

BAM 2023 CONFERENCE

US
UNIVERSITY
OF SUSSEX

**BUSINESS
SCHOOL**

Early birds and early worms: First-movers vs fast-followers in the introduction of new-to-market products

Alex Coad

Early birds and early worms: First-movers vs fast-followers in the introduction of new-to-market products

Abstract

Previous empirical investigations of first-mover advantages often focused on individual industries. We complement earlier work with large-sample evidence on the first-mover phenomenon. We present descriptive evidence on product performance using a detailed firm-product-level dataset from Indian manufacturing, with 128 confirmed cases of First Movers (FMs) introducing new products into various industries (as well as 101 Fast Followers (FFs) and 296 Slow Followers (SFs)). First Movers do not have superior outcomes. First Movers have significantly lower product-level sales than Fast Followers, and significantly lower product-level survival than Slow Followers. Policy could have a role in supporting First Movers.

1 Introduction

“The early bird gets the worm”

“The early worm gets eaten”

Ancient proverbs

A central topic for strategy researchers is the creation of competitive advantage and capturing the resulting value. The prototypical case of value creation corresponds to radical innovation of the type that involves introducing a new product into the market.

First movers into new markets have a number of advantages related to their privileged position in the order of market entry, even if fast followers attempt to imitate and enter shortly afterwards. Lieberman and Montgomery (1988) make a pioneering contribution to the strategy field by weaving together various facets of first mover advantages (FMA) in the context of a unified conceptual framework and critical assessment of the literature. Lieberman and Montgomery (1988) put forward three categories of FMA: technological leadership, pre-emption of strategic assets and factors, and buyer switching costs. However, first movers may also be adversely affected by specific obstacles that can be grouped together as late mover advantages, or LMA (or alternatively, first-mover liabilities), such as free-riding by followers, benefitting from lower uncertainty; benefitting from new emerging technological opportunities ('technological gateways'); and leapfrogging over incumbents who have grown inert to environmental change.

Since publication, Lieberman and Montgomery (1988) won a prize from the Strategic Management Society and has influenced a considerable body of subsequent research, which has taken a variety of forms. Like Lieberman and Montgomery (1988), a number of literature reviews (Kerin et al., 1992; Robinson et al., 1994; Lieberman and Montgomery, 1998, 2013) have sought to categorize the various types of FMA and LMA by drawing on disparate strands of literature. Some papers are purely conceptual discussions e.g. Makadok (1998) on sustaining FMA in industries with low barriers to entry or imitation, Markides and Sosa (2013) on business models and FMAs, Vecchiato (2015) on strategic agility, and Suarez et al. (2015) on the distinction between dominant category and dominant design. More recently, theoretical analytical models (e.g. Flor and Moritzen, 2020) and also several simulation models (Capone et al., 2013; Querbés and Frenken, 2017; Chen et al., 2019) have emerged.

Naturally, the FMA literature has also produced empirical work, such as case study approaches (e.g. Eggers, 2014; Greve and Seidel, 2014, 2015). The case study approach has provided some rich examples. Greve and Seidel (2014, 2015) focus on the diffusion of the rival DC-10 and L-1011 aircraft, that can arguably be considered as "twins." The DC-10's one year lead gave it a decisive lead in the market, despite the L-1011's

technical superiority, suggesting that “being early beats being better.” In contrast, Eggers (2014) focuses on flat-panel computer displays (55 firms from the 1980s to the 2000s) and observes that superior outcomes were observed by firms that initially invested in a losing technology and later on switched to the winning technology. Overall, therefore, the case study approach has given detailed analyses of individual cases with high internal validity, although the external validity is low (as might be expected) in the sense that it is not possible to generalize about FMA in other industries. Hence, it is difficult to see the bigger picture about the overall importance of FMA.

Empirical research into FMA has also produced several high-quality quantitative studies focusing on one industry at a time, such as Dobrev and Gotsopoulos (e.g. 2010) on the US automobile industry, Gómez and Maícas (2011) and Gomez et al. (2016) on EU mobile telecoms, Franco et al. (2009) on survival of firms in the disk drive industry; and also Sabatier and Chollet (2017) on FMA in the area of scientific production in nanotechnology. Similar to the drawbacks of case study research, however, quantitative empirical analysis of the histories of individual sectors (e.g. Dobrev and Gotsopoulos, 2010; Gómez and Maícas, 2011; Gomez et al., 2016; Franco et al., 2009; Sabatier and Chollet, 2017) makes it difficult to appreciate the relative importance of FMA and LMA in broader business contexts. To do this, we need rigorous large-sample analysis of many industries.

Nevertheless, a problem that is holding back large-sample empirical work, with regards to moving beyond case studies and the histories of individual sectors, is that it is challenging to systematically identify which firm is the first mover (Cho et al., 1998). Often, identifying the first mover, and subsequent entrants such as fast followers, requires detailed contextual knowledge which is prohibitively difficult to collect across industries and present in a concise econometric analysis. For example, in a study of how patenting confers FMA for entrants, it would probably need to be demonstrated that a patent directly corresponds to technological characteristics of the new product being introduced, which is empirically quite challenging. Another approach is taken by Hsiao et al. (2017), who identify first movers based on self-reported questionnaire responses (i.e. a dummy variable for “whether a firm belongs to the first-mover of their industry” (p.80)), but (as

they duly note) such information could be vulnerable to self-report biases.

To summarize, the FMA literature would benefit from large-sample evidence. However, information on whether a new product introduced by a firm is genuinely novel (thus defining the firm as a ‘first mover’) is usually not found in standard datasets such as representative firm-level datasets from national statistical offices or private data collection firms. We contribute to the debate with rich Indian census data on 128 new products introduced in India from 1990-2012, with firm sales disaggregated at the product-level, and with new product introductions being identified by manually verifying the identities of firms corresponding to first movers and followers in newly-created product categories.

We make several contributions to the literature on FMA and strategic management. First, we are able to measure FMA events for 128 new product categories, thus providing a broad view of the phenomenon of first-mover advantages to complement existing empirical analyses that have tended to focus on the evolution of individual industries. This ‘big picture’ view of the FMA phenomenon provides a more balanced understanding of the advantages and liabilities faced by first movers. Our approach is to present evidence on the scale and extent of the first mover and follower phenomena across industries, in the context of descriptive statistics and regressions, rather than causal evidence regarding the mechanisms and drivers of early entry.

Second, while some literature has focused on firm-level outcomes, we focus on product-level outcomes, that refer to the ‘new’ product the firm started to produce, which in the case of first-movers corresponds to the creation of the market. This seems to be the theoretically correct level of analysis, given that firm performance is usually aggregated over several product lines. This also seems empirically important, because in our sample only 9 out of 128 new products are introduced by new entrants, with the rest being introduced by firms already active in other product markets. Indeed, in our sample, the median number of products of first movers is actually 3.

