THREE ESSAYS ON ENTRY TIMING

by

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This dissertation is dedicated to my parents.

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ABSTRACT

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In this dissertation, I strive to enhance our understanding of the effect of entry timing on firm performance using both empirical and formal modeling techniques. I accomplish this through addressing three major unanswered issues in entry timing research. In the first essay of my dissertation, I theoretically examine the effect of selection bias on entry timing associated performance outcomes via the introduction of a novel concept called First-mover Benefits (FMB) which is both theoretically and empirically distinct from the traditional First-mover Advantages (FMA) concept. The second essay of my dissertation empirically investigates this distinction in a unique entrepreneurial setting: the marijuana retailing industry in the State of Washington. The randomized order of entry into the geographically separate jurisdictions in Washington State via the lottery system gives me the opportunity to look at the overlooked effects of two key macro-contingencies: market growth rate and rivalry intensity without any selection bias concern. The main result of this essay indicates that pioneering advantages are more likely to be found in markets with higher level of rivalry intensity. My final essay focuses on the sustainability dimension of pioneering advantage. Taking advantage of the Washington State marijuana retailing industry dataset that eliminates the selection bias issue, I examine how long entry timing associated performance benefits are sustained in this nascent industry context. I find that pioneering advantages last for only four quarters. Overall, this dissertation helps partially resolve the long-standing controversy surrounding the potential effect of entry timing on performance.

CHAPTER 1. INTRODUCTION

Entry timing choices are endogenous decisions (Boulding & Christen, 2003; Lieberman & Montgomery, 1988, 2013; Robinson, et al 1992). Potential entrants into a new market differ in terms of their resource and capabilities, and such heterogeneity can lead to differences in firms' preferences over their timing of entry (Lieberman & Montgomery, 1988; Robinson et al., 1992). Therefore, the observed treatment effect on the performance variable does not necessarily reflect the causal influence of entry order, rather the effect is confounded by the resource heterogeneity that exists between the early and late moving firms, and thus is biased. Despite its potential significance as a key factor behind contradictory findings in the first-mover advantages (FMA) literature, endogeneity issue has surprisingly remained underexplored to date outside few exceptions (Boulder & Christen, 2003). Unfortunately, those few papers that attempted at empirically illustrating how self-selection bias can affect empirical outcomes have produced conflicting results (e.g., Moore et al., 1991; Murthi et al., 1996). In that regard, my dissertation has two main objectives: The first objective is to form a theoretical foundation via an analytical model on how the endogeneity bias can influence entry timing associated performance outcomes in the presence of relevant micro and macro level contingencies. The second is to empirically test how exogenous FMA (named as FMB – first mover benefits) by effectively eliminating any endogeneity concern through a natural experiment where entry order is truly randomized.

Specifically, In the first essay of my dissertation, I introduce a theoretical concept called first-mover benefits (FMB) which is distinct from the first-mover advantages (FMA), with the former being counterfactual and (usually) unobserved pure treatment effects and the latter being actual observed combination of treatment and selection effects. I examine this distinction via a formal model developing propositions on how FMA and FMB differ from each other. During model development, I take a holistic view by incorporating both industry-level and firm-level contingencies such as complementary assets, demand uncertainty, market growth, and rivalry intensity that are key and relevant to entry timing research. Overall, the results show that FMA is not an appropriate proxy for FMB and diverges more from FMB when firms are more heterogeneous especially when that heterogeneity occurs in combination with either high demand growth or high uncertainty. The findings also reveal that endogeneity exerts an upward bias on FMA, main effects of market rivalry and growth on FMA as well their interaction effect on FMA.

