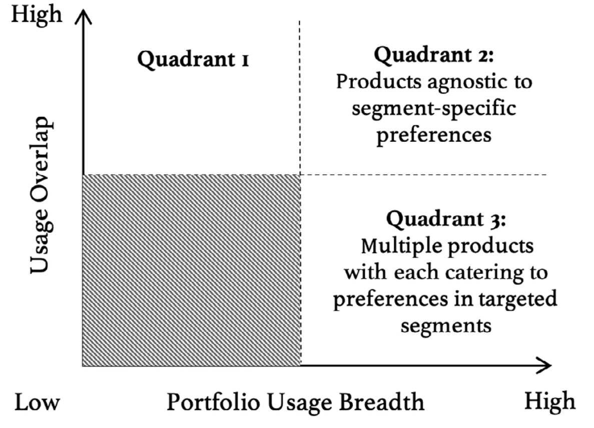


**FIGURE 1** Typology of product portfolios

which targeted customer segments of each of a firm's products overlap with its other products, separating high breadth portfolios built of segment-agnostic products targeting several segments (Quadrant 2) from high breadth portfolios built of multiple products each catering to idiosyncratic needs in specific segments (Quadrant 3).

To measure usage breadth, we calculate an HHI-type index, as one minus the summation of squared shares of frequency counts of exemptions that a firm's drones received in each segment. This measure reflects the extent to which a firm's drones are distributed among numerous segments, rather than concentrated in one or few segments. Smaller values imply lower breadth. Our analyses include two alternative measures. First, we calculate a count variable, as the number of segments for which a drone has received exemptions. Second, we use a binary variable, equal to one if a firm's drones have received exemptions in more than one segment.

To measure usage overlap, we first depict each drone with a vector in the 5-dimensional space of distinct segments. We next compute the pairwise cosine similarity index between each drone's vector of usage segments and that of every other drone in a firm's portfolio. To calculate usage overlap, we average the cosine similarity index across all drone pairs in the portfolio. Intuitively, the cosine of the angle between two overlapping vectors equals one, whereas two diverging vectors exhibit a smaller cosine. In our context, lower values indicate a greater divergence between targeted customer segments across products in a portfolio. Our analyses include an alternative binary measure that is equal to one if each of a firm's drones perfectly overlaps in its usage with all other drones in the portfolio.

## 4.5 | Explanatory variables

### 4.5.1 | Pre-entry use experience

We measure pre-entry use experience as a binary variable equal to one if a firm or its founders were previously active in segments that adopted drones, including photography, motion pictures, real estate, energy and utilities, mining, insurance, telecommunications, geological surveying, agriculture, and retail. Firm and founder data come from firm websites, Crunchbase, LinkedIn, AUVSI directory, industry reports, FAA, and other news sources. For entrants lacking use experience, prior industries largely consist of aviation, electronics, robotics, and RC devices.

#### 4.5.2 | Diversifying entrant

We include a binary variable that is equal to one if a firm was active in another industry before drone manufacturing and is equal to zero if founded as a drone manufacturer.

#### 4.5.3 | Control variables

To separate the effect of a firm's pre-entry use experience from other possible explanations, we include control variables pertaining to firms, exemptions, and industry trends.

We start by describing firm attributes. First, a firm's technical knowledge can condition its entry strategy. We account for technical knowledge by using the logged number of U.S. patents in aviation (Derwent class Q25: mechanical systems related to aircraft, aviation, cosmonautics) and computing (Derwent class T01: digital computing) that a firm applied for during the four-year window prior to the first filing of an exemption for its drones. Second, old and large firms may have more financial resources. We measure firm age as the logged difference in years between its drones' first exemption and its founding year. We also include the logged number of employees. Third, before the commercial drone industry, drones were used in the military. Because military contractors might have existing drones that could be repurposed for commercial use, we include a binary variable that equals one for firms or founders with prior military drone activity. We collect a complete list of pre-2014 military drone contractors from the U.S. Department of Defense Unmanned Systems Roadmap as well as the FAA certificates of authorization granted to the U.S. Army, Navy, Air Force research lab, and DARPA. Fourth, despite restrictions about commercial drones in the U.S. before 2014, China provided incentives for drone businesses (Yu & Armanios, 2021). We include a binary variable that equals one if a firm's main office is in China. Fifth, for timing of entry, we include a binary variable identifying early entrants as firms whose drones started to receive petitions in the first 9 months of the Section 333 process. Sixth, we include a binary variable for firms that introduced only one drone model to account for any differences between single-product and multi-product firms. Finally, we control for parallel provision of drone services to external customers or internal divisions. We include a binary variable that is equal to one if a firm's name is listed as the petitioner on one of its own drone's exemptions and remove self-petitions for customer training, drone testing, or public demonstrations.

We also include a control variable for exemption intensity, as the average monthly number of exemptions that a firm's drones received between its first and last petitions. Drones with numerous exemptions might appear in more segments, as various petitioners could discover more uses for them.

For industry-wide trends, we control for fragmentation in the demand environment, measured as HHI-type index of industry-wide distribution of exemptions across segments 2 months before a firm's first exemption. Second, for competition, we include the logged cumulative number of drone models in all usage segments 2 months before a firm's first exemption.

### 4.6 | Summary statistics

Table 3 presents descriptive statistics and the correlation matrix. Of 230 firms, 26.5% have pre-entry use experiences and 36.1% are diversifying entrants. Figure 2 shows the cumulative number of drone manufacturers in the sample per month, by experience type. The industry has seen a steady rise in manufacturers with and without use experience in this timeline. On average, drones in a firm's portfolio span 2.46 usage segments. The average number of segments for firms with use experience is 1.93 (HHI = 0.30) but increases to 2.65 (HHI = 0.45) for firms without. Figure 3 shows the density distribution histogram of drones' number of segments. With use experience, it is skewed toward one or two segments, whereas it is symmetrically spread for entrants without use experience.