Third, we undertake a fine-grained analysis of entry order and distinguish between first movers, fast followers, and slow followers (where the two latter groups are distinguished in terms of years since the product was first introduced). This fine-grained analysis seems

valuable because many of the alleged FMAs are relative rather than absolute, for example uncertainty about the new technology and lack of legitimacy in the eyes of consumers are problems that are not necessarily resolved by the time of a fast follower’s entry, although they could be lessened by the time of a slow follower’s entry. Such a fine-grained analysis of fast vs slow followers is not common in the literature. We observe that slow followers are indeed different from fast followers, which could explain in part why previous work has shown conflicting results.

Fourth, we present evidence for a developing country (namely, India), which has been highlighted as an important gap in the literature (Lieberman and Montgomery, 1998, p1121), given the intensive use of samples from the USA and relative neglect of other countries, especially developing countries. The FMA literature has rarely investigated developing countries, let alone India.¹ Indian manufacturing is an interesting case because of its large market size characterized by a strong role of domestic demand offers a rich setting for studying new-to-country innovations.

First mover events are identified in terms of manual searches for information regarding “new” products that correspond to a new NPC (National Product Classification) 6-digit category. Our analysis shows that, out of 128 first-mover events, 85 have no FFs, (while 43 have one or more FF), 27 have no SFs (while 101 have one or more SF), and only 8/128 cases have no followers at all. The vast majority (119/128) of first movers are multiproduct firms. First movers have, *ceteris paribus*, fewer products than both fast-followers and slow-followers. First movers are more likely to be R&D investors than slow-followers, but less likely to be R&D investors than fast-followers. First-Movers generally have lower product-level survival rates than followers, with Slow-Followers having product-level survival rates that are significantly higher. First-Movers also generally have lower product-level sales than followers (highly statistically significant in the case of Fast Followers), and these differences in product-level sales persist in the years after product introduction. Fast Followers generally have a higher sales in the year of entry, and this scale advantage is visible even 5 years later.

¹See however Fuad and Sinha (2018) on entry timing for merger waves in India.

The paper proceeds as follows. Section 2 presents the theoretical background. Section 3 details on the data, section 4 shows evidence on characteristics of First-Movers, Fast Followers and Slow Followers, as well as evidence on differential performance of First-Movers in comparison with followers. Section 5 concludes.

2 Background

Lieberman and Montgomery (1988)’s contribution was to categorize into a unifying framework the dispersed literature on the various mechanisms and factors that could affect first movers. Our discussion below starts by discussing first mover advantages, then discuss first mover liabilities (or late mover advantages).

2.1 First mover advantages

Lieberman and Montgomery (1988) organized the literature relating to FMA into three categories: technological leadership; preemption of scarce assets; and consumers’ switching costs.

Technological leadership offers various benefits to first movers. Perhaps the most obvious case corresponds to patent races, where the first firm to patent a technology enjoys, in principle, monopoly rights to the profits derived from that technology. Such monopoly rights are immensely valuable in industries where appropriability is high (such as in pharmaceuticals, Hall et al., 2014), although in other industries patents can be less effective against ‘me-too’ products from imitators. First movers can also move faster down the learning curve to enjoy lower production costs that come from more efficient processes and routines (Chen et al., 2019). Another advantage for first movers is that they can shape the standards of the emerging technology and industry to suit their own circumstances.

Pre-emption of scarce assets, the second category of FMAs, includes a broad range of assets such as ownership and access to natural resources, as well as access to prime real estate locations for purposes of production, distribution, retailing, and so on. The

principle here is that the first mover, who pursues the business opportunity first, has the first pick of assets and resources, that so far are underpriced with respect to their value to the emerging industry. At a more micro level, first movers may benefit from first choice of shelf space in supermarkets to promote their products, or first choice of profit maximizing product attributes in a multidimensional product characteristics space. Pre-emption of scarce assets, factors, and resources can bring other advantages, such as scale economies, as well as entry deterrence operating via the (threatened or real) levels of commitment to productive capacity (Lieberman and Montgomery, 1988).

Switching costs constitute the third category of FMAs (Lieberman and Montgomery, 1988). These can take various forms, such as initial transaction costs, contractual switching costs created by the seller, or investments in supplier-specific learning made by the buyer. Subsequent theorizing in Lieberman and Montgomery (1998) discusses how network externalities can benefit the first mover and constitute a formidable barrier to entry. Gómez and Maícas (2011) find that switching costs are an important mechanism for FMAs in the European mobile telecommunications industry. Denrell and Liu (2021) explain how lower-quality products can enjoy favorable market outcomes because of initial momentum and reinforcing processes.

2.2 First mover liabilities

Lieberman and Montgomery (1988) also identified four broad categories of “first mover disadvantages,” that others have referred to as “latecomer advantages” (Cho et al., 1998) or “late mover advantages” (e.g. Shankar et al., 1998; Querbés and Frenken, 2017). Four categories can be mentioned: free rider effects; resolution of technological or market uncertainty; shifts in technology or customer needs; and incumbent inertia.

Free rider effects take on many forms. A major liability for technology-intensive firms involves leakages of strategically valuable technical knowledge due to R&D spillovers or mobility of researchers and technicians, as well as inter-firm diffusion of knowledge due to research publication, informal technical communication, ‘reverse engineering’, and so on. Follower firms may free-ride on investments made by the first mover to educate

buyers about the proposed solution to their needs; and the development of infrastructure with the supply chain and with other stakeholders. Follower firms may also find ways to imitate the first mover, and imitation generally costs much less than the initial outlays for innovation.

Technological and market uncertainty may also disproportionately affect first movers. First movers may invest large amounts in pivots and product iterations to set up a dominant design and industry standards that can be adopted relatively easily by new entrants. New entrants may be able to learn from the failure experiences of prior entrants and avoid repeating these costly mistakes, although of course learning from the experiences of others is not always easy (Yang et al., 2015). The emergence of a dominant design has been suggested to be a theoretically important landmark regarding the ideal timing of entry (Eggers, 2014; Suarez et al., 2015). Dobrev and Gotsopoulos (2010) extend the FMA discussion to new institutional concepts of legitimacy, and discuss how first movers operate in a “legitimacy vacuum,” while late movers can enter once this vacuum and related uncertainties have been reduced. Greve and Seidel (2015) observe that the McDonnell Douglas DC10 was stricken with design flaws, although these first mover liabilities turned out to be insufficient to outweigh the gains from earlier market growth.

Technological gateways for new entry may also give new entrants an opportunity to leapfrog over incumbents, if discontinuities in technological progress suddenly erode the value of the capabilities and assets accumulated by incumbents. Given that strategic investments in assets and resources can involve a tradeoff between commitment and flexibility (Trigeorgis and Reuer, 2017), entrants may benefit at certain junctures (such as the emergence of a dominant design) from having the flexibility to invest in state-of-the-art production capacity.

Relatedly, incumbent inertia can provide nimble entrants with privileged access to market opportunities. Incumbents may be slow to respond to the emergence of new opportunities if they are organizationally inflexible, which can be due to accumulated rules, routines, and procedures, or due to being locked-in to operating with specific fixed assets. Incumbents may also shy away from introducing new products and services for

fear of cannibalizing existing product lines. Incumbents that enjoyed success in the past may also have grown complacent, as Eggers (2014) observed in the flat panel computer displays industry.