In the second essay of my dissertation, exploiting a unique experimental setting in the retailing marijuana industry in Washington State, I investigate the existence of first-mover advantages as well as the impact of two key macro-environmental contingencies namely, rivalry intensity and market growth rate, on the entry order associated performance outcomes. The recent legalization of marijuana in the state of Washington provides a rare and unique experimental setting where I can effectively deal with the endogeneity problem through the randomized entry order, and thus directly draw causal inferences between the timing of entry and performance. In such a setting where the entry order is randomized, the firms in the pioneer group and follower group would be interchangeable where the counterfactual for the group receiving the treatment (entry order) would be the other group that did not receive it. In other words, the counterfactual for the early entrants would be the late entrants since both groups are equivalent in terms of their both observable and unobservable characteristics including their resource profiles due to random assignment. Such randomization allows for making precise causal inferences without any contamination through the direct measurement of FMB. In that regard, this unique setting would allow me to help resolve the long-standing controversy with regard to the potential impact of entry timing on performance outcomes. The results of this study indicate that early movers tend to outperform late-movers in markets characterized by higher rivalry intensity. Therefore, the level of rivalry in a market forms a boundary condition, and serves as a key determinant of performance heterogeneity between pioneers and followers

In the final essay of my dissertation, I examine how long the pioneering advantage could be sustained taking advantage of the same marijuana industry dataset. The main result of this study shows that pioneering advantage is sustained only for four quarters in this market following a gradually declining pattern.

CHAPTER 2. FIRST-MOVER ADVANTAGES VERSUS FIRST-MOVER BENEFITS IN INDUSTRIES WITH NETWORK EXTERNALITIES

2.1 Introduction

The issue of entry timing, often framed in terms of first-mover advantage (FMA), has been researched extensively in the fields of strategy, marketing, and economics, due to its implications for a broad range of outcomes, including firm performance, distribution of market shares, industry structure, and public welfare. Despite decades of interest in entry timing, empirical research on FMA is still inconclusive, with mixed and often contradictory results. Among the potential reasons, endogeneity-induced selection bias is considered a major factor that may confound empirical results and thus impedes the progress of research in this area (Fosfuri, Lanzolla, & Suarez, 2013; Lieberman & Montgomery, 2013a; Zachary, Gianiodis, Payne, & Markman, 2015). Specifically, biases may arise from the fact that early movers and later movers are different firms, differing in their strengths and weaknesses, which means that they may not benefit equally from early entry. Depending upon their complementary assets (Teece, 1986) and capabilities, some firms would be expected to benefit more from early entry into a particular market while others might benefit more from later entry into that same market (Hawk, Pacheco-de-Almeida, & Yeung, 2013; Lieberman & Montgomery, 1988, 1998). So, the benefit of early entry into any given market should differ between firms of different capabilities, and may be both positive for some and negative for others. Therefore, the observation that early-moving firm X performs better than late-moving firm Y does not necessarily imply that firm Y's performance would have been better if it had entered first. Given firm Y's unique collection of strengths and weaknesses, late entry may have been its best choice. So, a comparison between the actual performances of an early mover and its later-moving rival does not necessarily reflect the results of a comparison between the actual performance of an early mover and the counterfactual performance that this same firm would have obtained if it had delayed its entry. In order for research to progress in a cumulative manner where new studies build upon older ones, it must be possible to conduct meaningful "apples to apples" direct comparisons between the results of different studies (Oxley, Rivkin, & Ryall, 2010), yet the problem of endogeneity-induced selection bias makes such comparisons impossible, thereby impeding progress. After all, without knowing how badly each study is biased by endogeneity, one cannot know how to adjust their results to make them comparable.

In addition to being a potential source of measurement bias, conflicting results, and non-comparability between studies, the heterogeneity between early entrants and late entrants is not merely an empirical issue, but rather also has a deeper theoretical implication – that the entire conceptual construct of first-mover advantage may not be meaningful at all. The basic problem is that FMA has been presumed to capture the performance boost that ***any*** firm would gain if it entered the market first. Since FMA is assumed to apply equally to any firm that enters first, it is really a ***market-level*** construct, rather than a firm-level construct. Yet if we take seriously the idea that inter-firm differences in pre-existing resources make some firms benefit more than others from early entry (and may even make some firms benefit more from later entry), then it is clear that what we really need here is a ***firm-level*** conceptual construct.

