

First mover, Fast Second or Later Mover in Platform Industries?

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First mover, Fast Second or Later Mover in Platform Industries? An Integrated Model of Entry Timing Advantages

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Abstract

Strategy scholars have long investigated entry timing advantages, in particular the mechanisms, environmental conditions and firm-level resources and capabilities that are associated with the success of early and late entrant competitors. Research has not been conclusive on the existence of first mover advantage, which has led several scholars to propose the existence of first mover disadvantage and to propose specific times of entry (e.g. a "fast second") that could more likely lead to advantage. Data limitations in most extant empirical work confines the study of entry timing strategies. Our paper attempts to overcome some of those limitations by integrating many of the strategic entry timing dimensions into a conceptual framework and a model which allows us to explore a range of competitive outcomes associated with different entry strategies. Our analysis also departs from the outsized focus on first movers in the literature, presenting the implications on the later entrant strategies.

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Abstract

Strategy scholars have long investigated entry timing advantages, in particular the mechanisms, environmental conditions and firm-level resources and capabilities that are associated with the success of early and late entrant competitors. Research has not been conclusive on the existence of first mover advantage, which has led several scholars to propose the existence of first mover disadvantage and to propose specific times of entry (e.g. a “fast second”) that could more likely lead to advantage. Data limitations in most extant empirical work confines the study of entry timing strategies. Our paper attempts to overcome some of those limitations by integrating many of the strategic entry timing dimensions into a conceptual framework and a model which allows us to explore a range of competitive outcomes associated with different entry strategies. Our analysis also departs from the outsized focus on first movers in the literature, presenting the implications on the later entrant strategies.

Keywords: first mover advantage, fast second, platforms, competition, system dynamics

INTRODUCTION

There is a long and ongoing debate among scholars on the performance benefits of entering a new market early (Lieberman and Montgomery, 2013). The concept of “first mover advantage,” has enjoyed much appeal and attention among practitioners, but has proved to be rather elusive and difficult to study for management researchers. Early research identified several “isolating mechanisms” that enabled first mover advantage (Lieberman and Montgomery, 1988), namely technology leadership, preemption of scarce assets, and buyer switching costs. Network effects, a demand-side phenomenon particularly relevant for platform industries, is now considered a fourth isolating mechanism (Farrell and Saloner, 1985; Katz and Shapiro, 1986; Farrell and Klemperer, 2007; Eisenmann et al., 2011). Despite the identification of the mechanisms that create first mover advantage (FMA), empirical evidence remains unclear and the answer to whether FMA exists is still inconclusive, after decades of research on the topic. There are many studies that confirm and many that negate the existence of first mover advantage (Huff and Robinson, 1994; Brown and Lattin, 1994; Lieberman and Montgomery, 1998; Sheremata, 2004; Cennamo and Santalo, 2013).

Scholars have found that several contingencies affect the likelihood of first mover advantage. A stream of research has studied the role of firm capabilities on first mover advantage (Schoenecker and Cooper, 1998; Lee, 2009). Klepper and Simons (2000), for instance, document how the capabilities of US radio producers helped their successful entry in the nascent television manufacturing industry. Another stream has studied how environmental dynamics can modulate the strength of first mover advantage (Suarez and Lanzolla, 2007). Gomez, Lanzolla and Maicas (2016), for instance, find that market growth and technological discontinuities affect negatively

the existence of first mover advantage. Kapoor and Furr (2013), study the effect of firm pre-entry capabilities and complementarities in the existing industry ecosystem, on entry timing advantage. These detailed studies of early-mover contingencies add to our understanding of FMA, but they also make it harder to empirically capture the combined effect of these contingencies and the isolating mechanisms.

In this paper, we provide what we believe is a first attempt to explore directly how each of these different contingencies and their interactions influence first mover advantage in a new platform market. The underlying premise of platform competition is that the emergence of a dominant platform is driven by the adoption decisions of users and complementors. This premise relies and emphasizes positive feedback loops, driven by firm agency, to attract and retain large numbers of users and complementors so as to deter later entrants from entering the market due to the power of direct and indirect network effects (McIntyre et al., 2021). The emphasis on feedback loops suggests taking an endogenous perspective in exploring these issues (Sternan, 2000; Epstein, 2007). We thus develop a model that captures some of the most salient elements of the isolating mechanisms, firm resources, and environmental factors. The empirical complexity and data limitations that partition research on first mover advantage and hinder its progress are conditions conducive to a longitudinal approach with modeling and simulation (Langley, 1999; Langley et al., 2013) of dynamics and relationships that are not easily captured by empirical research, thus providing new theoretical insights (Harrison et al., 2007; Davis et al., 2007; Burton and Obel, 2011). Our model draws directly from existing theory and allows us to respond to the call by Lieberman and Montgomery (2013) that, to make progress, the elements of first mover advantage theory “should be studied individually and in interaction” (p. 324).

The model is set up in a platform-mediated industry, which allows us to include and observe the implications of network effects on first mover advantage. The model considers two firms, a first mover that enters at the outset of the new platform market, and a second mover that can enter soon after, i.e. “fast second” (Lee, 2009) or several years after the first mover “late entrant” (Shankar et al., 1998). The model captures the dynamics of technology learning, resources, product characteristics and the environmental conditions that entrants face, and their effect on firm performance. It, thus, allows exploration of how their change might compound, compensate for, or even reverse, the effect of changes in others. Entrant performance is measured as market share, as done in many entry timing studies, even though other measures are also in use, such as profitability (Van der Werf and Mahon, 1997; Lieberman and Montgomery, 2013). Our model shows how the performance outcomes of different entry strategies can vary depending on the underlying dynamics of the industry, and how firms can better exercise agency if they know which strategy dimension to focus on for a given situation. For instance, we show that being a “fast second” is not always the best strategy, and that strategies that act on different dimensions simultaneously can lead to greater performance differences.

Our analysis illustrates the strategic tradeoffs that platform firms face in their entry strategies and their corresponding performance implications. We then show the value of the model for application to specific industry cases to explore the effect of strategies that firms could have adopted, different from the ones they adopted in reality. The model therefore allows us to explore implications that go beyond what can be accomplished with empirical research (e.g. Huff and Robinson, 1994; Brown and Lattin, 1994), and, in particular, provide new theoretical insights.

For instance, we show the implications of firm-level strategies that create stronger network effects for a firm's products than those of its rivals.

ENTRY TIMING AND FIRM ADVANTAGE

Four isolating mechanisms

Research on first mover advantage during the 1970s and 1980s culminated in the seminal work of Lieberman and Montgomery (1988), who proposed three isolating mechanisms for first mover advantage: technological progress down the learning curve, preemption of scarce resources, and customer switching costs. Either of these isolating mechanisms, or several of them acting simultaneously, could bring advantages to an early entrant in a market. For instance, in a platform market, an early entrant can pre-empt and exploit scarce resources such as key talent with specialized knowledge to improve the platform's technology performance (Schilling, 1998). If these specialized resources are scarce and take time to build, the early entrant may enjoy significant benefits (Dierickx and Cool, 1989; Rahmandad and Repping, 2016). Empirical research also suggests that technological superiority does not always play a significant role in technology battles (Utterback, 1994), as noted in the case of Sony Betamax over JVC VHS (Rosenbloom and Cusumano, 1987).

In the 1990s, researchers added an isolating mechanism that came directly from platform theory: network effects. These arise in markets where the value of using a platform increases with the number of its users (Katz and Shapiro, 1986; Farrell and Klemperer, 2007). Network effects have been shown to play a large role in the performance of firms in diverse industries, from video games to business software to banking products (Gupta et al., 1999; Eisenmann et al.,

2006). Network industries are characterized by path dependence, whereby current market performance depends on past events and seemingly minor or idiosyncratic strategic actions by a firm may be magnified over time (Arthur, 1989; Katz and Shapiro, 1992). Positive feedback dynamics operate in these markets in ways that, over time, can “tip” the market in favor of a single dominant platform, a so called “winner-take-all” outcome (Katz and Shapiro, 1994; Shapiro and Varian, 1998; Eisenmann et al., 2006; Lee et al., 2006; Farrell and Klemperer, 2007; Zhu and Iansiti, 2012; Cennamo and Santalo, 2013).

Recent theoretical and empirical research suggests that firms have a certain agency in shaping their platform’s network effects, in part due to structural network characteristics such as the average strength of ties among network users (Suarez, 2004; Kane et al., 2014) and the technological superiority of the core product (McIntyre and Subramaniam, 2009). This research suggests that network size and other characteristics matter (Shankar and Bayus, 2003; Suarez, 2005; McIntyre and Subramaniam, 2009; Suarez and Kirtley, 2012; Afuah, 2013; Gawer, 2014; Lee et al., 2016; McIntyre et al., 2021). While larger networks of users may generally confer greater value to platform participants via direct and indirect network effects, the gross size of the network (i.e., total number of participants) may not be the most critical indicator of the platform’s value to a set of users (McIntyre et al., 2021). In certain cases, platform participants may prefer a smaller, more tightly-connected network to a larger, more diffuse network. This network variation gives rise to variation in switching costs and search costs among platform users.