## 5 | EMPIRICAL FINDINGS

### 5.1 | Hypothesized relationships

Table 4 reports results for dependent variables of usage breadth and overlap, which are jointly estimated in a system of equations to allow for possible correlation across their error terms. Models 1–2 show an OLS structural equation model for continuous measures of breadth (HHI distribution) and overlap (cosine similarity). Models 3–4 report a generalized structural equation model that uses a Poisson estimation of the count measure of breadth and a logit estimation of the binary measure of overlap. Models 5–6 present a bivariate probit model for breadth and overlap as binary variables.

Allowing for the residuals of breadth and overlap to co-vary reveals a covariance of −0.006 ($p$ = .000) and −0.006 ($p$ = .000) in Models 1 and 2. Further, the tetrachoric correlations between breadth and overlap are −10.68 ($p$ = .635) and −14.69 ($p$ = .000) in Models 5 and 6. These statistics corroborate the need for joint estimation of dependent variables, particularly for interaction effects.

Models 1, 3, and 5 examine the direct effect of use experience. In these models, use experience is negatively related to usage breadth. Models 2, 4, and 6 add interaction terms. For diversifying entrants, these models show that use experience's negative link with breadth and positive link with overlap becomes stronger. Results are robust to adding a firm's parallel provision of drone services using the self-petition variable as a third dependent variable, as reported in Online Appendix A3.

Since our main interest is in joint predicted probabilities, Table 5 builds on bivariate probit estimations in Models 5–6 in Table 4 and reports the average marginal effects of use experience on the joint likelihood of having product portfolios exhibiting low/high breadth and low/high overlap.[6]

Column 1 shows the likelihood of a low breadth portfolio (quadrant 1). Consistent with H1, the average marginal effect of use experience is positive (AME = 0.107; $p$ = .000), implying an increase from 29.21 to 47.32% in the average predicted probability. In support of H2, when separating startups and diversifying entrants, the average marginal effect of use experience for diversifying entrants (AME = 0.304; $p$ = .000) is larger than that for startups (AME = 0.014;

[6]For ease of exposition of empirical results, we consider one customer segment as a cutoff for low breadth. However, we note that the theoretical construct of breadth along a spectrum does not necessitate strict boundaries.

**TABLE 3** Summary statistics and correlation table

| | | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Portfolio usage breadth, HHI | 0.41 | 0.31 | 1.00 | | | | | | | | | | | | | | | | | |
| 2 | Portfolio usage breadth, count | 2.46 | 1.28 | .92 | 1.00 | | | | | | | | | | | | | | | | |
| 3 | Portfolio usage breadth, binary | 0.66 | 0.47 | .96 | .82 | 1.00 | | | | | | | | | | | | | | | |
| 4 | Portfolio usage overlap, similarity | 0.92 | 0.19 | −.35 | −.40 | −.33 | 1.00 | | | | | | | | | | | | | | |
| 5 | Portfolio usage overlap, binary | 0.75 | 0.43 | −.47 | −.58 | −.41 | .79 | 1.00 | | | | | | | | | | | | | |
| 6 | Pre-entry use experience | 0.27 | 0.44 | −.21 | −.25 | −.17 | .13 | .16 | 1.00 | | | | | | | | | | | | |
| 7 | Diversifying entrant | 0.36 | 0.48 | .03 | .05 | −.02 | −.02 | −.03 | .06 | 1.00 | | | | | | | | | | | |
| 8 | Patents* | 62.52 | 684.46 | −.03 | .02 | −.07 | −.02 | −.03 | −.07 | .26 | 1.00 | | | | | | | | | | |
| 9 | Employee count* | 4741 | 38615 | .14 | .18 | .10 | −.19 | −.19 | −.15 | .50 | .49 | 1.00 | | | | | | | | | |
| 10 | Firm age* | 9.80 | 14.82 | .11 | .14 | .05 | −.11 | −.15 | −.04 | .72 | .36 | .51 | 1.00 | | | | | | | | |
| 11 | Chinese firm | 0.07 | 0.25 | .15 | .18 | .12 | −.19 | −.24 | −.16 | .33 | −.01 | .38 | .12 | 1.00 | | | | | | | |
| 12 | Military contractor | 0.04 | 0.19 | .00 | −.02 | .00 | −.06 | −.04 | −.12 | .08 | .31 | .15 | .16 | −.06 | 1.00 | | | | | | |
| 13 | Early entrant | 0.18 | 0.38 | .16 | .26 | .12 | −.14 | −.26 | .00 | .05 | .15 | .16 | .11 | .01 | .08 | 1.00 | | | | | |
| 14 | Single product firm | 0.61 | 0.49 | −.30 | −.40 | −.25 | .57 | .72 | .08 | −.03 | −.03 | −.15 | −.14 | −.20 | −0.02 | −.19 | 1.00 | | | | |
| 15 | Self-petition | 0.46 | 0.50 | −.26 | −.26 | −.25 | .17 | .16 | .20 | −.05 | .14 | −.13 | −.11 | −.25 | .13 | .01 | .02 | 1.00 | | | |
| 16 | Exemption intensity* | 2.47 | 15.90 | .11 | .21 | .06 | .06 | −.16 | −.10 | .00 | .16 | .14 | .08 | .12 | −.03 | .12 | −.31 | −.03 | 1.00 | | |
| 17 | Use environment fragmentation | 0.72 | 0.09 | −.10 | −.17 | −.07 | −.03 | .10 | .08 | .02 | −.10 | −.10 | .00 | −.10 | .01 | −.34 | .13 | .10 | −.54 | 1.00 | |
| 18 | Competing products* | 179.50 | 135.08 | −.24 | −.36 | −.19 | .18 | .35 | −.01 | −.06 | −.16 | −.18 | −.09 | −.09 | −.02 | −.81 | .27 | −.05 | −.24 | .43 | 1.00 |

*Note*: Variables indicated with * are log transformed in the correlation table and regressions. Summary statistics are reported untransformed.