Our label for this desperately needed firm-level construct is ***first-mover benefit*** (FMB), which is conceptually distinct from FMA. The difference between FMB and FMA is illustrated in Figure 2.1: FMA represents the actual *ex post* performance advantage that the first-mover gained over its later-moving rivals. Since there can only be one ***actual*** entry order in any given market, FMA is a market-level construct. By contrast, FMB represents, for any given firm, the *ex-ante* incremental boost in performance that this particular firm would gain by moving first rather than later. Since different firms may experience different boosts in performance (including the possibility of being negative, i.e., a performance decline), FMB is a firm-level construct. However, it is also a ***counterfactual*** construct, since it requires a performance comparison between the actual entry order and some other hypothetical entry order. In other words, FMA compares the performance of two different firms under a single entry-order scenario, while FMB compares the performance of a single firm under two different entry-order scenarios. So, FMA is market-level while FMB is firm-level. As a market-level concept, the entire idea of FMA is at the wrong level of analysis – regardless of how it is measured.

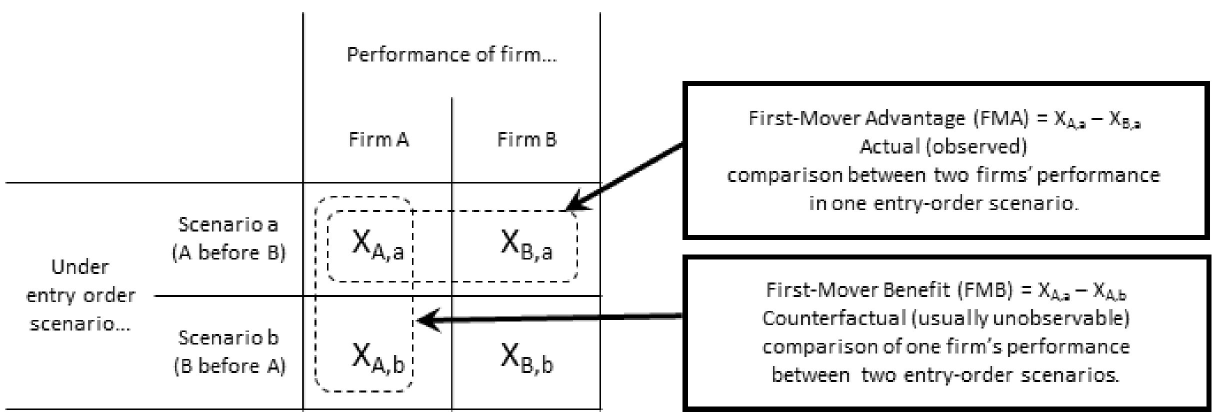

Figure 2. 1 FMA vs FMB

One important implication of this misplaced level of analysis is that any prescriptive managerial implications derived from empirical FMA studies may simply be meaningless: If each firm differs in the extent to which it benefits from early entry (i.e., its unique FMB), then prescriptive managerial implications based on FMA results simply cannot apply to all firms.

Furthermore, it is unclear which specific firms these prescriptive managerial implications apply to, and which firms would require different prescriptions. Yet existing empirical studies often make prescriptive-sounding claims, presenting their results as if they had uniform implications for the entry-order decisions of ***all*** firms, as indicated by articles whose titles proclaim “The importance of being first” (Gorecki, 1986) or ask “When to lead or follow?” (Parry & Bass, 1989) or whose conclusions state, “These findings obviously have implications for management decision-making” (Lambkin, 1988: 137), “The implications for strategic decision-making are striking” (Mitchell, 1991: 99), “the model also should act as a useful decision-making aid for managers” (Green, Barclay, & Ryans, 1995: 14), “our analysis could be used as a basis for optimal entry timing analysis” (Shankar, Carpenter, & Krishnamurthi, 1998: 67), “Our findings have three primary implications for managers” (Bohlmann, Golder, & Mitra, 2002**,** “This principle is often high on managers' list of arguments to justify strategic moves” (Boulding & Christen, 2003), or “This study suggests several important managerial implications” (Lee, 2008). These blanket market-level prescriptive claims about FMA make little sense in a world where: (1) firms differ in their pre-existing resources and capabilities, (2) these pre-existing differences imply differences in firms’ incentives to enter early versus late, and (3) endogenous entry-order choices based on those incentives not only ensure that early entrants and late entrants differ systematically in their FMB’s, but also that their FMB’s will diverge from the observed FMA.