Certain firms seem more able to develop stronger, more persistent, and more responsive networks (Shankar and Bayus, 2003). This suggests that significant progress can be made by

relaxing the assumption of homogeneous market-level network effects and allowing for the strength of network effects to vary at the level of the product or the platform's sponsoring firm(s) (Rietveld and Schilling, 2020). The notion that the intensity of network effects can vary both across and within markets shifts the competitive advantage focus from an industry to a firm-level perspective (Gawer, 2014; McIntyre and Srinivasan, 2017).

Firm-level factors

While the isolating mechanisms play an important role in entry timing advantages, the materialization of entry advantage also largely depends on a firm's resources and how and when it chooses to deploy them. Two firms that enter the industry at the same time and, say, access the same levels of isolating mechanisms, might still achieve very different results depending on their internal capabilities and resources (Teece, 1986; Teece et al., 1997; Fuentelsaz et al., 2002). Core and complementary resources can help generate viable initial products, support production scale and commercialization, and ensure greater chances of long-term survival and financial success (Brown and Eisenhardt, 1995; Helfat and Raubitschek, 2000). There is much agency in first mover advantage, and firm-level factors can shape the final market outcome.

For instance, a platform firm among early entrants that has agile rather than rigid processes and a company culture that fosters experimentation is likely to make faster progress along the technology performance curve than competitors and will achieve FMA (Leonard-Barton, 1992; Zollo et al., 2002). Competitors and particularly late market entrants in such a setting would have to learn and improve even faster to stand a reasonable chance of market

survival, a very tall order given the speed and agility of the early entrant (Lieberman and Montgomery, 1988; Zhu and Iansiti, 2012).

Environmental Dynamics

Another research stream focuses on the environmental conditions that can enable first mover advantages. This perspective builds on decades of management research on the role of the environment on the performance of organizations (Lawrence and Lorsch, 1967; Pfeffer and Salancik, 1978, Miller and Friesen, 1983; Dess and Beard, 1984; Anderson and Tushman, 2001; Rothaermel and Hill, 2005), and research in strategy (Teece, 1986; Porter, 1985; Stieglitz et al., 2015) that links firm performance to industry characteristics. Kapoor and Furr (2013) broaden the relevant context outside the firm to include the resources available in the relevant industry ecosystem. The key insight from this work is that the environment of the firm might aid or abate efforts to gain a first mover competitive advantage over later entrants.

Suarez and Lanzolla (2005; 2007) integrate existing research on environment and firm performance with first mover advantage. They argue that two environmental elements capture the essence of the interplay between the environment and the isolating mechanisms that give rise to FMA: the pace of technological evolution and the pace of market evolution. These can be represented with the “S-curve” framework of technological discontinuities and market adoption. The core proposition is that the rapid pace of technology evolution in an industry can render early entry advantages ineffective if later entrants can take advantage of the improved technology to create superior products. Similarly, a rapid pace of market evolution would allow later entrants to avoid competing directly with early entrants for their customers, since the later entrants will

benefit from a large influx of new potential users in the market. Gomez et al. (2016) provide some empirical evidence for these propositions that market growth and technological discontinuities negatively affect the existence of FMA.

First Mover, Fast Second and the Elusive Window of Entry

Decades of inconclusive research on first mover advantages motivate the search of the “right” temporal window of entry into a nascent industry. Some scholars propose that it is not the first movers but firms that quickly follow them -- “fast second” firms -- that enjoy a market advantage (Huff and Robinson, 1994; Brown and Lattin, 1994; Markides and Geroski, 2004; Vidal and Mitchell, 2013). The logic here is that first movers need to spend significant time and resources to create a market, while the fast second firms still benefit from early entry without having to spend the same level of resources in market creation. Scholars in the industry lifecycle tradition propose that the window of entry must relate to the patterns of industry evolution (Christensen et al., 1998). In this logic, early entrants face hard odds because a nascent industry is characterized by high uncertainty in technology and market, while late entrants face hard odds because a dominant design has already emerged (Suarez and Utterback, 1995). Thus, the best window for industry entry is set to be in an in-between period, just prior to the emergence of a dominant design (Christensen et al., 1998; Suarez et al., 2015).

Anecdotal evidence lends some support to this later proposition, even in platform-mediated industries. While the role of network effects (Rochet and Tirole, 2003; Parker and Van Alstyne, 2005) suggests that early entry increases a firm’s chances to capture early market share and develop a critical mass of adopters that can become a powerful advantage, recent history shows that many platform industries are now dominated by later entrants that dislodged the

early movers. Facebook and Google, for instance, dominant firms in their industries were not first movers¹, but managed to dominate their industries. This suggests that the advantage of an initial installed base is not enough to deter competition from new entrants, as a smaller installed user base may be enough to ensure market growth (Shankar and Bayus, 2003). Many late entrants have been shown to effectively outcompete incumbents and take over their early leadership positions (Tellis et al., 2009).

Other elements in first-mover advantage theory can also influence the position and duration of the window of entry, such as a firm's ability to learn fast and achieve quality parity with later entrants in order to retain and increase market position (Zhu and Iansiti, 2012). A firm must maintain a high rate of learning compared to later entrants to defend its market share (e.g. Levin, 2000). Firms can also design products that are easy to upgrade or that can be upgraded automatically as is the case of some physical products (e.g. smartphones) and other digital products today.

All things considered, despite significant progress in understanding first mover advantage, there is still a need for studies that integrate different perspectives and streams and allow us to explore how different mechanisms and contingencies enable or disable first mover advantage. This is particularly important for platform industries, given their importance in today's economies and the fact that the strong role ascribed by theory to network effects in these industries does not seem to be consistent with what we see in different industries. Understanding the factors that underlie platform persistence is seen as a critical next step in the domain of strategy in digital

¹ Friendster was founded in 2002, Myspace in August 2003, Facebook in February 2004.

markets (McIntyre et al., 2021). Our study provides an integrative perspective on entry-timing advantages and offers new insights to extend our understanding of this important phenomenon.

MODEL DEVELOPMENT

Our model represents a situation often considered in theoretical studies on platforms and entry timing advantages: a first entrant (C_1) into a market (in this case, a platform-mediated market) faces the competition of a later entrant (C_2) for market share and dominance (Farrell and Saloner, 1985, 1986; Zhu and Iansiti, 2012; Garcia-Sanchez et al., 2014). We use this context to explore market share outcomes depending on the strength of the factors we discussed in the previous section: network effects, firm-level characteristics and environmental conditions.

Consistent with extant theory, our model explores entry timing advantages in the period of an industry evolution in which the timing of entry can make a difference in firm performance. Agarwal et al. (2002) proposed the notion of “onset of maturity” as a “point in time in an industry’s history [when] a structural change occurs that changes the resource conditions associated with competitive advantage” (2002: 976). This notion is also consistent with the classical writings on industry evolution which suggest that at some point nascent industries move from a “ferment stage” (Anderson and Tushman, 1990) to a phase where economies of scale and process innovation become more critical to firm competitiveness (Abernathy and Utterback, 1978; Klepper, 1996). The notion is also consistent with work in entry timing advantages that stress the need to focus on the time window in which the mechanisms of early entry advantage have the greatest potential to affect market performance (Suarez and Lanzolla, 2007). Our model operationalizes the “onset of maturity” (see next section) as the point from which the industry’s S-curve of technology begins to plateau. More

specifically, we argue that the period during which first mover advantages are most likely to accrue occurs from the point in which the S-curve of technology starts to take-off (the well-known hockey stick shape) to the point in which it begins to plateau – which corresponds to the most active period in the era of ferment. In our model, these two points occur at years 6 and 10, respectively. This conceptualization is consistent with the empirical work of Christensen et al. (1998), that suggests a 3-year “window of opportunity for entry” for the disk drive industry starting in 1980, roughly seven years after the start of the industry.