3 Data

The paper employs firm-level and product-level data on Indian manufacturing firms (1988-2012) from the Prowess database, provided by the Centre for Monitoring Indian Economy (CMIE), which covers both publicly listed and unlisted firms. The companies covered account for around 70 percent of industrial output in the manufacturing sector in India. The data are collected by the CMIE from company balance sheets and income statements and cover both publicly listed and unlisted firms, and the companies covered account for around 70 percent of industrial output, 75 percent of corporate taxes, and more than 95 percent of excise taxes collected by the Government of India. The product-level information is available for 85 percent of the manufacturing firms, who collectively account for more than 90 percent of Prowess’ manufacturing output and exports. More importantly, product-level sales comprise 99 percent of the (independently) reported manufacturing sales. Prowess is therefore particularly well-suited for understanding how firms adjust their product lines over time. Previous studies which used the same firm-product-level data include Goldberg et al. (2010a) on the relationship between declines in trade costs, the imports of intermediate inputs and domestic firm product scope; and Goldberg et al. (2010b) who focus on the characteristics of multi-product firms and the link between product rationalization and trade reforms in India. The products are classified in a way similar to the harmonised system classification for products, and for this study we use products at the 6-digit level of classification.

3.1 Identifying first movers

The main challenge faced in this work is to identify the “first-movers”, (defined as the first firms to introduce a new product to the market), since this kind of information is

not available in firm-level datasets. Indeed, also our database does not provide such information and hence we complement this data with manually-collected data. First, we consider all the products that are new in each year in our data, throughout the whole time period. In each year, a “new” product is identified as a new NPC (National Product Classification) 6-digit category that was never reported by any firm before, thereby corresponding to the emergence of a new industry.

The database gives detailed information on the commercial name of the product and also the name of the firm, which enables advanced Google searches for articles/news with the name of the particular firm with the name of the “new product” around the years of introduction of the product in the database.² Hence, for the products that appear new in the database, the newspaper articles provides us with information on whether the product that is new to the firm is also new to the country.

The theoretically correct starting point in the FMA literature is not the time of patenting, or time of preparation or development, but actual market entry (Lieberman and Montgomery, 1988), and we take this approach.

The total number of firm-product combinations that we found with such a manual check is 128, and therefore we have 128 firms that are first-movers. Followers are defined as the firms that started the production of a product that is already introduced by First-movers, in any of the following years. We also perform the analysis for Fast Followers, defined as followers acting within one year of the introduction of the new product. Furthermore, we perform a robustness check by modifying the definition of fast-followers by also including the followers that act within the first 2 years and first 3 years, and the main results still hold. In line with the call by Lieberman and Montgomery (2013, p. 318) to “define a continuum of entrants and use more continuous timing measures”, we therefore distinguish between fast-followers and slow-followers. Slow followers are defined as those firms that are followers, but not fast-followers.

Overall, therefore, we have 128 First Movers, as well as 101 Fast Followers (FFs) and

²In most cases, the newspaper articles related to the new product introduced by the firm were published in the preceding year (in some cases 2 years before) of the year in which the new product appeared in the database. These articles mostly reported the details of the new product with the name of the firm that introduced it.

296 Slow Followers (SFs). Of the 128 industries, 85 have no FFs, while 43 have one or more FF. Of the 128 industries, 27 have no SFs, and 101 have one or more SF. Of the 128 industries, 8 have no followers at all, and these cases are mostly from the machinery sector.³

Even though our database offers a wide coverage of firms within Indian manufacturing, we do not have the full coverage of all firms. This might lead to omission of some new products introduced and some firms belonging to different categories - first movers and follower firms. However, in the sample that we use, we observe that most of the firms that are first movers and followers (both fast and slow ones) are large firms, and given the vast coverage of large firms in our database, we believe the results are not heavily biased.

Table 1 defines the categories of entrants.

— Table 1 about here —

3.2 Dependent variables

Foundational conceptual work in the FMA literature (Lieberman and Montgomery, 1988, 1998) recommended that appropriate dependent variables were profits, market share, or survival. These were usually measured at the level of the firm. In our case, we have product-level data, which seems more appropriate as a level of analysis for our dependent variable, given that the vast majority (119 out of 128) of our First Movers are multiproduct firms that would survive and enjoy positive sales (and perhaps also profits) even if the focal new product disappeared. We therefore have two dependent variables, product-level sales, and survival at the product level.

³Most of these belong to machinery sector, mostly complex capital goods produced by (likely) the biggest public sector firm in India (Bharat Heavy Electricals Ltd.). The 8 products are these: Hydro Sets – Hydro Turbine; Ap Cartridge Tapered Roller Bearings; Turbochargers; Tea Dryer; Freight Loco Transformers; Machines (Shot Blasting Equipment); Hydro Sets – Hydro Generator; and Railway Track Clips.

3.3 Independent variables

Our independent variables are fairly standard for investigations of firm performance. The independent variables include *SIZE*, defined as log of total sales of the firm; *AGE*, defined as the number of years since the year of incorporation of the firm; an *R&D* dummy which takes value one if the firm invests in *R&D* and zero otherwise; *INV* denotes firms' investment intensity, which is equal to firms' total investment divided by total sales; *LEVERAGE* is the ratio of firms' total borrowings over total assets; *CASH* is the liquid cash-in-hand left after payment of all expenses for the year; *SELLEXP* is the ratio of selling, distribution and marketing expenses over total sales of the firm; *PROFIT* is the ratio of total gross operating margins over total sales; *GROWTH* denotes firm growth defined as difference in log sales between t and $t - 1$; and *PDTCOUNT* is the number of products produced by the firm at the 6-digit level.⁴

In table 2, we report some summary statistics on the number of firms that are first-movers, fast-followers and slow-followers. Interestingly, we find that much of the first product introductions are done by multi-product firms (119 out of 128), which highlights that a new product introduction rarely happens without some pre-existing firm capabilities and complementary assets. This underscores the importance of measuring performance at the product level, whereas previous FMA analyses have generally focused on the firm level.

— Table 2 and 3 about here —

4 Results

4.1 Characteristics of first-movers vs followers

In this section we analyze the firm characteristics of first-movers, fast-followers and slow-followers.

We estimate the following multinomial logistic (MNL) regression equation:

⁴The classification of products is similar to harmonized system 6 digit level. Further details on the data are in Dosi et al. (2017).

$$\begin{aligned}
P(y_i = k \in \{FM, FF, SF\}) = & \phi(\beta_1 SIZE_{it-1} + \beta_2 AGE_{it-1} + \beta_3 R\&D_{it-1} + \beta_4 INV_{it-1} + \\
& \beta_5 LEVERAGE_{it-1} + \beta_6 CASH_{it-1} + \beta_7 SELLEXP_{it-1} + \beta_8 PROFIT_{it-1} + \\
& \beta_9 GROWTH_{it-1} + \beta_{10} PDTCOUNT_{it-1} + s_i + d_t + e_{it})
\end{aligned} \tag{1}$$

where the dependent variable y_i is one of {First Mover; Fast Follower; Slow Follower}, with the omitted baseline category being slow followers. Indices refer to firm i and product j . s_i is a set of 12 two-digit industry dummies, and d_t are year dummies. Each firm-product combination indicates that the FM, FF or SF statuses are present only in specific years, since it is a one-time event for each product. Therefore, the time indexes simply indicate that the independent variables (on the right hand side of the equation) are lagged by one year.