Yet the problem with taking FMA as a prescriptive proxy for FMB isn’t ***only*** that different firms have different FMB’s. Indeed, even if we were ***only*** concerned about drawing prescriptive inferences for a “typical” firm based on the average FMB across firms, then FMA would still be a biased proxy for this average FMB, except under extraordinary circumstances where at least one of two unusual conditions was true: Either there would have to be little or no heterogeneity between firms, or else entry-order decisions would have to be made in an exogenously, rather than endogenously, in a way that was uncorrelated with differences between the firms' underlying resources and capabilities.

Consider each of these two conditions in turn: (1) If there were no heterogeneity between firms, then all firms would share the same FMB. Also, FMA would exactly equal that shared FMB, as indicated in Figure 2.1, because an early entrant and a late entrant would be valid counterfactuals for each other. That is, the early mover's performance would be the same as the performance that a late mover would have achieved if it had entered early, and a late mover's performance would be the same as the performance that an early mover would have achieved if it had entered late.
(2) If entry timing decisions were not made endogenously, but rather were made in an exogenous way that was uncorrelated with differences in firms' resources and capabilities, then the firms would differ in their FMB's, but FMA would nevertheless provide an unbiased (although perhaps noisy) estimate for the average firm's FMB.

So, it is the combination of ***both*** heterogeneity and endogeneity that makes FMA a biased measure for the average firm's FMB. Unfortunately, both inter-firm resource heterogeneity and endogeneity of entry timing decisions are the norm in the vast majority of industries. It is highly unusual to find any industry with either homogeneous firms or exogenously-determined entry order. So, if we take seriously the reality of inter-firm resource heterogeneity and endogeneity of entry timing decisions, then drawing truly valid and meaningful managerial prescriptions about the entry timing decisions of any particular firm requires abandoning the FMA concept entirely and replacing it with FMB. Surprisingly, this issue has received little attention from researchers despite its significance, and those few empirical studies that examine this issue have yielded conflicting findings (Moore, Boulding, & Goodstein, 1991; Murthi, Srinivasan, & Kalyanaram, 1996).

As a starting point for the journey toward correcting this problem, one would at least like to have basic answers to a few fundamental questions: For what kinds of firms, and in what kinds of markets, would we expect FMA to diverge the most from the specific firm's FMB? In what direction would we expect this divergence? What factors or conditions would we expect to make this divergence increase or decrease? Given that the problem arises from the combination of ***both*** heterogeneity and endogeneity, how would we expect each of these two conditions, separately and jointly, affect the divergence of firms FMB's from each other and from FMA? A primary motivation for this paper is to begin to answer these questions.

Although these questions are of paramount importance to advancing research on the effects of entry-timing decisions, they are nevertheless hypothetical questions, due to the fundamentally counterfactual nature of the FMB concept. So, the answers to these questions can only be found ***in theory***, by resorting back to first principles of economic logic. Accordingly, we develop a formal economic model that allows us to conduct the hypothetical comparisons between FMA and FMB that are necessary in order to answer these questions.

Naturally, the results of any formal economic model are dependent upon its underlying assumptions. In particular, for a model focused on the impact of entry timing decisions on performance, the most important and central assumption is about the specific preemptive mechanism that benefits the performance of early entrants. In any given empirical context, the specific biases that arise from conflating FMA with FMB may differ according to the specific preemptive mechanism by which early commitment may boost performance in that particular context. Lieberman and Montgomery (1988) identify several such preemptive mechanisms, including technological leadership, preemption of scarce assets, customer switching costs and network externalities. Due to problems of tractability, it is impractical to incorporate all of these preemptive mechanisms into the same formal model. So, we must choose to focus on one.