The model conceptually integrates the mechanisms and firm-level factors associated with entry timing performance (Lieberman and Montgomery, 1998; Zhu and Iansiti, 2012; Gawer, 2014; Lee et al., 2016; McIntyre and Srinivasan, 2017) and the environmental factors associated with entry timing (Suarez and Lanzola, 2007; Gomez et al., 2016). Technological change in the industry is represented as a S-curve, representing the leading edge technology performance. We assume that new entrants are at the leading edge technology at market entry. Market evolution is also represented as a S-curve of adoption, following prior research (Geroski, 2000). The technology and market S-curves are approximated with a general logistic curve given by²:

$$Y = A + \frac{K - A}{\left(1 + Q \cdot \exp(-B \cdot (t - M))\right)^{1/\nu}} \quad (1)$$

where A , and K are the lower and upper asymptotes, B is the growth rate, ν affects the position where the maximum growth occurs. M is the time at which maximum growth occurs. Q determines how close the S-curve begins to the lower asymptote. Users evaluate and select

² S-curve parameter values used for results are in Appendix B

platforms based on their overall performance payoff P_i (Abrahamson and Rosenkopf, 1997; Loch and Huberman, 1999; Lee et al., 2006):

$$P_i = T_i + \gamma S_i \quad (2)$$

where T_i is the performance level of technology i , S_i is the market share of technology i users, and γ is the strength of direct network effects. It is assumed that prices for the two platforms are relatively close so they can be omitted; this assumption is consistent with evidence from several platform industries such as the video games and it simplifies the model, conceptually aligning it with prior work, such as Zhu and Iansiti (2012). Users choose a technology platform or switch to another based on their evaluation P_i , which in turn determines demand D_i for technology i . The model makes the simplifying assumption that consumers are perfectly informed regarding product performance. Demand is given by standard multinomial logit choice models (McFadden, 2001) as the exponential function of the utility of platform i as evaluated by the user of platform i :

$$D_i = \exp\left(\delta \frac{P_i}{P_i^*} - 1\right) \quad (3)$$

Where δ is the sensitivity of utility to technology performance and P_i^* is the initial technology evaluation that is updated as the technology evolves. Market share rather than profitability is used as a measure of platform success, as done in many studies of entry timing advantages (Agarwal et al., 2002; Tellis and Golder, 1996; Van der Werf et al., 1997). Profitability can be a distorting measure for two reasons: because early entrants may enjoy lower costs due to learning that can partially offset the detrimental effects of market loss (Gomez et al., 2016); and because platforms often sacrifice profitability after entry to grow their installed base as fast as possible (Eisenmann et al., 2006). The share of users that choose technology i is given by:

$$\sigma_i = \frac{D_i}{\sum_i D_i} \quad (4)$$

The user stock for technology i increases with σ_i and the number of potential users U_M that is driven by the rate of market S-curve evolution. The market share S_i is given by:

$$S_i = \frac{1}{U_T} \int_0^t U_M \sigma_i dS \quad (5)$$

Where U_T is the total number of users. We sample market share at 11 years based on the take-off and plateau points of the S-curve in our model. The take-off point corresponds to the point at which the second derivative of the S-curve reaches a maximum, that is, the first inflection point on the S-curve of the rate of technology change (first-order derivative). The plateau point corresponds to the second inflection point of the S-curve of the rate of technology change (first-order derivative), where the second derivative reaches its minimum. The take-off point represents the start of the most active part of the “ferment stage” (Anderson and Tushman, 1990), which will ultimately lead the industry to transition to the onset of maturity, represented by the plateau point. As noted, these two points occur at years 6 and 10 in our model, respectively. This period, according to received theory (Agarwal et al., 2002; Christensen et al., 1998), represents the span of time in which firm entry timing can make a difference, before other strong industry dynamics predominate. We therefore sample the market share of the later entrant C_2 at year 11, the year that follows the industry’s onset of maturity. The level of technology T_i at the firm level is given by:

$$T_i = \int_0^t \lambda R_i \frac{T - T_i}{T_i} dT \quad (6)$$

where λ is the learning rate, the difference $T - T_i$ models the potential technology improvement that a firm can achieve, and the denominator T_i accounts for the increasing difficulty to do so late in the technology cycle. It is assumed that each competitor enters the

market with its technology level T_i at the technology frontier. Once in the market, firms progressively fall behind the technology frontier and while catching up is possible, it is difficult (Bohmann et al., 2002). This is done to account for “vintage effects” in high-velocity technology environments, whereby rapid technology evolution may render first entrant knowledge obsolete and erode its competences faster than that of later entrants, prompting users to shift toward the later entrant products that feature newer technology (Tushman and Anderson, 1986; Leonard-Barton, 1992; Bohmann et al., 2002). The entry resources typically are only the initial stock of resources that the firm will need to develop its product technology further (Lieberman and Montgomery, 1998). Thus, firm level resources R_f are given by:

$$R_i = \int_0^t \frac{S_i - R_i}{R_i} dR \quad (7)$$

USING THE MODEL TO TEST EXTANT THEORY

We first check if the model behavior is consistent with received theory. As noted, several authors have proposed that late entry is more likely to succeed in situations in which technology changes rapidly, either by a succession of technology generations, or rapid technological change along a particular trajectory (Franco et al., 2009) or when both technology and market develop quickly (Suarez and Lanzolla, 2007). Figure 1 shows that this is the case with our model. The figure’s Y-axis shows C_2 market share sampled 11 years after C_1 entry.

The C_2 entry timing is relative to C_1 entry, which is fixed at year 0 and represents the the industry onset. The left and right panes in Figure 1 represent the cases of slow and fast technology evolution, while the two curves in each pane present the cases for fast and slow market evolution in our model. Technological progress can vary across industries, so we vary the scale of the technology s-curve from 1 to 100. This difference is probably a conservative estimate. The difference in real life when comparing, say, vacuum cleaning with personal computers, is probably much greater than that.

The pace of market growth can also make a difference for entry timing advantages, which is represented by the two curves in each of the panes in Figure 1. The solid line in each pane portrays the case of slow market evolution, while the dotted line corresponds to a fast market evolution. Unlike what happens with technology, most markets have a natural ceiling related to some degree to the total size of population in the relevant market (e.g. a country) and therefore the differences between the slow and fast cases in our model tend to be less pronounced for the case of market evolution than with technology evolution. As we did with technology, we opt for a relatively conservative slow-fast difference in model setup.

Figure 1 shows that the late entrant does significantly better in the case of fast technology (right pane) than in slow technology (left pane), consistent with theory (Franco et al., 2009; Suarez and Lanzolla, 2007). With slow technology (left pane) a “fast second” C_2 seems to be the best late-entrant strategy. In the fast technology case, a window of entry opens between 6 and 9 years after C_1 entry. The results illustrate that the effect of the pace of technological change on the late entrant market share is much larger than the effect of the pace of market growth³. The difference between the left and right panes in Figure 1 is structural, it persists in all the scenarios we tried. In the remainder of the paper, we focus on the effect of slow and fast technological change (corresponding results for demand growth pace are in Appendix B).

³ This is because market share is a rivalrous resource so C_2 has to attract new and C_1 customers to gain market dominance eventually. Technology is assumed to be a non-rivalrous resource so C_2 improvement of technology performance at, and after, market entry is not hindered by C_1 technology performance level.

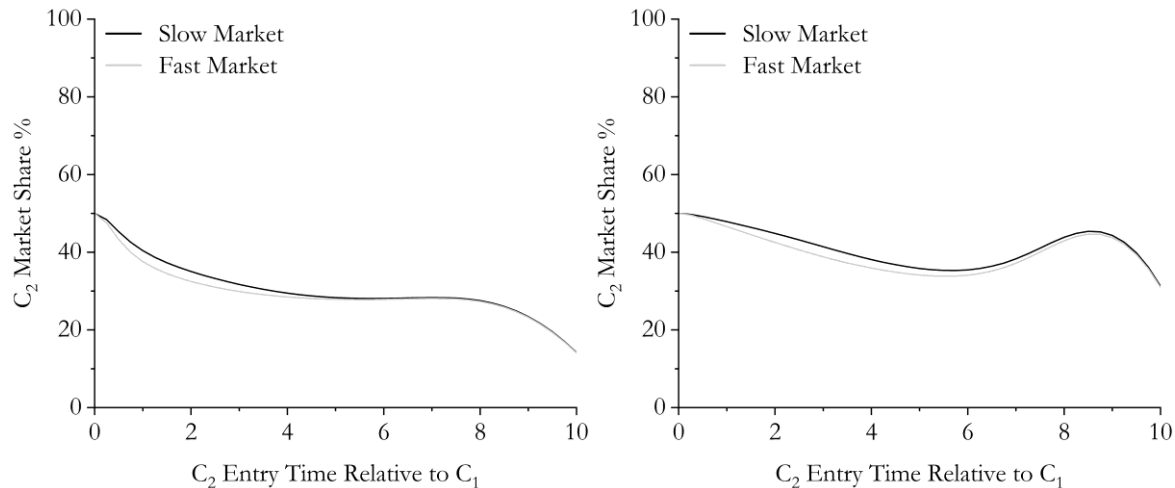


Figure 1 The effect of slow technology with slow and fast market on C₂ market share (left), the effect of fast technology s-curve with slow and fast market s-curve on C₂ market share (right).