Multinomial Logistic regression results are in Table 4. Column 1 corresponds to First Movers, Column 2 refers to Fast Followers, and the omitted baseline category is Slow Followers. First Movers have, *ceteris paribus*, fewer products than SFs, and *a fortiori* fewer products than FFs. Both First Movers and Fast Followers are smaller than Slow Followers in terms of size (i.e. log of sales). First Movers are older than SFs, but younger than FFs. First Movers are more likely to be R&D investors than SFs, although this is not true when compared to FFs. FFs are at least equally well positioned with regards to R&D investors, perhaps because their R&D investments are made from the perspective of cultivating enough absorptive capacity to keep up with industry developments, and enter as fast followers before all technological uncertainty has been resolved. Interestingly, FFs have significantly higher ratios for selling, distribution and marketing expenses over total sales of the firm, perhaps indicating that they have the complementary assets in place to enable them to overcome the entry barriers and first mover advantages.

— Table 4 about here —

Lieberman and Montgomery (1988) proposed that firms that enter first in the market have skills more related to new product development while the later entrants have more relative strengths in marketing, since by the time they enter, the initial market and technological uncertainties have been resolved. Several empirical studies, in particular in marketing literature tested this proposition. For instance, Robinson et al. (1992) found that firms with greater marketing skills tend to be followers.

4.2 Product performance of first-movers, fast-followers and slow followers

We now investigate the differential performance of the three categories of firms: first-movers, fast-followers and slow followers. One important issue is that most previous works investigate the relationship between entry timing and firm-level performance, instead of focusing on the product-level performance in the market where the firm is a first-mover or early-entrant. This paper investigates the performance of the firm in the market where it is a first-mover. Here, market refers to the product the first-mover firm started to commercialize. Hence, we look at the product performance of first-movers with respect to followers, focusing on two dimensions of product performance. *First*, we look at the product survival, to analyse the different probabilities of product dropping by firms belonging to the aforementioned categories. *Second*, we look at the size of the product, proxied by total value of sales of the product in the following years after its introduction.

4.2.1 Product-level survival

To investigate the relationship between the status of being a first-mover and product survival, we estimate the following equation:

$$\begin{aligned}
PDTDROP_{ijt} = & \alpha + \beta_1 PDTSIZE_{ijt-1} + \beta_2 FIRMSIZE_{it-1} + \beta_3 AGE_{it-1} + \beta_4 R\&D_{it-1} \\
& + \beta_5 INV_{it-1} + \beta_6 LEVERAGE_{it-1} + \beta_7 CASH_{it-1} + \beta_8 SELLEXP_{it-1} \\
& + \beta_9 PROFIT_{it-1} + \beta_9 D_{FM_{ij}} + p_j + s_i + d_t + e_{ijt}
\end{aligned} \tag{2}$$

where $PDTDROP_{ijt}$ takes value 1 if firm i stops producing the product j at year t and zero if the product is still being produced.⁵ Our main variable of interest, $D_{FM_{ij}}$ represents three different dummies defined to capture the differences in entry timings: The dummy ALL_FOLL takes value 1 for any follower and 0 in the case of a first mover. ALL_FOLL is then disaggregated into $FAST_FOLL$ and $SLOW_FOLL$. The dummy $FAST_FOLL$ takes value 1 for a fast follower and 0 for other categories (first movers and slow followers). The dummy $SLOW_FOLL$ takes value 1 for a slow follower and 0 for other categories.

$PDTSIZE$ is the size of the product proxied by log sales of the product. $FirmSize$ is proxied by the size of the firm removing the product under analysis, i.e. (log of) sum of sales of the products of the firm removing the product in analysis. This is done since total firm sales and product size (of the product in analysis) are highly correlated, since the former includes also the latter.⁶ The other independent variables are the same as in equation 1. In addition to sector (s_i) and time (d_t) dummies, we also add product dummies (p_j) to control for product-specific effects. Equation 2 is estimated using a Logit specification.

Table 5 reports the regression results. The significant negative coefficient of -0.5569 in Column (1) indicates that followers have a significantly lower chance of product exit. Column (2) reports the marginal effects of ALL_FOLL on the probability of product

⁵To be precise, exit by firm i of product j at year t corresponds to the case where firm i reports non-zero firm-level sales for year t while not reporting sales for product j for year t . This ensures that product-level exit does not mistakenly correspond to cases of merely neglecting to report non-zero sales.

⁶Pearson pairwise correlation coefficient $\rho = 0.4761$, with p-value < 0.0001 .

dropping. The coefficient of -0.0604 indicates that the expected probability of product exit decreases by 0.0604 if the firm is a follower instead of a first mover. Column (3) disaggregates the results for followers to distinguish between fast followers and slow followers. Fast followers do not have any significant difference from firm movers in terms of product survival, but slow followers have a higher chance of product survival. Column (4) reports marginal effects for fast and slow followers; the coefficient reported for slow followers suggests that the probability of product dropping decrease by 0.0905 if the firm is a slow follower.

We further check whether our results are robust to using a Cox proportional hazard model. Estimating the hazard of exit using a Cox proportional hazard specification complements the Logit specification as it models both the event of failure and the time it takes a product to fail (gets dropped). The results are reported in Table 8 in Appendix A. We find that probability of product dropping is lower for followers, in particular slow followers. This further substantiates the results we observe with a Logit specification.

— Table 5 about here —

4.2.2 Product size

In this section, we look at the second dimension of product performance - the size of the product defined in terms of log sales of the product. To investigate the product performance of first-movers, slow and fast followers, we estimate equation (3) using a pooled OLS regression.

$$\begin{aligned}
 PDTSIZE_{ijt} = & \alpha + \beta_1 FIRM SIZE_{it-1} + \beta_2 AGE_{it-1} + \beta_3 R\&D_{it-1} \\
 & + \beta_4 INV_{it-1} + \beta_5 LEVERAGE_{it-1} + \beta_6 CASH_{it-1} + \beta_7 SELLEXP_{it-1} \\
 & + \beta_8 PROFIT_{it-1} + \beta_9 D_{FM_{ijt}} + p_j + s_i + d_t + e_{ijt}
 \end{aligned}
 \tag{3}$$

As we defined before, $D_{FM_{ij}}$ represents three different dummies, ALL_FOLL, FAST_FOLL and SLOW_FOLL. In table 6, Column (1) reports the results of all followers while Column (2) reports the results disaggregated into fast and slow followers. We find that the coefficient for ALL_FOLL is positive and statistically significant (p -value = 0.002), indicating that followers have greater product sales compared to first movers. Disaggregating this to fast and slow followers, we find that fast followers have significantly more product sales than first movers, as reported in column 2.