The particular preemptive mechanism modeled in this paper is network externalities, wherein the utility a consumer derives from adopting a particular firm's product is an increasing function of the number of other consumers who have also adopted that same firm's product.[1] Under network externalities, market share asymmetries tend to get amplified over time, a dynamic that can significantly favor early movers, and possibly also lead to critical capability advantage shifts (Shankar & Bayus, 2003) including winner-take-all situations (Schilling, 2002). We choose to focus on this particular preemptive mechanism because of the growing importance of network externalities across many industries throughout the economy, especially with the proliferation of two-sided markets and platform-based businesses. The spread of inexpensive information technology (IT) has spawned network-based business models not only in IT-based industries like computers, software, and telecommunications, but also in a broad range of industries that had never previously relied much on IT and had never previously had much experience with network externalities, including retailing (Amazon), toys (Webkinz), coffee (Keurig), and even

[1] Network externalities can be either direct or indirect. Under direct network externalities, the value derived by the user is directly linked to the size of the product's installed base. Under indirect network externalities, the size of the installed base is important to potential users only because it attracts complementary product developers (Katz and Shapiro, 1995.) In either type, network size underlies the positive effects. This paper's model focuses on direct network effects, leaving indirect effects for future research.

refrigerators (Samsung Family Hub).[2] Although there may ultimately be practical economic limits to the range of industries touched by network externalities, it is not yet clear what those limits are, and it is clear that those limits have not yet been reached. This phenomenal growth highlights the importance of network externalities for business strategy, marketing, and public policy in an increasingly information-driven economy. Yet this growing importance has not yet elicited sufficient research on the specific topic of entry timing issues in network-based industries, as indicated by Lieberman and Montgomery's (2013b) call for further research on this topic. In this paper, we respond to that call by moving beyond the simple "main effect" observation that network externalities benefit early movers, and instead investigating the conditions under which this benefit is stronger or weaker. Specifically, we examine how FMB is affected by the interaction effect of network externalities in combination with both firm-level micro-contingency factors (such as the firm's advantage in complementary assets) and market-level macro-contingency factors (such as the market's growth rate). We use FMB as the dependent variable for these effects because our goal is to make predictions about the entry timing decisions of particular firms in network-based industries, and only a firm's unique FMB captures its individual incentive to enter early versus late.

[2] Other industries where the infiltration of information technology has recently boosted the importance of network externalities would include televisions (Smart TV), automobiles (CarPlay, Android Auto), restaurants (McPlay, OpenTable), movies (Netflix), music (iTunes), books (Kindle), encyclopedia publishing (Wikipedia), advertising (Google AdSense and AdWords), classified advertising (Craigslist), flea markets (eBay), travel agencies (Orbitz and Expedia), taxicabs (Uber), lodging (Airbnb), health care (Medicast, Heal), babysitting (Care.com), tutoring (WyzAnt), home repairs (Angie's List), lawn maintenance and snow removal (Plowz & Mowz), executive recruiting (LinkedIn), freelance professional services (Fiverr), private aviation (NetJets), thermostats (Nest), lighting (WeMo), parking (SpotHero, Luxe), matchmaking (eHarmony), personal ads (Tinder), dog walking (Wag! Labs), farm equipment (MachineryLink), laundry (Washio), road maps (Waze), craft fairs (Etsy), groceries (Instacart), genealogy (Ancestry.com), venture finance (Kickstarter), pet ID tags (HomeAgain), education (Udacity, Coursera, Khan Academy), real estate (Zillow), and even illegal drug trafficking (Silk Road).

Our results suggest that: (1) A firm's FMB exceeds FMA when the firm has a complementary asset disadvantage relative to its rivals, and its FMB falls short of FMA when it has a complementary asset advantage over its rivals. Thus, the difference between FMA and a firm's FMB is increasing in the firm's complementary asset advantage. (2) This effect of a firm's complementary asset advantage on the difference between FMA and its FMB becomes stronger as either demand growth rate or demand uncertainty increase. (3) The positive effect of network externalities on a firm's FMB becomes stronger as either the market's growth rate or the firm's complementary asset advantage increases, and even more so as they increase together. (4) FMA, and the effect of market growth on FMA, are more likely to be positive when entry order is determined endogenously rather than exogenously.