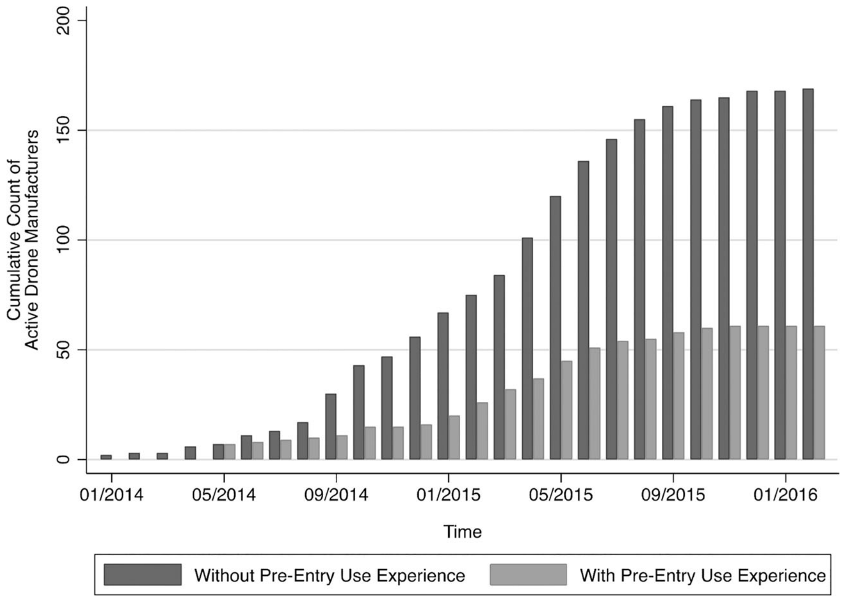


**FIGURE 2** Cumulative number of commercial drone manufacturers

$p$ = .000). Being a user diversifying entrant increases the average predicted probability from 21.46 to 63.98%, whereas being a user startup leads to an increase from 32.40 to 35.99%.

Column 2 relates to the joint likelihood of a high breadth and high overlap portfolio (Quadrant 2), and Column 3 focuses on a high breadth and low overlap portfolio (Quadrant 3). In support of H1, firms lacking use experience are likely to exhibit either type of high breadth portfolio, as indicated by the negative average marginal effects of use experience in both Columns 2 and 3.

Next, consistent with H3, startups without use experience are likely to introduce high breadth portfolios consisting of products agnostic to customer preferences in targeted segments (AME = 0.052; $p$ = .000). Being a startup without use experience increases the average predicted probability of introducing this type of portfolio from 36.23 to 44.50%. By contrast, being a diversifying entrant without use experience only increases the average predicted probability from 36.01 to 41.66%.

In line with H4, diversifying entrants lacking use experience are more likely to have high breadth portfolios consisting of multiple products each catering to customer preferences in targeted segments (AME = 0.298; $p$ = .000). The distinction with startups is notable, as startups are likely to avoid this type of high breadth portfolio (AME = -0.035; $p$ = .002). Being a diversifying entrant without use experience increases the average predicted probability from 0.00 to 36.53%, whereas being a startup without use experience leads to a decrease from 27.70 to 23.05%.

## 5.2 | Exploring mechanisms and assumptions

### 5.2.1 | Link to pre-entry use segment

Our hypotheses draw on the mechanism of a link between a firm's pre-entry segment and the segment in which its product is specifically used. Table 6 examines this mechanism using linear

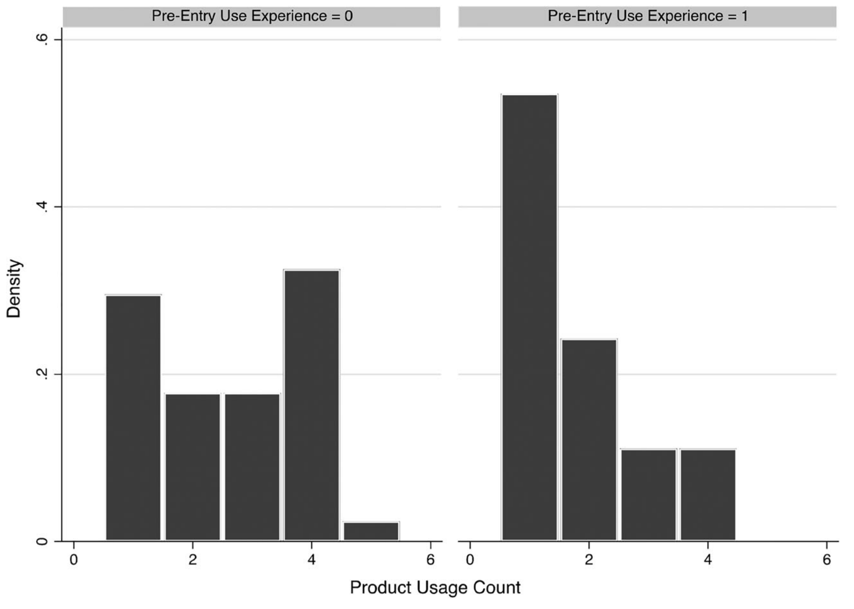


**FIGURE 3** Histogram of usage count by pre-entry use experience

probability estimations of the likelihood that a drone is used only for each segment. The explanatory variables are five binary variables for use experience in each segment: (a) photography for photography and real estate experience, (b) inspection for insurance, energy, and utilities experience, (c) surveying for oil and gas exploration, telecommunication, mapping, and geosurveying experience, (d) agriculture for farming and farm equipment experience, and (e) supply-chain for retail and supply chain experience. Other variables are the same as in Table 4, except for demand and competition variables, which are decomposed into five variables corresponding to each segment; that is, the logged cumulative number of petitioners and usage-specific drones in the respective segment. Consistent with the mechanism, Models 1, 3, 5, 7, and 9 show that experience pertaining to a usage is positively related to offering drones for the segment. For example, entrants with inspection experience are 59.5% ($p = .012$) more likely to introduce an inspection-specific drone, whereas surveying experience increases the likelihood of introducing a surveying-specific drone by 38.0% ($p = .013$). Further, when coefficients for unrelated experience for each usage exhibit statistical significance, the coefficients are negative, reinforcing our proposed mechanism.