— Table 6 about here —

Further, we analyze product performance separately for each year after the introduction of the product. Cross-sectional year-wise regressions are performed separately for each yearly slice of equation (3) in the years after the introduction of the product, pooling all the firm-product combinations since the year of introduction of the product. Therefore, for the first year regression, the observations include the first year of introduction of the product for the first-mover and follower. While these firm-product observations are pooled from different calendar years, we include time dummies (d_t) which are related to calendar years in order to control for any role of year-specific factors.

The results are reported in table 7. Each column refers to the different yearly slices. The coefficient of FAST_FOLL is positive and significant in all the years indicating that fast followers have significantly higher product sales compared to first movers.

— Table 7 about here —

Our evidence offers little support to notions of first-mover advantage, because these appear to be outweighed by late-mover advantages. What we find is not merely an absence of first-mover advantage, but rather that the followers have better outcomes. In the case of product survival, slow followers are significantly better off than the first movers, while there is no difference between fast followers and first movers, which indicates that there is no incentive for firms to be the first mover in a market. While in the case of

product size, fast followers are significantly better off suggesting that, it is advantageous for firms to be fast followers instead of first-movers. Kim and Lee (2011) analyse data on Korean manufacturing firms, and find that early-entrants have a lower rate of market share growth than other late entrants, but the tendency is reversed in regimes with low levels of technological opportunity and high levels of R&D appropriability. The present study has the advantage of using a large-scale comprehensive database with detailed product-level information and an accurate definition of first-movers.

Figure 1 below shows the evolution of (log of) average product sales for FM, FF and SF. It is interesting to see that FF almost always have higher log of average product sales, even in year 1 (i.e. in their first year in the market, which is 1 year after the year that the FM started selling the product in the market). Figure 2 shows kernel density plots of (log) product sales for FM, FF and SF in the year of entry and 5 years after entry. In both cases, the distribution for fast followers dominates the one of first movers, indicating higher product sales for fast followers when compared to first movers.

— Figure 1 and Figure 2 about here —

Figure 3 shows the Kaplan Meier survival estimates for the three categories (FM, FF, SF) in the years after entry. Survival rates are very high for the first 7 years or so, but afterwards First Movers have the lowest survival rates out of the three categories. This highlights the risky nature of new product introductions, and suggests that latecomer advantages outweigh first-mover advantages when it comes to product survival.

— Figure 3 about here —

5 Conclusion

Innovating firms enjoy a number of first-mover advantages, while also being vulnerable to being overtaken by imitators and followers (Lieberman and Montgomery, 1988; Cho et al., 1998). While much previous research has focused on case studies and individual industries (e.g. Dobrev and Gotsopoulos, 2010; Greve and Seidel, 2015), we contribute to

the literature with a relatively large-sample analysis of first mover events from a broad range of industries. First mover events are identified in terms of manual searches for information regarding “new” products that correspond to a new NPC (National Product Classification) 6-digit category.

Out of 128 first-mover cases, only 8 have no followers at all. The vast majority (119/128) of first movers are multiproduct firms. First movers have, *ceteris paribus*, fewer products than both fast-followers and slow-followers. First movers are more likely to be R&D investors than slow-followers, but less likely to be R&D investors than fast-followers. Considering also that fast-followers have the largest expenditures for selling and distribution, it seems that absorptive capacity (via R&D) and complementary assets (via selling and distribution expenditures) are important for a Fast-Follower strategy. First-mover outcomes are generally inferior to those of followers. Slow Followers have statistically significantly longer product-level survival than first-movers. Fast Followers have significantly larger product-level sales than First Movers. Fast followers generally have a higher sales in the year of entry, and this scale advantage remains even 5 years later.

We complement the existing literature (which has often focused on individual industries) with large-scale evidence on the scale and extent of the first mover and follower phenomena across industries. This is done using descriptive statistics and regressions, rather than causal evidence regarding the mechanisms of early entry. Future work could apply causal empirical frameworks to better understand the drivers of the decision to enter first or delay entry, or to estimate the causal effect (premium or liability) of being a pioneering first-mover. For example, future work that applies a causal empirical framework could investigate the counterfactual case of a potential First-Mover firm that instead waits to be overtaken and then enters as a Fast-Follower. Future work could also investigate whether the lack of first-mover advantages observed in our large-sample dataset on Indian first-mover events is also observed in other institutional contexts outside India.

Overall, our results suggest that first movers are a valuable yet vulnerable species of ‘optimistic martyrs’ (Dosi and Lovaglio, 1997). In general, first movers are quickly over-

taken by fast followers who are large R&D investors with considerable absorptive capacity, as well as complementary assets and capabilities, to have larger sales than the first mover in the year that they enter. First movers also have relatively high rates of exiting from the product market, compared to fast followers and also slow followers. These results can be considered alongside observed recent trends that firms are investing less in R&D (Chesbrough, 2003) and in basic science (Arora et al., 2018) and that promising innovators are often gobbled up through ‘killer acquisitions’ (Cunningham et al., 2021), while unsuccessful innovators will perish by themselves. Care should be taken that the incentives for innovators do not fall to dangerously low levels. Innovation policy instruments (e.g. IP protection, competition policy, public procurement of innovation, innovation grants) could be adjusted to ensure that first movers are rewarded for their efforts rather than being trampled by large nimble followers. It would be reckless to assume that innovators will continue to appear, despite weakening incentives, through the force of sheer irrational optimism alone.

References

- ARORA, A., S. BELENZON, AND A. PATACCONI (2018): “The decline of science in corporate R&D,” *Strategic Management Journal*, 39, 3–32.
- CAPONE, G., F. MALERBA, AND L. ORSENIGO (2013): “Are switching costs always effective in creating first-mover advantage? The moderating role of demand and technological regimes,” *Long Range Planning*, 46, 348–368.
- CHEN, J. S., M. J. LEIBLEIN, AND H. E. POSEN (2019): “Uncertainty in learning curves: implications for early mover advantage,” *Unpublished*.
- CHESBROUGH, H. W. (2003): *Open innovation: The new imperative for creating and profiting from technology*, Harvard Business Press.
- CHO, D.-S., D.-J. KIM, AND D. K. RHEE (1998): “Latecomer strategies: Evidence from the semiconductor industry in Japan and Korea,” *Organization Science*, 9, 489–505.
- CUNNINGHAM, C., F. EDERER, AND S. MA (2021): “Killer acquisitions,” *Journal of Political Economy*, 129, 649–702.
- DENRELL, J. AND C. LIU (2021): “When Reinforcing Processes Generate an Outcome-Quality Dip,” *Organization Science*.
- DOBREV, S. D. AND A. GOTSPOULOS (2010): “Legitimacy vacuum, structural imprinting, and the first mover disadvantage,” *Academy of Management Journal*, 53, 1153–1174.
- DOSI, G., M. GRAZZI, AND N. MATHEW (2017): “The cost-quantity relations and the diverse patterns of learning by doing: Evidence from India,” *Research Policy*, 46, 1873–1886.
- DOSI, G. AND D. LOVALLO (1997): “Rational entrepreneurs or optimistic martyrs? Some considerations on technological regimes, corporate entries, and the evolutionary role of decision biases.” in *Technological innovation: Oversights and foresights*, ed. by R. Garud and P. R. Nayyar, New York: Cambridge University Press.
- EGGERS, J. (2014): “Get ahead by betting wrong,” *Harvard business review*, 92, 25–26.