Overall, this paper makes several contributions: First, as a contribution to the theory of entry timing, it highlights an important but largely overlooked problem by introducing the FMB concept, explaining how FMB differs from FMA, and using a formal model to demonstrate the conditions under which FMA and FMB would be expected to diverge the most from each other, and also to demonstrate how endogeneity of entry timing decisions would be expected to affect observed FMA. Second, as a guide for future empirical research, this paper identifies and discusses a set of seven distinct methods that future studies could use for measuring FMB, thereby avoiding the biases inherent in FMA research. Third, as a contribution to the theory of network externalities, this paper examines the combination of both firm-level and market-level conditions under which the strength of network externalities would be expected to have the greatest effect on FMB, and thereby provide the greatest incentive for a particular firm to enter early (which may therefore predict actual entry-timing decisions). By combining the effects of both firm-level and market-level contingency factors, as well as their interaction effects, this paper answers the call by several researchers (Lieberman & Montgomery, 2013b; Zachary, Gianiodis, Payne, & Markman, 2014) for a more holistic approach to understanding how macro and micro level factors jointly shape entry timing decisions and their performance consequences.

2.2 Theoretical Overview: Entry Timing, Network Externalities, and Firm Performance

The subject of entry timing has been extensively studied by researchers in both strategic management and marketing due to its potentially strong links with firm performance. Entry timing decisions reflect a trade-off between flexibility and preemption (Ghemawat, 1991), since irreversible commitments made by early movers can have both beneficial and harmful effects that must be weighed against each other. On the negative side, early entrants have limited information about consumer preferences and therefore have a much higher risk of committing to the wrong type of product or business model to meet the demands of constituents in its environment, while later entrants who wait until more information is available about environmental demands can more easily avoid such mistakes. On the positive side, the benefit of an early entrant's costly irreversible investments is that such commitments can have a deterrent effect on subsequent entrants, since early entrants who lock up key resources or exclusive relationships may block later entrants, or at least severely restrict their range of action (Dixit, 1992; Kim & Miner, 2007; Mitchell, Shaver, & Yeung, 1994; Pindyck, 1991).

In line with this, Lieberman and Montgomery (1988) in their seminal paper point to several preemptive mechanisms that underlie first-mover advantages such as technological leadership, preemption of scarce assets, customer switching costs and network externalities. They also classify first-mover disadvantages that can benefit late movers in four main areas: free riding on pioneers' investments, resolution of technological and market uncertainty, incumbent inertia, and taking advantage of shifts in technology or market demand. Early entrants have limited information about consumer preferences and therefore have a much higher risk of making costly irreversible commitments to the wrong type of product for the market (Lieberman & Montgomery, 1988, 1998; Mitchell, 1989, 1991; Mitchell et al., 1994). Later entrants who wait until more market information is available can more easily avoid such mistakes (Dixit, 1992; Kim & Miner, 2007; Mitchell et al., 1994; Pindyck, 1991).

Empirical research on entry timing has produced either mixed or contradictory results. While some research emphasizes the positive effects of pioneering (Lambkin, 1988; Makadok, 1998; Urban, Carter, Gaskin, & Mucha, 1986; Yip, 1982), other research suggests that early entry can be harmful (Golder & Tellis, 1993) and that late entry can also be advantageous (Cho, Kim, & Rhee, 1998; Christensen & Bower, 1996; Shamsie, Phelps, & Kuperman, 2004; Shankar et al., 1998). In an attempt to explain the mixed findings in the literature, various researchers have drawn attention to internal and external contingency factors (Lieberman & Montgomery, 2013b; Suarez & Lanzolla, 2007a). For example, firm capabilities such as knowledge related assets (Li & Calantone, 1998)**,** speed capabilities (Hawk et al., 2013) as well as technological capabilities (Franco, Sarkar, Agarwal, & Echambadi, 2009; Sosa, 2009) have been demonstrated as internal factors that moderate the link between entry timing and competitive outcomes. Others have pointed out industry type (Kalyanaram & Winer, 1995; Schoenecker & Cooper, 1998), and parameters such as industry dynamism (Christensen, Suarez, & Utterback, 1998), competition level (Makadok, 1998), and evolution (Suarez & Lanzolla, 2007a) would influence the strength of first-mover advantages. As mentioned earlier, our model aims to help disentangle these conflicting results by predicting what biases may arise due to researchers' inability to adequately control for the sampling problems that arise from heterogeneous firms' endogenous entry-timing decisions (Boulding & Christen, 2003; Lieberman & Montgomery, 1988, 1998; Robinson, Fornell, & Sullivan, 1992).