IMPLICATIONS OF THE MODEL: SIMULATION EXPERIMENTS

We use our model to explore conditions of practical and theoretical interest for which data is not readily available and therefore empirical research is limited. The conditions we explore concern the main variables built into the model: network effects, learning, resources and the pace of technological change.

Network Effects and Entry Timing Advantages

Extant literature has mainly considered network effects as an industry-level phenomenon that applies equally to all firms in an industry. However, they are not necessarily uniform within an industry (Lee et al., 2006; Afuah, 2013). Different firms within the same industry can develop network effects of varying strength. The ability of firms to create network effects through their investments in technology and new business models has increased significantly. Early work on network effects has also suggested that the strength of network effects is not only related to the size of the network, but also to the strategies followed by the specific firms in the industry (Suarez, 2005; Suarez and Kirtley, 2012; Afuah, 2013). For example, Book Stacks Unlimited, was

a true pioneer but did not benefit from network effects. Amazon begun selling books online in 1995 and benefitted from network effects with the “stars” rating system and allowed customers to write feedback. That user information was valuable for customers and became more useful and accurate as more consumers contributed with feedback on a given product.

Consistent with the evidence from practice and theory, we evaluate the results of our model in four distinct cases where: (i) both first entrant (C_1) and late entrant (C_2) have weak network effects, (ii) C_1 and C_2 have strong network effects; (iii) C_2 is able to create strong network effects and C_1 is slow to react and match them (iv) C_2 is able to create strong network effects but C_1 reacts quickly and matches them. We test these cases and vary the time elapsed between the entries of C_1 and C_2 as suggested in Liebermann and Montgomery (2013), under two different regimes of technological dynamism.

Figure 2 shows the effect of increased gamma on C_2 market share 11 years after C_1 entry. The black lines in both panes represent the case of uniform, industry-wide network effects which we conceptualize as “weak” ($\gamma=1$ for all firms; solid black line) and “strong” ($\gamma=2$ for all firms; dotted black line) – basically, in the latter case network effect are twice as strong (the specific numbers are unimportant). The black curves confirm what we saw in Figure 1: that a context with a slow technology development (left pane) favors C_1 over C_2 . The disadvantage of C_2 is exacerbated under “strong” industry network effects and slow technology evolution (left pane, dotted black line). In other words, a slow technology development is detrimental for the late mover, and increasingly so the stronger the industry-wide network effects are.

However, we noted earlier that our model allows for the possibility to relax the assumption present in most theoretical and empirical work so far, that the strength of network

effects is the same for all firms in the industry. We explore a case where C_2 enters the market with an ability to create stronger network effects than C_1 . Facebook, for instance, which entered shortly after the early entrants Friendster and MySpace, was able to create much stronger network effects by quickly adding features such as the “news feed” (latest postings from friends --i.e. direct network effects), the “like” button, and opening up the platform to 3rd parties (e.g. game developers -- i.e. indirect network effects).

Our model shows that, if C_2 can create network effects twice as strong as C_1 , then it can capture a commanding market share even with slow technology, as long as C_1 does not react rapidly (Figure 2, left pane, solid green line). If C_1 reacts and matches C_2 strategy quickly in this scenario of slow technology (left pane, dotted green line), then C_1 advantage persists⁴. Figure 2 illustrates the power of a model that allows to explore how the different conditions and strategies interact, which have important strategy implications for firm entry.

Another insight from our model concerns the advantages of being a “fast second” (Markides and Gerosky, 2004). Our results show that the ideal strategy for a late entrant is more nuanced than what this concept suggests. A fast second strategy (entering within two years after C_1 entry) gives C_2 an advantage only in the case of slow technology growth and a slow reaction from C_1 . While a fast second strategy still maximizes C_2 market share in all scenarios in the left pane of Figure 2, we cannot speak of a C_2 “advantage” (larger market share than its rival), except when C_2 manages to surprise C_1 who consequently cannot react quickly. In the case of a fast moving technology (right pane in Figure 2), our model suggests that a fast

⁴ With 1yr - fast reaction to gamma, C_1 gamma goes from 1 to 1.57 within a year. A 57% increase
With 3yr - slow reaction to gamma, C_1 gamma goes from 1 to 1.08 within a year. An 8% increase.

second strategy is simply not the best possible strategy for the later entrant. Instead, the model suggests that the best “window of entry” for a late entrant opens a few years after the first mover enters the market and lasts only a few years before it closes for good. This finding questions the validity of the popular “fast second” concept but is consistent with theoretical predictions from the lifecycle literature which suggest that the window of entry occurs right before the onset of maturity in the industry (Agarwal et al., 2002).

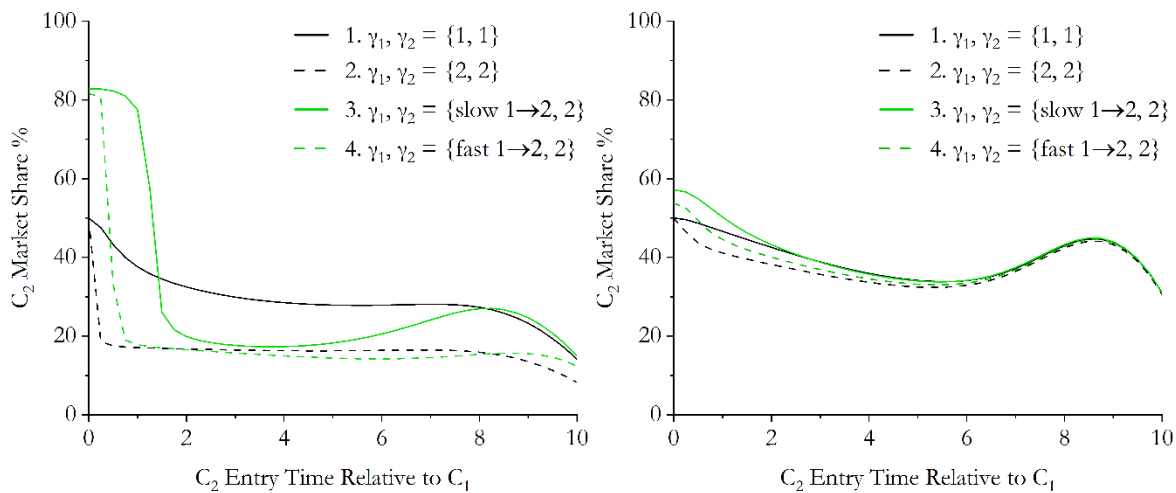


Figure 2 Effect of γ on C_2 market share with C_2 entry 0-10yr relative to C_1 and slow technology (left), fast technology (right)

Firm Learning and Entry Timing Advantages

For decades, scholars have studied the role that organizational learning has in the survival and success of firms, and consequently, economic growth (Simon, 1955; Cyert and March, 1963; Nelson and Winter, 1982, Levitt and March, 1988; Huber, 1991; Levinthal and March, 1993). Organizational learning has been shown to be crucial in an organization’s ability to cope with changes in its environment (Lawrence and Lorsch, 1967). A nascent industry is by definition in flux (Abernathy and Utterback, 1978; Anderson and Tushman, 1990), and in such contexts, early

entrants need to respond to late entrants. Classical entry-timing literature identifies the inability of firms to learn fast as one of their main vulnerabilities, often referred to as “inertia” that limits their ability to respond to competitive threats (Lieberman and Montgomery, 1998).

In a new industry, changes that require learning and adaptation might not only come from competitors, but also from demand side changes, since customer preferences are still in flux (Adner and Levinthal, 2001). Our analysis below captures the implication of individual firm learning in the context of entry timing advantages by considering four cases: (i) C_1 and C_2 have a low learning rate (slow learners), (ii) C_1 and C_2 have a high learning rate (fast learners); (iii) C_2 enters with a higher rate than C_1 and C_1 reacts slowly and only gradually catches up in learning rate; and (iv) C_2 enters with a higher rate than C_1 but C_1 reacts rapidly and catches up quickly with C_2 's learning rate.

Although there are not many studies documenting differences in the rate of learning of early and later entrants into a nascent market, a reasonable proxy is the difference in the rate of new product launches. For instance, available data since the inception of the hybrid car segment in the auto market in the car industry, shows that companies that historically have been leaders in lean methodologies, such as Toyota and Honda (Cusumano, 1989), launched roughly twice as many hybrid models as other large competitors in the industry. Consistent with this, in our model, the firm with a high-learning rate learns twice as fast as in the baseline scenario.