- FLOR, C. R. AND M. R. MORITZEN (2020): “Entering a new market: Market profitability and first-mover advantages,” *Journal of Corporate Finance*, 62, 101604.
- FRANCO, A. M., M. SARKAR, R. AGARWAL, AND R. ECHAMBADI (2009): “Swift and smart: the moderating effects of technological capabilities on the market pioneering–firm survival relationship,” *Management Science*, 55, 1842–1860.
- FUAD, M. AND A. K. SINHA (2018): “Entry-timing, business groups and early-mover advantage within industry merger waves in emerging markets: A study of Indian firms,” *Asia Pacific Journal of Management*, 35, 919–942.
- GOLDBERG, P. K., A. K. KHANDELWAL, N. PAVCNIK, AND P. TOPALOVA (2010a): “Imported Intermediate Inputs and Domestic Product Growth: Evidence from India,” *The Quarterly Journal of Economics*, 125, 1727–1767.
- (2010b): “Multiproduct firms and product turnover in the developing world: Evidence from India,” *The Review of Economics and Statistics*, 92, 1042–1049.
- GOMEZ, J., G. LANZOLLA, AND J. P. MAICAS (2016): “The role of industry dynamics in the persistence of first mover advantages,” *Long Range Planning*, 49, 265–281.
- GÓMEZ, J. AND J. P. MAÍCAS (2011): “Do switching costs mediate the relationship between entry timing and performance?” *Strategic Management Journal*, 32, 1251–1269.
- GREVE, H. R. AND M.-D. L. SEIDEL (2014): “Being early beats being better,” *Harvard business review*, 92, 30–31.
- (2015): “The thin red line between success and failure: Path dependence in the diffusion of innovative production technologies,” *Strategic Management Journal*, 36, 475–496.
- HALL, B., C. HELMERS, M. ROGERS, AND V. SENA (2014): “The choice between formal and informal intellectual property: a review,” *Journal of Economic Literature*, 52, 375–423.
- HSIAO, Y.-C., C.-J. CHEN, R.-S. GUO, AND K.-K. HU (2017): “First-mover strategy, resource capacity alignment, and new product performance: a framework for mediation and moderation effects,” *R&D Management*, 47, 75–87.

- KERIN, R. A., P. R. VARADARAJAN, AND R. A. PETERSON (1992): “First-mover advantage: A synthesis, conceptual framework, and research propositions,” *Journal of marketing*, 56, 33–52.
- KIM, J. AND C.-Y. LEE (2011): “Technological regimes and the persistence of first-mover advantages,” *Industrial and Corporate Change*, dtr048.
- LIEBERMAN, M. B. AND D. B. MONTGOMERY (1988): “First-mover advantages,” *Strategic management journal*, 9, 41–58.
- (1998): “First-mover (dis) advantages: Retrospective and link with the resource-based view,” *Strategic management journal*, 1111–1125.
- (2013): “Conundra and progress: Research on entry order and performance,” *Long Range Planning*, 46, 312–324.
- MAKADOK, R. (1998): “Can first-mover and early-mover advantages be sustained in an industry with low barriers to entry/imitation?” *Strategic Management Journal*, 19, 683–696.
- MARKIDES, C. AND L. SOSA (2013): “Pioneering and first mover advantages: the importance of business models,” *Long Range Planning*, 46, 325–334.
- QUERBES, A. AND K. FRENKEN (2017): “Evolving user needs and late-mover advantage,” *Strategic organization*, 15, 67–90.
- ROBINSON, W. T., C. FORNELL, AND M. SULLIVAN (1992): “Are market pioneers intrinsically stronger than later entrants?” *Strategic Management Journal*, 609–624.
- ROBINSON, W. T., G. KALYANARAM, AND G. L. URBAN (1994): “First-mover advantages from pioneering new markets: A survey of empirical evidence,” *Review of Industrial Organization*, 9, 1–23.
- SABATIER, M. AND B. CHOLLET (2017): “Is there a first mover advantage in science? Pioneering behavior and scientific production in nanotechnology,” *Research Policy*, 46, 522–533.
- SHANKAR, V., G. S. CARPENTER, AND L. KRISHNAMURTHI (1998): “Late mover advantage: How innovative late entrants outsell pioneers,” *Journal of Marketing research*, 35, 54–70.

- SUAREZ, F. F., S. GRODAL, AND A. GOTSPOULOS (2015): “Perfect timing? Dominant category, dominant design, and the window of opportunity for firm entry,” *Strategic management journal*, 36, 437–448.
- TRIGEORGIS, L. AND J. J. REUER (2017): “Real options theory in strategic management,” *Strategic management journal*, 38, 42–63.
- VECCHIATO, R. (2015): “Creating value through foresight: First mover advantages and strategic agility,” *Technological Forecasting and Social Change*, 101, 25–36.
- YANG, J. Y., J. LI, AND A. DELIOS (2015): “Will a second mouse get the cheese? Learning from early entrants failures in a foreign market,” *Organization Science*, 26, 908–922.

Appendix

Appendix A: Cox Regressions

In this section, we assess the likelihood of survival of products for first movers, fast and slow followers. To do so, we perform a survival analysis, where the duration of products in the new market it was introduced is expressed in terms of a hazard function. The hazard function, also known as conditional failure rate measures the probability of product exiting a market given that it has survived up to a certain time period. We test if this hazard is a function of the status of the firm in terms of first mover, fast or slow follower. We employ the Cox (1972, 1975) semi-parametric hazard regression model as follows:

$$h(t, x_{it}) = h_0(t) \exp\left(\sum_{k=1}^K \beta_k x_{it}^k\right) \quad (4)$$

in which $h(t, x_{it})$ is the hazard faced by product i at a given time t . This hazard is dependent or conditional on a set of explanatory variables x_{it}^k as determined by the associated parameters β_k . The exponential is applied so that $h(t, x_{it}) \geq 0$. We denote $h_0(t)$ as the baseline or starting hazard for which all explanatory variables are equal to zero. The regression is implemented via maximum likelihood.

In table 8, we report the results from a cox proportional hazard model. The coefficient is negative and significant for SLOW_FOLL and ALL_FOLL suggesting that the probability of dropping a product is lower for these categories as compared with first movers.