This link is also noted by a few founders. Tony Carmean, a former film producer, founded Aerial MOB to specialize in professional cinematography drones. He viewed drones as a filming device in: “low-altitude cinematography. Think of that space in-between jibs and full-sized aircrafts. There's a big area that's not covered. … [drones] can replace dollies, jibs and cranes” (Hall, 2014). Matthew Barnard, a farmer, founded Crop Copter to specialize in agricultural drones, recounting his expertise: “[a salesman] tried to sell me a hobby-grade unmanned aerial vehicle. He didn't know anything about ag. He didn't know anything about my farm's needs or my concerns… Our team is directly involved with production agriculture. It's also why our tagline is By Farmers, For Farmers.” (Bedord, 2015).

By contrast, entrants without use experience tended to be unbiased to a specific segment. Helen Greiner, a robotics engineer, founded CyPhy Works with broad-use drones: “we're

**TABLE 4** Joint estimation of portfolio usage breadth and overlap

| | SEM OLS | | | | GSEM with Poisson & Logit Functions | | | | Bivariate Probit | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | |
| **Estimation Technique** | **Breadth (HHI)** | **Overlap (similarity)** | **Breadth (HHI)** | **Overlap (similarity)** | **Breadth (count)** | **Overlap (binary)** | **Breadth (count)** | **Overlap (binary)** | **Breadth (binary)** | **Overlap (binary)** | **Breadth (binary)** | **Overlap (binary)** |
| Pre-entry use experience = 1 | **−0.101** | **0.022** | −0.030 | 0.014 | **−0.244** | **1.547** | −0.105 | 0.560 | **−0.333** | **0.506** | −0.054 | −0.365 |
| | **(.000)** | **(.012)** | (.000) | (.018) | **(.000)** | **(.000)** | (.000) | (.000) | **(.000)** | **(.013)** | (.000) | (.001) |
| Use experience × Diversifying entrant | | | **−0.206** | **0.025** | | | **−0.431** | **17.601** | | | **−0.901** | **7.887** |
| | | | **(.000)** | **(.559)** | | | **(.000)** | **(.000)** | | | **(.000)** | **(.000)** |
| Diversifying entrant = 1 | −0.019 | 0.035 | 0.049 | 0.027 | −0.008 | 1.354 | 0.100 | 0.810 | −0.185 | 0.761 | 0.157 | 0.534 |
| | (.157) | (.175) | (.000) | (.505) | (.867) | (.000) | (.017) | (.046) | (.000) | (.000) | (.000) | (.000) |
| Patents | −0.023 | 0.001 | −0.030 | 0.002 | −0.022 | 0.532 | −0.037 | 0.907 | −0.199 | 0.313 | −0.250 | 0.440 |
| | (.000) | (.859) | (.000) | (.796) | (.047) | (.000) | (.003) | (.001) | (.000) | (.000) | (.000) | (.000) |
| Employee count | 0.006 | −0.010 | 0.007 | −0.010 | 0.006 | −0.087 | 0.008 | −0.104 | 0.035 | 0.025 | 0.038 | 0.081 |
| | (.300) | (.001) | (.228) | (.001) | (.628) | (.627) | (.512) | (.684) | (.056) | (.723) | (.052) | (.248) |
| Firm age | 0.019 | −0.003 | 0.018 | −0.003 | 0.029 | −0.502 | 0.031 | −0.965 | 0.075 | −0.468 | 0.086 | −0.830 |
| | (.000) | (.000) | (.000) | (.000) | (.000) | (.190) | (.000) | (.000) | (.000) | (.057) | (.000) | (.000) |
| Chinese firm | −0.013 | −0.022 | −0.053 | −0.017 | −0.053 | −1.388 | −0.116 | −1.171 | 0.110 | −0.912 | −0.152 | −1.042 |
| | (.230) | (.291) | (.000) | (.565) | (.002) | (.000) | (.000) | (.074) | (.525) | (.026) | (.000) | (.000) |
| Military contractor | 0.036 | −0.035 | 0.019 | −0.033 | −0.048 | −1.328 | −0.082 | −1.295 | 0.337 | −0.844 | 0.294 | −0.914 |
| | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) |
| Early entrant | −0.095 | 0.011 | −0.079 | 0.009 | −0.128 | 1.487 | −0.099 | 0.983 | −0.781 | 1.069 | −0.832 | 0.899 |
| | (.000) | (.704) | (.000) | (.724) | (.000) | (.000) | (.000) | (.004) | (.000) | (.000) | (.000) | (.000) |
| Single product Firm | −0.140 | 0.229 | −0.132 | 0.228 | −0.289 | 18.187 | −0.272 | 18.677 | −0.556 | 9.019 | −0.598 | 9.290 |
| | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) |