Teece (1986) identifies inter-firm differences in stocks of complementary assets as a particularly important form of heterogeneity that can affect an innovator's ability to capture value from its innovation, and hence also influence its entry-timing decision. He argues that many innovators fail to maintain their early lead position in the markets due to lack of complementary assets such as manufacturing capabilities, marketing skills, and after-sale service infrastructure, or even intangible assets like reputation, and thus are quickly replaced by followers that possess these assets. For instance, EMI, as the firm that first introduced the CT scanner, lost its early lead to GE due to the lack of complementary assets required to support the main product and ensure successful market penetration. Our model explicitly incorporates heterogeneity in complementary assets by including a parameter representing any differential in customers' willingness to pay for different firms' products that are not due to network externalities.

2.2.1 FMA vs. FMB

Since the performance consequences of firms' entry timing decisions depend upon their unique stocks of pre-existing resources, so too are their entry-timing decisions also likely to depend upon those unique resource stocks (Lieberman & Montgomery, 1988; Moore et al., 1991; Robinson et al., 1992, Murthi et al., 1996; Boulding & Christen, 2003). Consequently, early movers are likely to be systematically different from late movers in their resource stocks. Due to such resource heterogeneity between early and late movers, unfortunately, researchers have often conflated two related but conceptually distinct constructs – the *ex post* performance advantage that a first-mover gains over its later-moving rivals (i.e., first-mover advantage, or FMA) and the firm's *ex ante* incremental increase in performance that it would gain by moving first rather than later (i.e., first-mover benefit, or FMB). In other words, FMA compares the performance of two different firms under a single entry-order scenario, while FMB compares the performance of a single firm under two different entry-order scenarios. Figure 2.1 illustrates this conceptual distinction.

On one hand, first-mover advantage is easier to observe empirically than first-mover benefit, since measuring first-mover advantage only involves comparing two firms' actual performance results while measuring first-mover benefit would requires a comparison between an actual performance result and a hypothetical counterfactual performance result. On the other hand, first-mover benefit is more relevant to a firm's actual entry-timing decisions than first-mover advantage. When deciding whether to pioneer or delay, it is more relevant to know which option is more profitable for the firm (FMB) than to know whether pioneering would allow the firm to outperform subsequent entrants (FMA), although the two are related. FMA and FMB are only guaranteed to be the same when competing firms are identical in every way except for the timing of their entry – e.g., having identical pre-existing resources and capabilities, so that neither the first-mover nor the later-mover has any pre-existing competitive advantage over the other. Otherwise, FMA and FMB may differ significantly, and may be affected differently by various contingency factors. Unfortunately, researchers have commonly interpreted empirical results about first-mover advantage as if they represented (or at least were a good proxy for) first-mover benefit, and therefore have presented these results as if they had clear, unambiguous, and uniform implications for all firms' entry-order decisions. One obvious problem, both conceptual and empirical in nature, is that using FMA as a proxy for FMB produces a measure at the wrong level of aggregation, since FMA represents a market-level construct, while FMB is a firm-level construct and is expected to differ between firms competing in the same market. So, one goal of this paper is to make predictions about how the difference between FMA and FMB in their levels of analysis can affect both empirical results and the interpretation of those results.

Yet the discrepancy between FMA and FMB raises more problems than just their differing levels of analysis, so that using FMA as an empirical proxy for estimating FMB almost always yields a biased estimate due to sample-selection biases. Such endogeneity-induced selection bias is regarded as a major methodological challenge that significantly slows theoretical progress in the area of FMA research **(**Fosfuri et al, 2013; Markman et al, 2015; Lieberman & Montgomery, 2013). After all, without knowing how severely each study is affected by this bias, it is impossible to know how to compare their results, which is a requirement in order for research to progress in a cumulative manner where new studies build upon older ones (Oxley et al., 2010).