Tables

Table 1: **Definitions of different categories**

	Definition
First Mover (FM)	Firms that introduce a specific product in India for the first time
Followers	Firms that started the production of a product already introduced by First-movers, in any of the following years
Fast Follower (FF)	Followers acting within one year of the introduction of the new product
Slow Follower (SF)	Firms that are followers, but not fast-followers
Early Entrants (EE)	Firms that have entered the market early, which includes both first movers and fast followers (Capone et al., 2013).

Table 2: Summary Statistics: First-movers, Fast-followers and Slow-followers. One observation per firm, corresponding to the year that the firm enters.

Categories	Single-product firms	Multi-product firms	Total firms
First-movers	9 (7.03)	119 (92.96)	128 (100)
Fast-followers	24 (23.76)	77 (76.23)	101 (100)
Slow-followers	75 (25.34)	221 (74.66)	296 (100)

Table 3: Summary Statistics: Product count of First-Movers, Fast-Followers and Slow-Followers. One observation per firm, corresponding to the year that the firm enters.

	First-Movers	Fast-followers	Slow-followers
Mean	4.48	2.58	3.01
Median	3	2	2
SD	3.15	1.80	2.42
Min	1	1	1
Max	22	12	20

Table 4: **Multinomial Logit Regression**

	First Movers	Fast Followers
Product Count	-0.2239 (0.0853)	0.0913 (0.0483)
Firm Size	-0.4090 (0.1711)	-0.6173 (0.1510)
Age	0.6945 (0.2321)	1.1907 (0.2059)
R&D Dummy	0.7731 (0.3192)	0.9034 (0.2720)
Investment Intensity	1.5800 (1.0762)	1.7871 (1.0077)
Leverage	0.2338 (0.1372)	0.2561 (0.1197)
Cash balance	0.0703 (0.0910)	0.2237 (0.0751)
Sell. & Distr. Exp.	0.0479 (0.1171)	0.2362 (0.1017)
Profitability	-2.2178 (2.0964)	-2.2997 (1.7483)
Firm Growth	-0.2476 (0.4721)	-0.5770 (0.4356)
[1em] Time Dummies	Yes	Yes
Sector Dummies	Yes	Yes
Observations	684	
Pseudo R^2	0.246	

Standard errors (clustered at the firm level) in parentheses
Base: Slow-followers

Table 5: **Logistic duration model for product survival**

	(1)	(2)	(3)	(4)
	All followers	Marginal Effects (All Followers)	FF vs SF	Marginal Effects (FF vs SF)
Product Size	-0.0212 (0.0317)	-0.0028 (0.0029)	-0.0204 (0.0284)	-0.0027 (0.0028)
Firm Size	0.0681 (0.1540)	0.0039 (0.0137)	0.0991 (0.1549)	0.0061 (0.0133)
Age	0.3165 (0.1968)	0.0273 (0.0187)	0.2862 (0.2111)	0.0252 (0.0176)
R&D Dummy	0.4136 (0.3330)	0.0372 (0.0316)	0.3477 (0.3472)	0.0353 (0.0308)
Investment Intensity	1.3266 (1.1945)	0.0526 (0.0849)	0.9496 (1.1996)	0.0235 (0.0797)
Leverage	0.0324 (0.1552)	0.0027 (0.0133)	0.0064 (0.1613)	0.0016 (0.0134)
Cash balance	0.0220 (0.0941)	-0.0012 (0.0070)	0.0244 (0.0878)	-0.0014 (0.0069)
Profitability	2.1966 (2.1704)	0.3519 (0.2001)	2.6531 (2.3292)	0.3762 (0.1975)
Sell. & Distr. Exp.	0.0250 (0.1050)	-0.0029 (0.0103)	0.0278 (0.1191)	-0.0027 (0.0102)
ALL_FOLL	-0.5569 (0.2780)	-0.0604 (0.0295)		
FAST_FOLL			0.1479 (0.4551)	-0.0052 (0.0416)
SLOW_FOLL			-0.8655 (0.3133)	-0.0905 (0.0393)
Time Dummies	Yes		Yes	
Product Dummies	Yes		Yes	
Sector Dummies	Yes		Yes	
Observations	686	686	686	686
Pseudo R^2	0.044	0.044	0.059	0.059

Dependent variable: survival = 0, exit = 1.

Standard errors (clustered at the firm level) in parentheses

Table 6: **Pooled OLS regressions for Product Size.**

	(1)	(2)
	All Followers	FF vs SF
Firm Size	0.6194 (0.1333)	0.6054 (0.1581)
Age	0.0458 (0.2365)	-0.1450 (0.2289)
R&D Dummy	-0.1387 (0.1819)	-0.0155 (0.1966)
Investment Intensity	0.3357 (0.4640)	0.5933 (0.6186)
Leverage	-0.0131 (0.0838)	-0.0019 (0.0869)
Cash balance	-0.0176 (0.0434)	0.0055 (0.0386)
Profitability	-0.9954 (0.9943)	-0.9065 (1.0154)
Sell. & Distr. Exp.	0.1516 (0.1067)	0.1510 (0.1232)
ALL_FOLL	1.1153 (0.3561)	
FAST_FOLL		1.5227 (0.3706)
SLOW_FOLL		0.3816 (0.3579)
Time Dummies	Yes	Yes
Product Dummies	Yes	Yes
Sector Dummies	Yes	Yes
Observations	604	604
R^2	0.212	0.239

Dependent variable: log of product-level sales.

Standard Errors (clustered at the firm level) in parentheses

Table 7: **Product Size (Cross sectional regression)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1st Year	2nd Year	3rd Year	4th Year	5th Year	6th Year	7th Year
Firm Size	0.4152 (0.0966)	0.5427 (0.0911)	0.5516 (0.0986)	0.6084 (0.1159)	0.6674 (0.1200)	0.8296 (0.1178)	0.8448 (0.1003)
Age	-0.3408 (0.1619)	-0.5079 (0.1801)	-0.3050 (0.2231)	-0.1511 (0.2396)	-0.4537 (0.2996)	-0.4284 (0.3463)	-0.1515 (0.4213)
R&D Dummy	0.4424 (0.3003)	0.2179 (0.3038)	0.0162 (0.3744)	0.1020 (0.3141)	-0.5657 (0.3952)	0.2349 (0.4275)	-0.1282 (0.5353)
Investment Intensity	0.0924 (0.6136)	-0.5448 (0.9435)	-1.2930 (0.7014)	1.6634 (0.7348)	0.8479 (1.1620)	-1.6058 (3.9006)	-0.9738 (2.7396)
Leverage	0.2668 (0.1192)	0.1352 (0.1469)	-0.0018 (0.0974)	0.2747 (0.2084)	0.1257 (0.1466)	0.0686 (0.1163)	-0.1926 (0.1789)
Cash balance	0.0562 (0.0761)	-0.0359 (0.0800)	0.0734 (0.1007)	0.0035 (0.0864)	-0.1876 (0.0938)	-0.2554 (0.1063)	-0.0466 (0.1178)
Profitability	0.1108 (0.2820)	0.2802 (0.2962)	0.1809 (0.3364)	0.1426 (0.3976)	0.0624 (0.4229)	-0.1748 (0.4825)	0.6100 (0.4486)
Sell. & Distr. Exp.	0.1986 (0.0861)	0.1798 (0.0832)	0.0664 (0.0980)	0.0943 (0.1088)	0.2098 (0.1348)	-0.0389 (0.1313)	-0.1843 (0.1555)
FAST_FOLL	0.8828 (0.3103)	0.9043 (0.3138)	1.4581 (0.3116)	1.2550 (0.3559)	0.8176 (0.4436)	1.0948 (0.4599)	1.4063 (0.4635)
SLOW_FOLL	0.6482 (0.2755)	0.2371 (0.2932)	0.4917 (0.3182)	0.6468 (0.3267)	0.3948 (0.3897)	0.4697 (0.4127)	0.4167 (0.4986)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	309	255	235	207	170	140	120
R^2	0.279	0.333	0.295	0.334	0.344	0.333	0.343

Dependent variable: log of product-level sales.