**TABLE 4** (Continued)

| Estimation Technique | SEM OLS (1) Breadth (HHI) | SEM OLS (1) Overlap (similarity) | SEM OLS (2) Breadth (HHI) | SEM OLS (2) Overlap (similarity) | GSEM with Poisson & Logit Functions (3) Breadth (count) | GSEM with Poisson & Logit Functions (3) Overlap (binary) | GSEM with Poisson & Logit Functions (4) Breadth (count) | GSEM with Poisson & Logit Functions (4) Overlap (binary) | Bivariate Probit (5) Breadth (binary) | Bivariate Probit (5) Overlap (binary) | Bivariate Probit (6) Breadth (binary) | Bivariate Probit (6) Overlap (binary) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Self-petition | −0.143 | 0.053 | −0.125 | 0.051 | −0.240 | 0.996 | −0.204 | 0.579 | −0.668 | 0.880 | −0.597 | 0.752 |
| | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.006) | (.000) | (.000) | (.000) | (.000) |
| Exemption intensity | −0.007 | 0.103 | −0.004 | 0.102 | 0.036 | 0.183 | 0.040 | 0.151 | 0.135 | 0.171 | 0.033 | 0.069 |
| | (.002) | (.000) | (.524) | (.000) | (.000) | (.669) | (.000) | (.741) | (.113) | (.485) | (.723) | (.741) |
| Use environment fragmentation | 0.154 | −0.051 | 0.115 | −0.046 | 0.586 | −8.182 | 0.517 | −7.883 | −4.490 | −4.014 | −5.945 | −3.529 |
| | (.001) | (.790) | (.003) | (.800) | (.000) | (.000) | (.002) | (.000) | (.000) | (.000) | (.000) | (.001) |
| Competing products | −0.078 | 0.014 | −0.074 | 0.014 | −0.160 | 1.499 | −0.153 | 1.438 | −0.477 | 0.833 | −0.499 | 0.736 |
| | (.000) | (.180) | (.000) | (.167) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) |
| Constant | 0.821 | 0.663 | 0.796 | 0.666 | 1.470 | −1.895 | 1.416 | −0.493 | 6.647 | −1.517 | 7.810 | −0.648 |
| | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.673) | (.000) | (.000) | (.000) | (.000) |
| Log pseudo-likelihood | 106.52 | | 109.31 | | −403.26 | | −397.97 | | −152.58 | | −146.52 | |

*Note*: (a) *p*-values in parentheses, based on robust standard errors clustered on country variable; (b) bolded values show coefficients of interest; (c) firm-level analysis with 230 observations; (d) results are robust to measuring patents in 3- and 5-year windows, and use environment and competing products in 1- and 3-month windows.

**TABLE 5** Marginal effects of pre-entry use experience on product-portfolio quadrants

| | (1) Portfolio breadth: Low | (2) Portfolio breadth: High Portfolio overlap: High | (3) Portfolio breadth: High Portfolio overlap: Low |
|---|---|---|---|
| Use experience = 1 | 0.107 (.000) | −0.051 (.009) | −0.055 (.004) |
| Use experience = 1 x Diversifying entrant = 1 | 0.304 (.000) | −0.003 (.546) | −0.298 (.000) |
| Use experience = 1 x Startup entrant = 1 | 0.014 (.000) | −0.052 (.000) | 0.035 (.002) |

*Note*: (a) *p*-values in parentheses; (b) average marginal effects for H1 based on Model 5 in Table 4 over observed values; (c) average marginal effects for H2, H3, and H4 based on Model 6 in Table 4 over observed values.

building drones. I like to think of them as just flying robots" (Michel, 2015). Steve Gitlin, president of AeroVironment, recognized the presence of multiple segments but indicated the firm's priorities as: "[our strategy] will depend on market need. It's a question of what needs have to be satisfied, and what are the most effective ways to satisfy them. As we identify meaningful customer needs that represent significant growth, we'll develop solutions to address those needs" (Michel, 2014). Gitlin's comments are aligned with the possibility that entrants without use experience reduce their portfolio usage breadth over time and with knowledge accumulation about customer segments, as we show in Online Appendix A4.

### 5.2.2 | Response to competitive rivalry

Rivalry can deter entry and lead to repositioning to less rivalrous segments. Yet, if our proposed mechanisms hold, firms with use experience should enter segments, regardless of competition. Models 2, 4, 6, and 8 in Table 6 include an interaction term between each use experience and competition in that segment. Positive coefficients of interaction terms in Models 4, 6, and 8 reveal that entrants with respective experiences in inspection, surveying, or agriculture were likely to introduce a drone for that segment, despite intensifying competition. However, this link does not hold for photography, while the interaction term for supply chain could not be estimated due to limited variation. These results allude to the mechanism that entrants are cognitively primed by their experiences, to the extent that they may discount competitive rivalry in their familiar segments.

### 5.2.3 | Response to market size trends

Size and revenue potential can impact a segment's attractiveness and entice firm entry. But our proposed mechanism implies that firms with use experience may not pay attention to growth or revenue in other segments. To check this, we look at the approximate size of each segment. Figure 4 shows the monthly cumulative count of petitioners. In terms of petitioner count, the largest segment is photography (2,581 petitioners), followed by surveying (1,536 petitioners), inspection (1,350 petitioners), agriculture (962 petitioners), and supply chain (12 petitioners).

**TABLE 6** Linking entrant's experience to drone's specific usages

| | **Photo-specific drone = 1** | | **Inspection-specific drone = 1** | | **Surveying-specific drone = 1** | | **Agriculture-specific drone = 1** | | **Supply chain drone = 1** |
|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** |
| Photography: Experience | **0.286** | 0.769 | −0.047 | −0.046 | −0.027 | −0.030 | −0.038 | −0.038 | −0.000 |
| | **(.021)** | (.013) | (.022) | (.015) | (.041) | (.029) | (.005) | (.005) | (.885) |
| Photography: Experience × competition | | **−0.154** | | | | | | | |
| | | **(.014)** | | | | | | | |
| Photography: Competition | −0.168 | −0.068 | | | | | | | |
| | (.173) | (.114) | | | | | | | |
| Photography: Customer base | 0.126 | 0.087 | | | | | | | |
| | (.118) | (.071) | | | | | | | |
| Inspection: Experience | −0.088 | −0.091 | **0.595** | −0.048 | −0.007 | 0.006 | −0.045 | −0.041 | −0.016 |
| | (.063) | (.064) | **(.012)** | (.020) | (.673) | (.665) | (.027) | (.021) | (.138) |
| Inspection: Experience × competition | | | | **0.412** | | | | | |
| | | | | **(.012)** | | | | | |
| Inspection: Competition | | | −0.031 | −0.030 | | | | | |
| | | | (.249) | (.245) | | | | | |
| Inspection: Customer base | | | 0.019 | 0.016 | | | | | |
| | | | (.264) | (.273) | | | | | |
| Surveying: Experience | −0.137 | −0.143 | −0.071 | −0.071 | **0.380** | −0.392 | −0.051 | −0.049 | −0.020 |
| | (.009) | (.006) | (.052) | (.047) | **(.013)** | (.058) | (.024) | (.020) | (.053) |
| Surveying: Experience × Competition | | | | | | **0.288** | | | |
| | | | | | | **(.035)** | | | |
| Surveying: Competition | | | | | 0.068 | 0.055 | | | |
| | | | | | (.050) | (.117) | | | |