We test these cases under two regimes of technological dynamism in the business environment by varying the lead time between the entries of C_1 and C_2 (Huff and Robinson, 1994; Brown and Lattin, 1994). Figure 3 shows results for different learning scenarios for the cases of slow and fast technology development. We use the same reference run as in Figure 2. As we see

in Figure 3, C_2 investments in learning have a positive impact on its performance in both cases of technology change contexts. However, doubling the learning rate in the case of a slow technology growth provides C_2 with a small advantage if it follows a “fast second” strategy and C_1 does not react fast (left pane, solid blue line). If C_2 waits more than two years after C_1 entry, then its performance decreases rapidly with any further entry delay. The result is different for the case of a fast-moving technology (right pane), where a learning advantage over C_1 provides C_2 with the opportunity to acquire a commanding market share, particularly if C_1 reacts slowly. C_2 maintains some advantage over C_1 even in the arguably most realistic scenario in which C_2 starts with a learning advantage but C_1 reacts rapidly to catch up in learning (right pane, dotted blue line). In both, cases during a fast-moving technology scenario C_2 advantage is not associated to a fast second strategy but to a strategy that has it entering a few years later, as shown in Figure 3. Once again, our model shows that a fast second is not an advantageous strategy for a late entrant in the case of a fast moving technology. The window of opportunity for entry in such a scenario opens a few years after the first mover enters the market and lasts for only a few years, before the onset of maturity.

It is also interesting to compare the right panes of Figure 2 and Figure 3. The comparison suggests that, for a late entrant in an industry with a fast-moving technology, investments in improving its learning rate are likely to pay more than investments in improving its network effects. While investments in the creation of network effects seems to be the best strategy for a late entrant in a context where technology evolves smoothly, investments in improving its learning capabilities seems to be the best strategy for a later entrant in markets in which technology changes rapidly.

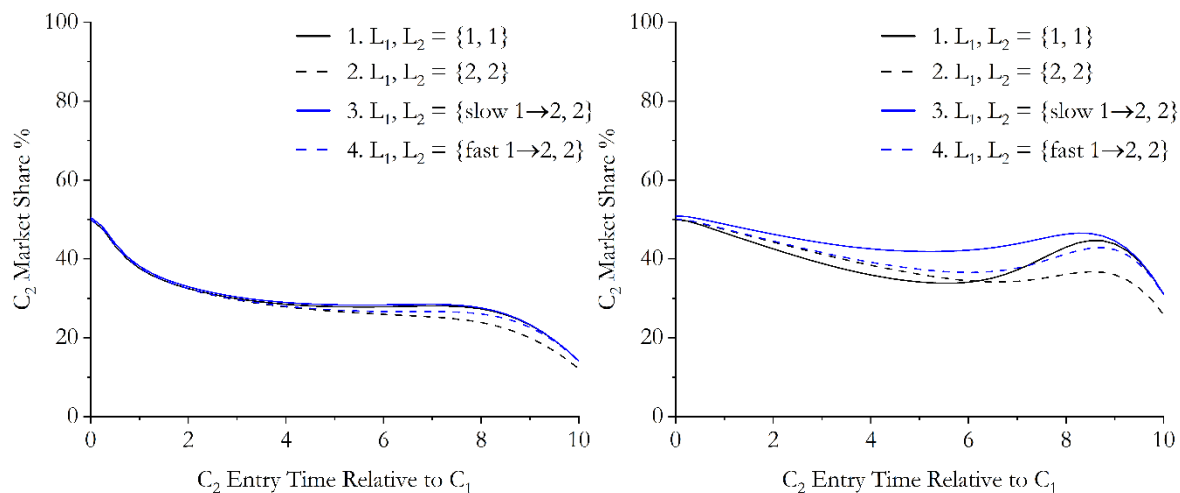


Figure 3 Effect of learning L on C_2 market share with C_2 entry 0-10yr relative to C_1 and slow technology (left), fast technology (right)

Firm Resources and Entry Timing Advantages

Scholars have identified and empirically tested for the “liability of smallness” effect, which, in the case of new entrants that are also startups, occurs in conjunction with the “liability of newness” (Stinchcombe, 1965; Freeman et al., 1983). There is a vast literature that confers resources a central role in the performance and survival of organizations (Wernerfelt, 1984; Barney, 1986; 1991; Kunc and Morecroft, 2010). Resources might also be particularly important in platform markets, where the ability to scale rapidly might help a firm to engage in promotion and brand building, and harness network effects earlier than its competitors (Eisenmann et al., 2011). For instance, Facebook was able to raise close to half a billion dollars in funding during the first four years of operations, which helped the company scale much faster than earlier entrants in the social network space, such as MySpace (Ceccagnoli and Rothaermel, 2016; Rothaermel, 2017).

We include resources into our analysis considering again four cases: (i) both C_1 and C_2 have a low level of resources, (ii) both C_1 and C_2 have a high level of resources; (iii) C_2 enters with

significantly more resources than C_1 and C_1 can only raise its resource level gradually to match C_2 ; and (iv) C_2 enters with significantly more resources than C_1 but C_1 can quickly raise its resource level to match C_2 . As we did with network effects and learning, we test these cases varying the time elapsed between the entries of C_1 and C_2 , and under two regimes of technological dynamism.

The results show that late entrant agency can make a difference in the final outcome, even in environments that are more conducive to first mover advantage. Figure 4 shows that a uniform increase in initial resources to both firms makes little difference, while a fivefold increase only in C_2 resources opens a 3 year late entry window under a slow technology s-curve⁵. In the fast technology (right pane), C_2 prospects are much better due to the combined effect of entering with state-of-the-art technology performance and higher entry resources. The drop in market share up to year 4 in the dotted line is the product of relative balance between two opposing factors. The late C_2 entry gives C_1 more time to establish an installed base, but at the same time the fast rise in technology gives a sufficient entry performance advantage to C_2 to overcome the C_1 FMA. Just as with learning, C_1 has the opportunity to respond and raise its learning pace. This limits losses to C_2 in the case of slow technology development (left), but C_2 maintains a late entry advantage with rapid technology development (right).

⁵ This is under the assumption that the resources are of the same nature and quality for both competitors and there are no asset co-specialization effects e.g. Jacobides et al. (2006), Kapoor and Adner (2012).

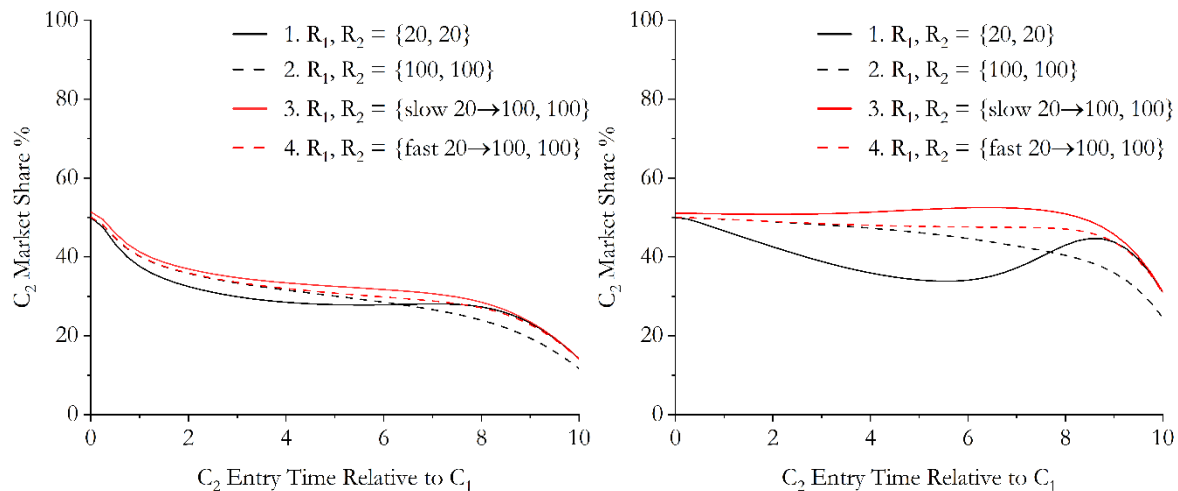


Figure 4 Effect of initial resources R on C_2 market share with C_2 entry 0-10yr relative to C_1 and slow technology (left), fast technology (right)

Combined Results of Network Effects, Learning and Resources on Entry Timing Advantages

Our model can be used to illustrate the power of using the different dimensions of entry strategy together. Figure 5 shows different combinations of resources, learning and firm-level network effects for each of the two contexts analyzed here, slow- and fast-moving technology (left and right panes, respectively). It also shows the dynamic nature of the analysis: the gain or loss of market share for any particular strategy combination varies depending on how early or late the second mover enters the market.