Standard errors (clustered at the firm level) in parentheses

Table 8: **Results of Cox regressions - Probability of dropping a product**

	(1)	(2)
	I	II
Product Size	0.0270 (0.0163)	0.0343 (0.0168)
Firm Size	-0.0638 (0.0823)	-0.0575 (0.0822)
Age	-0.7097 (0.0927)	-0.7654 (0.0965)
R&D Dummy	0.1795 (0.1143)	0.1707 (0.1146)
Investment Intensity	1.3936 (0.4057)	1.2854 (0.4024)
Leverage	0.1784 (0.0621)	0.1656 (0.0623)
Cash balance	0.0214 (0.0352)	0.0148 (0.0352)
Profitability	1.7903 (0.7954)	2.0108 (0.8014)
Sell. & Distr. Exp.	-0.0581 (0.0602)	-0.0542 (0.0599)
ALL_FOLL	-1.038 (0.1683)	
FAST_FOLL		-0.5254 (0.2215)
SLOW_FOLL		-1.3860 (0.2175)
Time Dummies	Yes	Yes
Product Dummies	Yes	Yes
Sector Dummies	Yes	Yes
Observations	377	377
Pseudo R^2	0.027	0.029

Standard errors (clustered at the firm level) in parentheses

Figures

Figure 1: Product level sales for FM, FF and SF

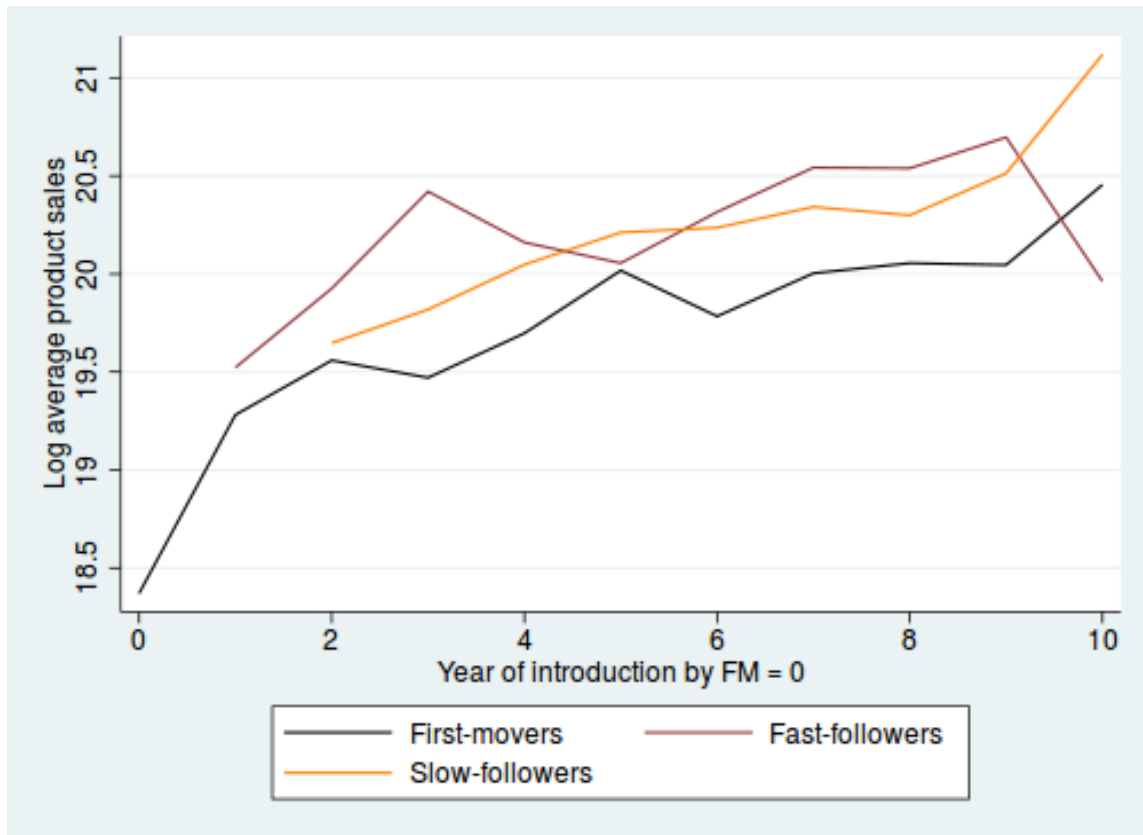


Figure 2: Total sales in the year of entry (left) and after 5 years (right) for FM, FF and SF

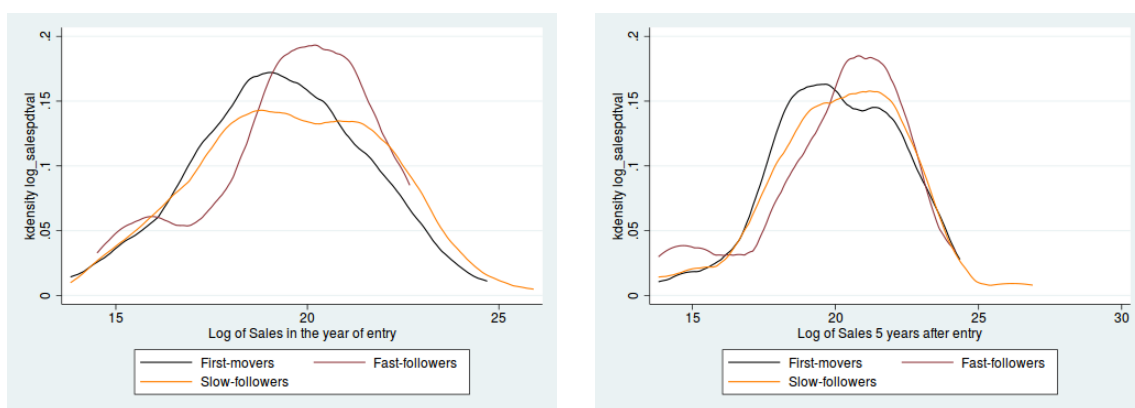


Figure 3: Kaplan Meier survival plot for the years after entry, for FM, FF and SF