**TABLE 6** (Continued)

| | Photo-specific drone = 1 | | Inspection-specific drone = 1 | | Surveying-specific drone = 1 | | Agriculture-specific drone = 1 | | Supply chain drone = 1 |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Surveying: Customer base | | | | | −0.020 | −0.013 | | | |
| | | | | | (.256) | (.466) | | | |
| Agriculture: Experience | −0.171 | −0.182 | −0.049 | −0.045 | −0.140 | −0.141 | **0.067** | −1.043 | −0.002 |
| | (.028) | (.001) | (.002) | (.014) | (.006) | (.006) | **(.006)** | (.006) | (.562) |
| Agriculture: Experience × Competition | | | | | | | | **0.533** | |
| | | | | | | | | **(.005)** | |
| Agriculture: Competition | | | | | | | −0.076 | −0.070 | |
| | | | | | | | (.103) | (.101) | |
| Agriculture: Customer base | | | | | | | 0.045 | 0.040 | |
| | | | | | | | (.106) | (.102) | |
| Supply chain: Experience | −0.003 | −0.019 | 0.124 | 0.083 | −0.108 | −0.099 | −0.022 | −0.018 | **0.793** |
| | (.978) | (.856) | (.376) | (.428) | (.182) | (.182) | (.098) | (.074) | **(.035)** |
| Supply chain: Competition | | | | | | | | | 0.027 |
| | | | | | | | | | (.488) |
| Supply chain: Customer base | | | | | | | | | −0.011 |
| | | | | | | | | | (.544) |
| Controls | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| R-squared | 0.18 | 0.21 | 0.30 | 0.36 | 0.08 | 0.08 | 0.08 | 0.10 | 0.32 |

*Note*: (a) *p*-values in parentheses, based on robust standard errors clustered on country variable; (b) bolded values show coefficients of interest; (c) estimation technique: linear probability model; (d) drone-level analysis with 431 observations; (e) controls included: diversifying entrant, patents, employee count, firm age, Chinese firm, military contractor, early entrant, single product firm, self-petition, exemption intensity; (f) the reference category is firms without use experience.

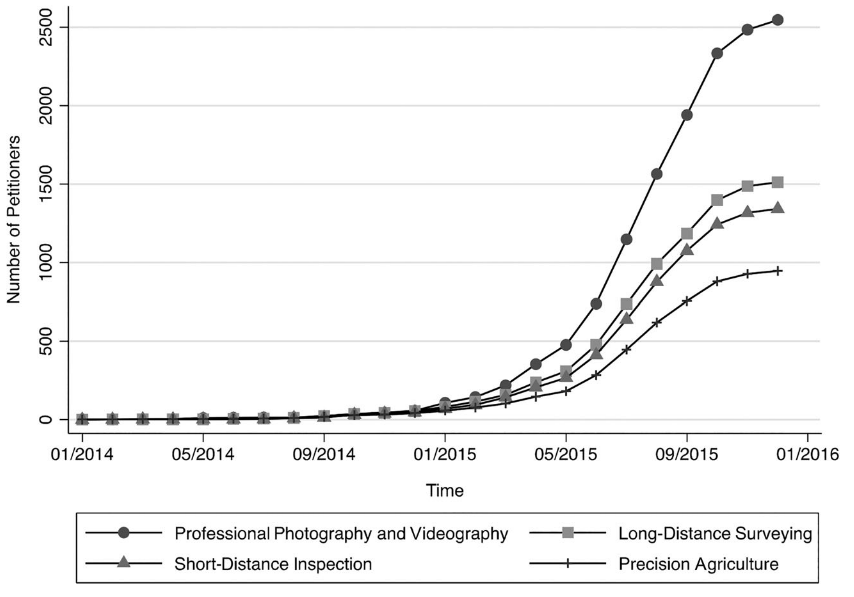


**FIGURE 4** Cumulative number of petitioners by usage segment

Since petitioners are not restricted in how many drones they can utilize, these statistics do not show the number of drones sold, and only reflect the number of customers. For example, a photographer may purchase one drone, whereas John Deere in agriculture or Walmart in supply chain may buy hundreds of the same drone model with one exemption. In terms of revenue, the most lucrative segment is surveying. Specialized drones differ in average price, with surveying drones being the most expensive ($49,900), followed by agriculture ($34,230), inspection ($15,700), and photography ($5,653) drones.

Drawing on these approximations, we explore whether emerging signals about the market size in photography or revenue potential in surveying attract firms with use experience in other segments. Table 7 reports the linear probability model estimations that a drone is used only for photography or surveying. Based on Models 1 and 3, use experience outside of photography ($\beta = -.124$; $p = .006$) and surveying ($\beta = -.035$; $p = .009$) is negatively related to offering a photography and surveying drone, respectively. From Figure 4, we observe that although all segments exhibited similar trends in the first 12 months, a distinction in growth rate of segments emerged afterward. Thus, we assume month 12 as the time marker when firms could detect divergence in market size and revenue potential. Models 2 and 4 include interaction terms between the binary variable for drones introduced after month 12 and two variables for use experience but in segments other than photography ($\beta = -.070$; $p = .348$) and surveying ($\beta = .016$; $p = .142$). The results do not show a change in entry patterns after Month 12. Entrants with use experience seem unlikely to respond to market signals from other segments, highlighting the strong role of use experience in linking entrants to their familiar customer segment.