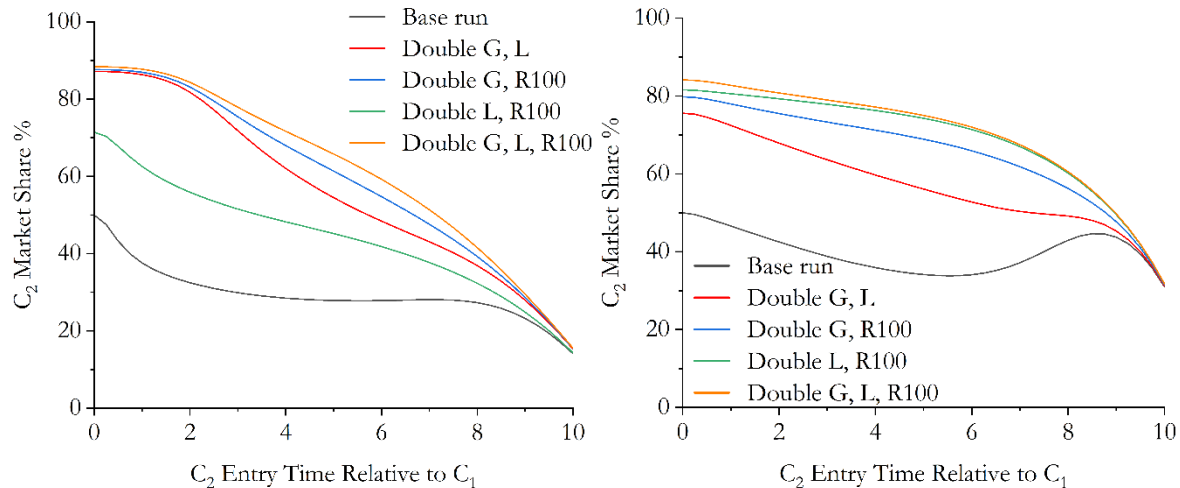


Figure 5 Effect of C_2 strategies on market share % with slow technology (left), fast technology (right)

INSIGHTS FROM MODEL APPLICATION TO REAL CASES

While all models necessarily simplify reality in search of parsimony, they can be of value in the analysis of real situations. The ability to represent real situations fairly well illustrates the value of the model for the analysis of “what if” situations. In this section, we test our model against the emergence of two important industries in recent times: electric vehicles and social networking.

Electric Vehicles

The Context. In 1996, GM launched the EV1 model, an electric vehicle designed from scratch and leased to highly satisfied customers for several years. For a series of complex reasons that are beyond the scope of this paper, the early start of the EV industry was aborted. Therefore, for all practical purposes, when Tesla entered the market in 2008 with its Roadster model, the company was widely considered as the “1st mover” in the EV market. As Figure 6 shows (below), the Nissan entry in 2010, can be considered a “fast second,”. However, Tesla entered

the luxury car segment, while Nissan competes squarely in the regular car segment (Nissan, like other firms, participates in the luxury car segment using another brand, Infinity). A third entrant, Mitsubishi, also entered in the regular car segment. The second entrant in the luxury segment after Tesla was BMW and Mercedes Benz. Unlike Tesla, both of these models were not designed from scratch as EVs but were adaptations of existing internal combustion models.

By the time BMW launched its VeE model, Tesla had already launched the Model S. By the time Mercedes Benz launched its B-Class EV, Tesla was deep in the design of its Model 3 and ramping up their global EV production capacity. Thus, overall, the rest of the auto industry only started to slowly react to EVs after Tesla introduced its Model S which sold very well in its target market.

Technology has been moving slow in the EV industry, which can be observed in the slow evolution of two key metrics of performance followed closely by customers: the range of autonomy that cars can offer, and the speed at which they can charge. The slow pace of change in these key performance metrics has been reflected in a slow market growth. To improve on these metrics, Tesla cars have led the industry in extending the range, offering around and above 300 miles of autonomy in their models. Moreover, Tesla started investing early, in 2012, in a network of proprietary charging stations deployed not only in cities but also in highways connecting different cities. This network of dedicated supercharging stations has been a key differentiator for Tesla. As of 2021, close to 1,200 Tesla supercharger locations cover most of the US. International expansion has also been fast: Tesla supercharger locations also cover most of Western Europe, and a significant part of China.

Despite Tesla’s success, late movers still had significantly more financial resources and manufacturing/distribution resources than Tesla. For example, the largest companies, Toyota and the VW Group, produced in 2021 more than 10 million cars per year, compared to over half a million for Tesla. Still, many of these companies entered the EV industry between 6 and 10 years after Tesla pioneered the EV market. The later entrants found that battery and EV technologies were not simple to master. Judging from how slow they have been to have competitive EV products in the market, their rate of learning has been slow, in part due to the need to go down the learning curve of a different technology and in part due to the organizational inertia coming from their size and structure.

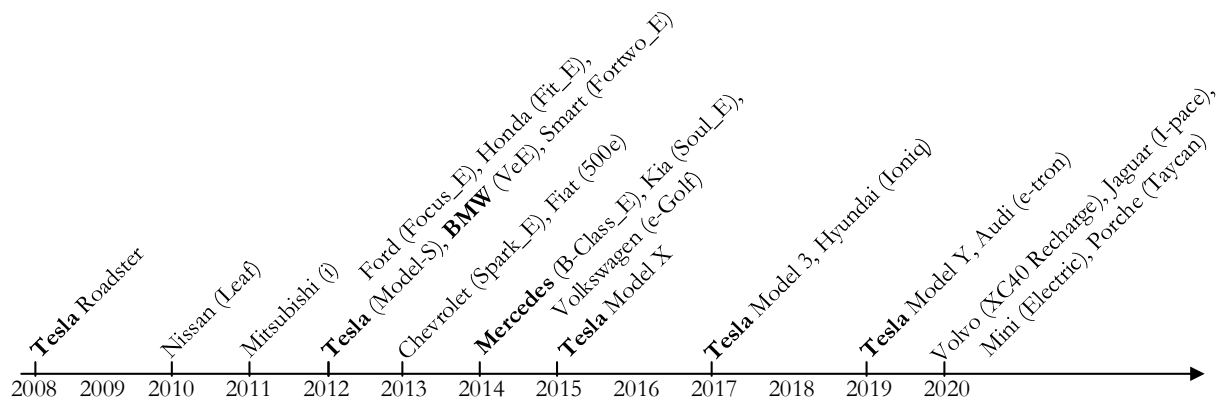


Figure 6 Timeline of EV entries in US market (luxury entries in bold)

As of 2021, the market has rewarded Tesla as it topped the best-selling luxury brand lists in the US and in Europe, with the Model 3 selling more than 3 times the number of cars in the US that its closest competitor, the Lexus ES. In September 2021, the Tesla Model 3 became the first electric vehicle to top the *general* list of best-selling cars in Europe. Tesla’s success is likely to continue, as the company is rapidly expanding its megafactories around the world, and the supercharger network, with plans to triple the number of stations in the next two years.

Model Results. Tesla's success in the nascent EV market is consistent with the insights coming results in Figure 4 above, left pane with a slow-changing technology in a market where the late entrant has much higher resource endowment than the first entrant. The late entrant could have had some success if it entered soon after Tesla did and had deployed many more resources than Tesla did (solid red line in the figure). However, most companies entered late and invested only a limited amount of resources in their EV launches. They also did not invest in setting up proprietary charging stations as Tesla did. As the graph shows, the market share of C_2 deteriorates the longer it waits to enter.

Our model suggests that in this slow-evolving technology scenario the first entrant has high chances of capturing a significant market share. The slow reaction of the incumbent firms compounds their problem and allows the rise of a new, formidable competitor which now is dictating the pace of the whole industry. In Figure 4, left pane, the fact that the C_2 market share drops significantly if it enters 8 or more years after the first entrant, reflects the onset of maturity in the industry (discussed above) and is in agreement with theory and ongoing market developments. Moreover, it is likely that competitors in the EV market engage in a sequence of further strategic moves that bring other competitive dynamics to the fore –not related to entry timing issues – as the years pass and the market develops. This makes extending the time horizon of the model further of little value.

Alternative Second Mover Strategies. Table 1 summarizes some of the possible C_2 strategies in the EV industry, while Figure 7 shows their effect on C_2 market share. Network effects are still not particularly salient in the EV industry; instead, the speed at which companies learn and the

level of resources they invest are crucial factors of competitiveness in which Tesla has excelled compared to the industry incumbents. Figure 7 shows that 10 years after Tesla entry, the market share of the second mover was roughly 20%, a figure that seems consistent with the commanding market share of Tesla in the EV market during the 2018-2020 period. However, the figure also shows that, if an incumbent had entered quickly after Tesla, with comparable levels of resources and investment that would have increased learnings to levels also comparable with Tesla (solid red line in the figure), the second mover could have captured closer to 20% of Tesla's market share.

Table 1 Model setup for Tesla

{Tesla, 2nd mover)	1. Base Tesla case	2. More 2nd mover Resources	3. 2nd mover Matches Tesla L fast	4. More 2nd mover Resources & Match Tesla L Fast
G	{1.5, 1}	{1.5, 1}	{1.5, 1}	{1.5, 1}
L	{2, 1}	{2, 1}	{2, 1→2}	{2, 1→2}
R	{20, 100}	{20, 400}	{20, 100}	{20, 400}

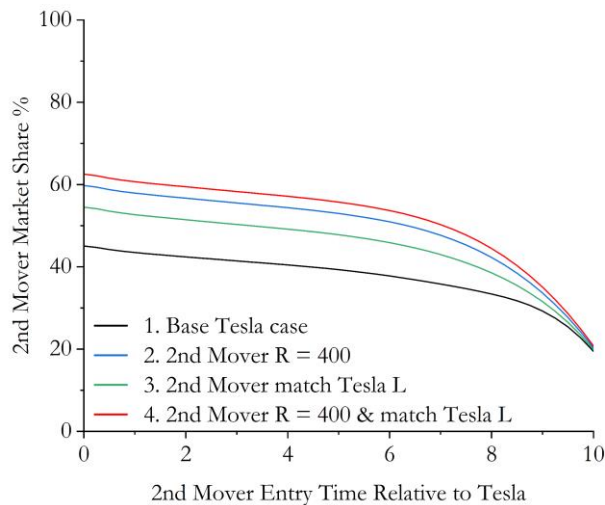


Figure 7 Comparison of the base Tesla case (1) with the effect of 2nd mover strategies (2-4) on market share % with slow technology (see Appendix A for model setup).

Social Networking industry

The Context.

Friendster, which for our purposes here is considered together with MySpace the first entrants to the industry, launched in 2003 when Internet penetration and technology was significantly more advanced. Friendster allowed users to share videos, messages, photos and comments. Despite a promising start, Friendster faced competition from newer social networking sites such as MySpace, which ultimately led the company to switch direction and redesigned itself as a social gaming site. They had some success mainly in Asia and were able to reach over 115 million users. However, their strategy was still short-lived, since other platforms that grew faster also added gaming to their offerings, so Friendster shut down in 2015.

MySpace was also founded in 2003, leveraging the 20 million user base of eUniverse, MySpace got a strong start and quickly became the leader of the social networking space. By 2006, the company had expanded internationally, had signed a lucrative exclusivity agreement

with Google, and had reached 100 million users. Facebook entered the social networking space in 2004, and is therefore considered a second entrant in our analysis. First available only in universities and high schools, the firm used its success in those closed communities to open up to the general public.

By 2008, Facebook had overtaken MySpace as the largest and fastest growing social network site. The company's success was based on the rapid and constant deployment of innovative features and the ability to match MySpace's deep pockets by raising large amounts of capital (1 US\$ Billion in the first 5 years). These important innovations gave Facebook a commanding lead over competitors and allowed the company to grow exponentially.

Model Test. Facebook competed in a market with fast changing technology (and rapidly-growing market), and was able to use the ability to raise resources to create new offerings that allowed their platform to create network effects in a way that the early entrants had not been able to do.

Alternative Second Mover Strategies. Our analysis explores what would have happened if MySpace reacted to the Facebook entry by investing in technology and software to match Facebook's network effects and their ability to learn fast and come up with new products. Table 2 summarizes these alternative strategies, and Figure 8 illustrates their outcomes. Had MySpace reacted quickly and aggressively to Facebook entry, they could have carved around 30% of Facebook's market share (difference between the solid black line with the solid red line).

Table 2 Model setup for Facebook

{Myspace,FB}	1. Base FB case	2. Myspace matches slow FB G	3. Myspace matches fast FB G	4. Myspace matches fast FB G & L
G	{1, 2}	{1→2, 2}	{1→2, 2}	{1→2, 2}
L	{1, 2}	{1, 2}	{1, 2}	{1→2, 2}
R	{100, 100}	{100, 100}	{100, 100}	{100, 100}

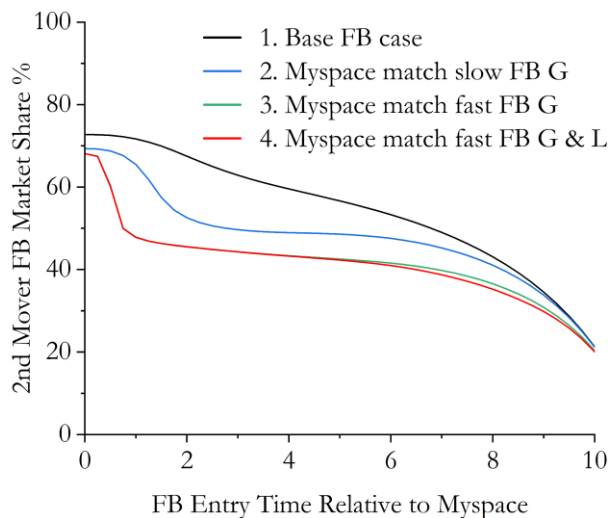


Figure 8 Comparison of the base Facebook case (1) with Myspace entry at year 0, with slow/fast response to Facebook G (2, 3) and fast response to G and L (4). It is only in the last case that Myspace maintains FMA (see Appendix A for model setup).

DISCUSSION

Our study set out to overcome some of the limitations of entry-timing advantage research to date, with an integrative model of entry timing advantages. The model is consistent with theory and empirical evidence, on how technology changes during the era of ferment in an industry, the transition to dominance and then the onset of maturity in the industry (Agarwal et al., 2002). Our results offer several insights that complement prior studies. For instance, the model shows (Figure 1) that, in most plausible scenarios, the performance implications of different entry times associated with changes in technology dynamics are larger than those associated

with changes in the market (demand) dynamics. This insight cannot be directly derived from existing theoretical work on entry timing (Lieberman and Montgomery, 1988; Suarez and Lanzolla, 2007).

Similarly, our simulation results illustrate more clearly the limitations of the somewhat popular concept of a “fast second” (Markides and Geroski, 2004). Our results suggest that a fast second strategy is most likely to be effective in industries with slow-changing dynamics. When the industry dynamics involve rapid change, often the better strategy for a second mover is not to enter close to the first mover, but several periods later, as shown in Figures 2, 3 and 4. Our work therefore adds important nuances to our understanding of the elusive best “window of entry” into an industry.

Results show how Tesla benefited from the fact that its industry was one of slow dynamics: technology and demand grew relatively slowly in the EV industry, compared to other industries. Still, our analysis shows that, had a second mover followed a “fast second” strategy and invested as aggressively as Tesla in resources and learning, it could have taken about 20 points of market share from Tesla. Such a move would have propelled this company to share Tesla’s unique position as an industry leader, with some of the associated brand image benefits that this has brought to the sole leader today.

Our results show how Facebook was able to overcome early entrants with a strategy that created network effects above and beyond what the early entrants had in their platforms. This is an under-researched issue in strategy and platform literature: the role of strategy and agency in the creation of network effects, and how that can have a major implication in entry

timing strategies. Our results show that, if MySpace had followed such a strategy they would have been able to steal about 30 points of market share from Facebook.

There are obviously limitations to our analysis, mainly derived from the fact that models, by definition, need to abstract reality to a manageable and finite set of variables and parameters. There might be indeed other factors that can come into play in the relationship between entry timing and performance that we have not considered here. For instance, our work focuses on the point in time when competitors enter the market. However, recent research shows that firm's actions taken prior to market entry may also influence performance after entry (Moeen, 2017). Similarly, we have modeled learning as it relates to technology, but there are other forms of learning and innovation that can also be associated with advantages after entry, such as innovation in modes of advertising (e.g. Huff and Robinson, 1994). Still, overall we believe our model captures many of the dynamic elements of entry timing in platform-mediated settings, and that our insights offer a fresh perspective to the literature on entry timing advantages.