### 5.2.4 | Performance implications

We have assumed that use experience provides entrants with superior demand knowledge about customer preferences in a segment. Such demand knowledge can improve the product

**TABLE 7** Entrants' response to market size trends

| | Photo-specific drone = 1 | | Surveying-specific drone = 1 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Use experience in photography | **0.288** | 0.288 | | |
| | **(.018)** | (.019) | | |
| Use experience not in photography | **−0.124** | −0.059 | | |
| | **(.006)** | (.387) | | |
| Use experience not in photography × post-month 12 | | **−0.070** | | |
| | | **(.348)** | | |
| Use experience in surveying | | | **0.378** | 0.379 |
| | | | **(.012)** | (.012) |
| Use experience not in surveying | | | **−0.035** | −0.047 |
| | | | **(.009)** | (.031) |
| Use experience not in surveying × post-month 12 | | | | **0.016** |
| | | | | **(.142)** |
| Controls | Y | Y | Y | Y |
| R-squared | 0.18 | 0.18 | 0.08 | 0.08 |

*Note*: (a) *p*-values in parentheses, based on robust standard errors clustered on country variable; (b) bolded values show coefficients of interest; (c) estimation technique: linear probability model; (d) drone-level analysis with 431 observations; (e) controls included: diversifying entrant, patents, employee count, firm age, Chinese firm, military contractor, early entrant, single product firm, self-petition, exemption intensity, post-month12; (f) competition and customer base variables for photography and surveying are included in models 1-2 and 3-4, respectively; (g) the reference category is firms without use experience.

development process in low breadth portfolios, attracting greater customer appreciation. Here, we examine how the development of segment-specific drones by entrants with use experience is affiliated with market share in respective segments. Table 8 reports the OLS estimation of the (logged) number of exemptions that a drone received for each use segment, as a proxy for market share. As stated before, the number of exemptions captures the number of customers, and not the number of drones sold. Models 1, 3, 5, and 7 show a negative relationship between segment-specific market share and offering market-specific drones. However, interaction terms in Models 4, 6, and 8 reveal that relative to drones introduced by firms without use experience, segment-specific drones introduced by firms with use experience received more exemptions in inspection ($\beta = .655$; $p = .067$), surveying ($\beta = .327$; $p = .102$), and agriculture ($\beta = .359$; $p = .005$).

## 5.3 | Empirical boundary conditions

To the extent possible, we report evidence to rule out alternative explanations and corroborate proposed mechanisms. However, the empirical results show statistical associations and not causality.

**TABLE 8** Performance implications of low usage breadth

| | # Photography exemptions | | # Inspection exemptions | | # Surveying exemptions | | # Agriculture exemptions | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Photo-specific drone = 1 | **−0.268** | −0.178 | | | | | | |
| | **(.091)** | (.281) | | | | | | |
| Experience × drone in photography | | **−0.253** | | | | | | |
| | | **(.169)** | | | | | | |
| Experience in photography = 1 | −0.002 | 0.093 | | | | | | |
| | (.955) | (.066) | | | | | | |
| Inspection-specific drone = 1 | | | **−0.212** | −0.291 | | | | |
| | | | **(.102)** | (.053) | | | | |
| Experience × drone in inspection | | | | **0.655** | | | | |
| | | | | **(.067)** | | | | |
| Experience in inspection = 1 | | | −0.141 | −0.558 | | | | |
| | | | (.147) | (.020) | | | | |
| Surveying-specific drone = 1 | | | | | **−0.256** | −0.230 | | |
| | | | | | **(.059)** | (.040) | | |
| Experience × drone in surveying | | | | | | **0.327** | | |
| | | | | | | **(.102)** | | |
| Experience in surveying = 1 | | | | | −0.061 | −0.275 | | |
| | | | | | (.147) | (.051) | | |
| Agriculture-specific drone = 1 | | | | | | | **−0.289** | −0.313 |
| | | | | | | | **(.002)** | (.001) |
| Experience × drone in agriculture | | | | | | | | **0.359** |
| | | | | | | | | **(.005)** |
| Experience in agriculture = 1 | | | | | | | 0.065 | 0.006 |
| | | | | | | | (.027) | (.346) |
| Controls | Y | Y | Y | Y | Y | Y | Y | Y |
| Number of observations | 274 | 274 | 238 | 238 | 305 | 305 | 214 | 214 |
| *R*-squared | 0.86 | 0.86 | 0.90 | 0.90 | 0.88 | 0.88 | 0.86 | 0.86 |

*Note*: (a) *p*-values in parentheses, based on robust standard errors clustered on country variable; (b) bolded values show coefficients of interest; (c) estimation technique: OLS; (d) drone-level analysis including firms active in each segment; (e) controls included: diversifying entrant, patents, employee count, firm age, Chinese firm, military contractor, early entrant, single product firm, self-petition, exemption intensity; (f) competition and customer base variables for photography in Models 1–2, inspection in Models 3–4, surveying in Models 5–6, and agriculture in Models 7–8 are included.

Two features of the single-industry design are noteworthy. First, public availability of basic drone technology reduced entry barriers for user entrepreneurs, whereas other technology-intensive contexts may exhibit less user activity. Airframe patents such as US3053480 titled "omni-directional, vertical lift, helicopter drone" and US3083934 titled "rotary wing aircraft" expired in the 1980s. Further, user entrepreneurs can learn from open-source communities, as at least 61 of 147 founders in our sample were members of the DIY Drones online community. The second feature is hobbyists' interest in recreational low-priced drones for personal photography (Bremner & Eisenhardt, 2021). Drone segments of inspection, surveying, agriculture, and supply chain present economy-wide commercial opportunities, but no hobbyist use. This can create an availability bias in favor of photography usage for amateur entrepreneurs assessing the drone landscape.

Finally, in contrast to historical studies that retrospectively interpret an industry's trajectory, our article relies on contemporary data. Currently, five robust and growing segments exist, each favoring technical designs that differ in architecture and details. It is not yet known whether these segments remain distinct (Klepper & Thompson, 2006) or whether customers coalesce around a single technical dominant design (Suárez & Utterback, 1995). Further, new usages as air taxis or pseudo-satellites for telecommunications may emerge. For example, after the timeline of this study, swarms of dancing drones have started to dazzle audiences in entertainment shows, a non-existent segment before 2016.

## 6 | DISCUSSION AND CONCLUSIONS

Based on patterns of entry in the commercial drone manufacturing industry, the central insight of this article is that pre-entry use experience influences entrants' product portfolios. We present theoretical mechanisms and empirical evidence that entrants with use experience are likely to introduce product portfolios with low usage breadth, whereas lacking use experience is linked to high breadth. By directing an entrant's cognition and privileging it with demand knowledge about familiar segments, pre-entry use experience shapes how entrants identify potential customer segments, evaluate which segments to target, and assemble knowledge and resources to offer the selected product portfolio.

We also show that portfolio usage breadth depends on whether pre-entry use experience resides in a diversifying entrant or a startup. Organizational resources and routines of diversifying entrants often underpin path-dependent entry to nascent industries, thereby leading to two outcomes. When coupled with use experience, these resources and routines can restrict the range of customer segments identified and targeted by an entrant's products. Absent use experience, diversifying entrants leverage resources not only to tackle a broader range of customer segments, but also to offer multiple products that each cater to idiosyncratic customer preferences in respective segments. For startups, the lack of use experience compounds their other resource shortcomings, and in turn results in product portfolios for a broad range of customer segments without distinctive attention to specific segments.

Our supplement empirical findings substantiate mechanisms and explore the role of cognition and knowledge for entry strategy. We find a link between entrants' background and the targeted segment, which suggests that entrants with use experience generally gravitate toward the segment from which they emerge. The findings also point to an intriguing entry pattern of firms with use experience: in a familiar segment, competitive rivalry does not deter entry, whereas in an unfamiliar segment, increasing market size and revenue do not induce entry.

This emphasizes demand-oriented cognition and knowledge in the choice of customer segments, possibly leading entrants to discount competitive and economic signals. Yet, these choices can pay off, as we find that entrants with use experience capture higher market share with their segment-specific products. This implies that superior demand knowledge can help them to introduce products appreciated by customers.

The study has several novel theoretical implications. First, our article extends the research stream about entry strategy into nascent industries, as we move beyond the classical view of entry as a binary choice. A firm's entry strategy includes intertwined choices about entry timing, technology, business model, and resource reconfiguration. While we recognize that accounting for the endogenous and simultaneous nature of these decisions is outside the scope of a single study, we highlight portfolio usage breadth as another interlinked aspect of entry strategy. Specially, given the strategic importance of product portfolio choices for revenue generation, growth trajectories, and survival (e.g., Giarratana & Fosfuri, 2007; Siggelkow, 2003; Sorenson, 2000), we shed light on its pre-entry antecedents.

Second, our article draws attention to strategic decision making under uncertainty. We highlight that immersion in a user context can condition how entrants face pervasive demand uncertainty in a nascent industry. To configure product portfolios, entrants need to confront partial knowledge about the variety of customer segments and varying customer preferences across segments. When coming from user contexts, experience-based cognition and knowledge often prevail in decision making, so that entrants circumvent uncertainty and focus on known segments. To the contrary, lack of use experience can prompt entrants to endogenously reduce uncertainty and generate demand knowledge about segments of interest, so that their decision making exhibits a scientific approach (Camuffo, Cordova, Gambardella, & Spina, 2020) and involves post-entry learning (Chen, Croson, Elfenbein, & Posen, 2018).

Third, by focusing on user diversifying entrants, our study advances the types of firm-level resources redeployed to a nascent industry. Past studies about diversifying entrants largely account for technologies and complementary assets (Helfat & Lieberman, 2002), abstracting away from experience as commercial users. In parallel, studies of user innovation often view use experience in the realm of startups (Baldwin et al., 2006), overlooking its ubiquity in established firms. We underline diversifying entrants as an important source of user-based demand knowledge about their respective segments.

Finally, our study points to the demand-side drivers of nascent industry trends. One industry milestone is sales takeoff, which marks an industry's transition to commercial viability. At sales takeoff, the acceleration in customers' product adoption stems from the rising product diversity that caters to diverse customer preferences (Moeen, Agarwal, & Shah, 2020). We raise the possibility that entrants with use experience can facilitate this product diversity, thereby advancing sales takeoff. This demand-side view can also be relevant for industry diffusion of general-purpose technologies (GPTs) such as drones. While GPTs' presence in many downstream markets multiplies productivity gains (Bresnahan & Trajtenberg, 1995), GPTs do not automatically reach this potential. Our study alludes to how the endogenous diffusion of GPTs may come from product customizations due to user innovation.

The limitations of the study offer avenues for future research. To what extent does cognition stemming from use experience override or surrender to specialized demand knowledge in shaping entrants' product portfolios? Our theoretical mechanisms and empirical evidence are consistent with both demand-oriented cognition and knowledge, although we cannot empirically rule out one over the other. How do various levels of usage breadth influence performance metrics beyond our findings about market share? Considering that our study focused on entrants' first products, how do product portfolios evolve over time? What types of pre-entry experiences and what initial product portfolios facilitate subsequent pivots? Do entrants with use experience retreat downstream to user industries if the industry's product is commoditized? As new segments appear, do existing incumbents occupy the new segments or do new firms with use experience from the respective segment successfully enter?

Overall, this study highlights a distinction in the pre-entry experiences of firms that we hope can generate new insights about the antecedents of entry strategy under conditions of demand uncertainty.

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## DATA AVAILABILITY STATEMENT

Parts of the data that support the findings of this study were derived from the following resources available in the public domain: The Federal Aviation Administration (FAA) database about Section 333 exemption, the FAA database about certificates of authorization; Firm websites, Crunchbase, and LinkedIn. Other parts of the data are available from the Association for Unmanned Systems International (AUVSI) directory and the Clarivate's Derwent World Patents Index. Restrictions apply to the availability of these data, which were used under license for this study.

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## SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

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