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Appendix A Model setup for results

S-curve reference setup

Table A3 Reference setup for s-curve

Parameter	Value
v: Max growth position	1
K: Upper asymptote	1
A: Lower asymptotes	0
M: Max growth time	0.3
B: Growth rate	7
Q: S-curve proximity to A	40

Table A4 Model setup for theoretical results

Test	Network effects G {G ₁ , G ₂ }	Learning pace L {L ₁ , L ₂ }	Entry Resources R {R ₁ , R ₂ }	S-curve K asymptote {Tech, Market}
1. Entry Parity - Low Level	{1, 1}	{1, 1}	{20, 20}	{1,50-100} {100, 50-100}
2. Entry Parity - High Level	{2, 2}	{2, 2}	{100, 100}	{1,50-100} {100, 50-100}
3. C ₂ advantage, slow C ₁ response (3yr)	{1→2, 2}	{1→2, 2}	{20→100, 100}	{1,50-100} {100, 50-100}
4. C ₂ advantage, fast C ₁ response (1yr)	{1→2, 2}	{1→2, 2}	{20→100, 100}	{1,50-100} {100, 50-100}

Table A5 Model setup for Tesla case

Test	Network effects G {Tesla, C ₂ }	Learning pace L {Tesla, C ₂ }	Entry Resources R {Tesla, C ₂ }	S-curve K asymptote {Tech, Market}
1. Base Tesla case	{1.5, 1.2}	{2, 1}	{20, 100}	{10,100}
2. More C ₂ resources	{1.5, 1.2}	{2, 1}	{20, 400}	{10,100}
3. Match Tesla L fast	{1.5, 1.2}	{2, 1→2}	{20, 100}	{10,100}
4. More C ₂ Resources & Match Tesla L Fast	{1.5, 1.2}	{2, 1→2}	{20, 400}	{10,100}

Table A6 Model setup for Facebook case

Test	Network effects G {C ₁ , FB}	Learning pace L {C ₁ , FB}	Entry Resources R {C ₁ , FB}	S-curve K asymptote {Tech, Market}
1. Base FB case	{1, 2}	{1, 2}	{100, 100}	{10,100}
2. Match FB G slow	{1→2, 2}	{1, 2}	{100, 100}	{10,100}
3. Match FB G fast	{1→2, 2}	{1, 2}	{100, 100}	{10,100}
4. Match FB G & L Fast	{1→2, 2}	{1→2, 2}	{100, 100}	{10,100}

Table A7 Model setup for EMI case

Test	Network effects G {EMI, GE}	Learning pace L {EMI, GE}	Entry Resources R {EMI, GE}	S-curve K asymptote {Tech, Market}
1. Base EMI case	{1, 1}	{1, 1}	{20, 200}	{50,100}
2. Less GE Resources	{1, 1}	{1, 1}	{20, 20}	{50,100}

Appendix B

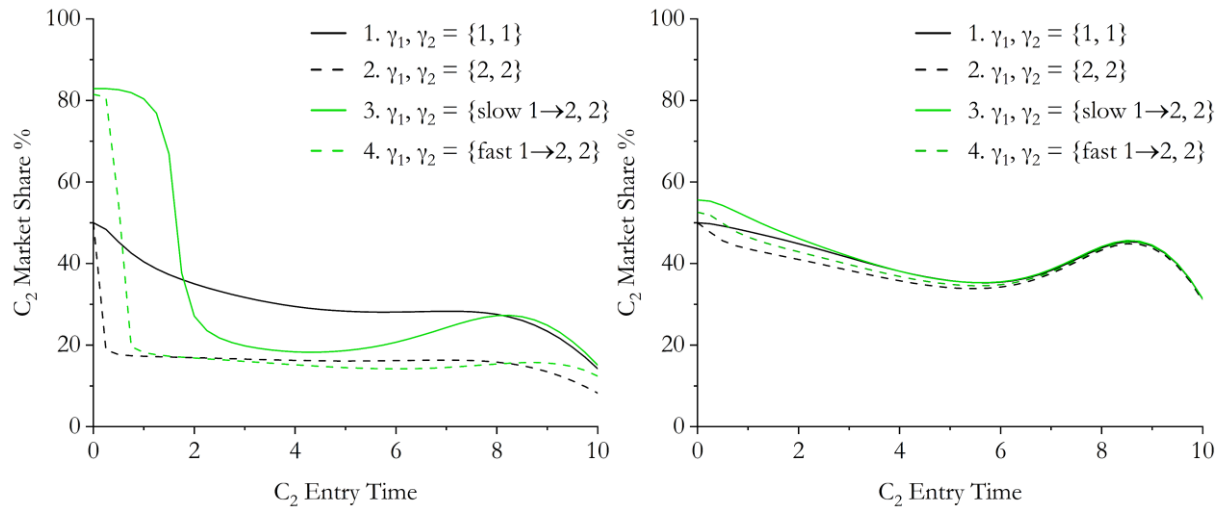


Figure 1. Effect of γ on C_2 market share at $t=10$ after C_2 entry with C_2 entry 0-10yr after C_1 and slow market (left), fast market (right)

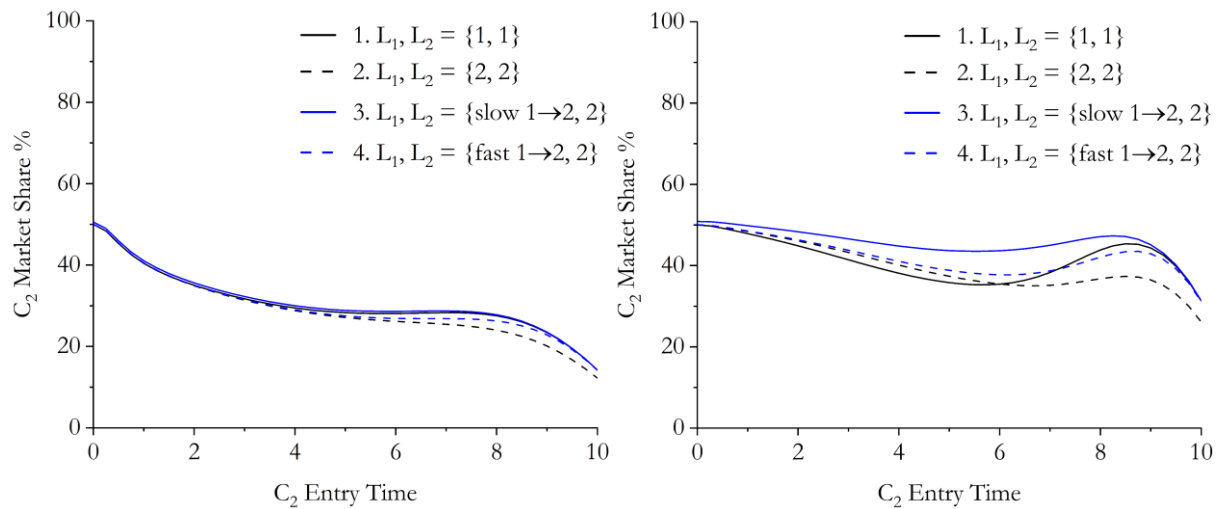


Figure 2. Effect of learning L on C_2 market share at $t=10$ after C_2 entry with C_2 entry 0-10yr after C_1 and slow technology (left), fast technology (right)

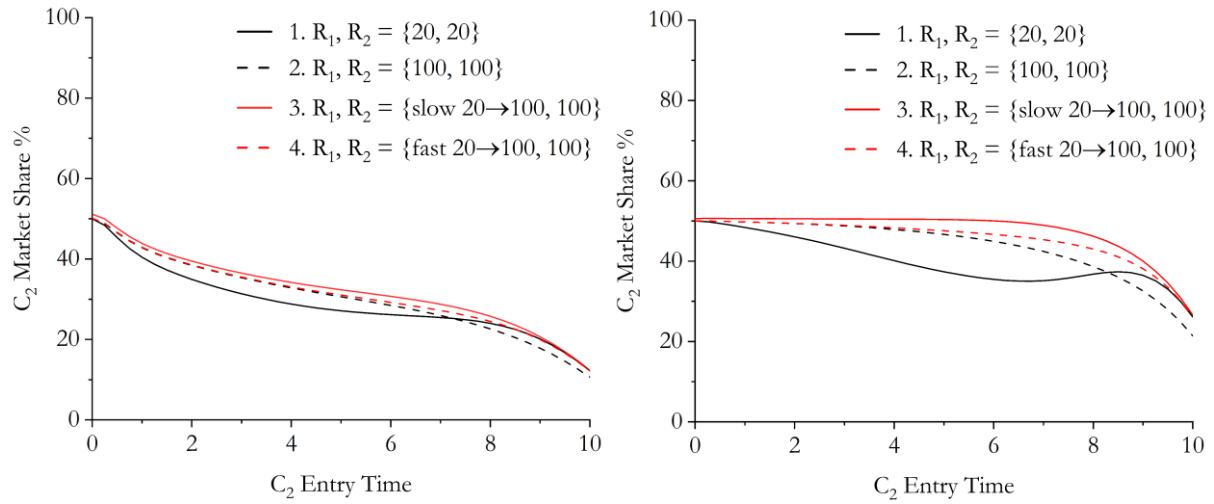


Figure 3. Effect of initial resources R on C_2 market share at $t=10$ after C_2 entry with C_2 entry 0-10yr after C_1 and slow technology (left), fast technology (right)