This empirical conundrum is due to the combination of two distinct but connected causes – heterogeneity in the complementary assets of different firms, and endogeneity of the entry timing choices of firms. If either one of these two factors could be eliminated or adequately controlled for, then it would be possible to make valid inferences about FMB (at least on average) from empirical observations of FMA. So, let us consider each of these factors in turn. First, inter-firm heterogeneity is what drives the wedge between FMA and FMB in the first place. After all, if a first mover and a second mover are *ex ante* identical in all relevant complementary assets or capabilities that can affect performance, then the second mover's performance must be the same as the performance that the first mover would have achieved if it had moved second instead. So, FMA and FMB are only the same if early and later entrants were *ex ante* identical in every determinant of performance except for their entry timing – e.g., in their complementary assets. Second, even when firms are *ex ante* heterogeneous in their complementary assets and capabilities, unbiased estimates of the average FMB for a typical firm could still be inferred from observed FMA if entry timing were not endogenous to firm heterogeneity – i.e., if heterogeneity among firms had no influence on their entry timing decisions. For example, if entry timing were under the direct control of the researcher and could therefore be assigned randomly in a controlled experiment, then heterogeneity could be factored out of the results (e.g., via a matched-pair experimental design). However, randomizing entry order is impossible in most real-world empirical settings, since firms' entry timing decisions are influenced by their complementary assets and capabilities (Lieberman & Montgomery, 1988, 1998; Robinson et al., 1992; Teece, 1986). Alternatively, endogeneity biases might be mitigated if these sample selection effects could be adequately controlled for, but such efforts (e.g., Moore et al., 1991; Murthi et al., 1996) have proven questionable since their results are just as inconsistent and inconclusive as the rest of the FMA literature, perhaps due to the inherent difficulty of accurately predicting entry timing.

So, in the absence of either empirical settings with randomized entry order or better methods to control for entry timing, using FMA as a proxy for FMB generally yields biased estimates, because it becomes difficult, if not impossible, to cleanly separate the profitability of heterogeneous capabilities from the profitability of entry timing. In other words, such a proxy inextricably blends treatment effects with the selection effects. Whereas the concept of FMB is a pure treatment effect of entry timing on subsequent performance, empirical measures of FMA almost inevitably and inseparably blend this treatment effect with the selection effects of anticipated future performance on entry timing.

FMA is much easier to measure empirically than FMB, since FMB involves a counterfactual comparison. Yet, for prescriptive purposes, it is FMB that matters, not FMA. That is, when deciding whether to pioneer or delay, it is more relevant to know which option is more profitable for the firm (FMB) than to know whether pioneering would allow the firm to outperform subsequent entrants (FMA), although the two may be related.

2.2.2 Why Bother to Theorize About FMB?

One might question the usefulness of this theoretical exercise on the grounds that, because FMB is so difficult to measure, it would be virtually impossible for any future empirical study to actually test the predictions of the theoretical model, so why should one bother to derive predictions that can never be tested? The answer is that, although heterogeneity and endogeneity certainly present challenging obstacles to measuring FMB, there are nevertheless at least seven different possible approaches that future empirical studies might use for overcoming these obstacles: First, if empiricists can develop models that can actually predict entry timing with a high degree of accuracy, then sophisticated econometric techniques using instrumental variables may someday be able to make indirect counterfactual inferences about the difference between FMA and FMB in a way that is more consistent and defensible than prior attempts (e.g., Moore et al., 1991; Murthi et al., 1996) have been. Second, researchers could examine situations where competitors are engaged in a true race to be the first to enter a new market, but some of these competitors have their entry delayed by an unanticipated exogenous disruption (e.g., a natural disaster). A third approach would be to conduct stock-market event studies on firms that have already announced their intention to pioneer a new market by a particular date, but then later must announce a substantial delay in that planned entry.

Fourth, lab experiments could use popular classroom industry simulations to compare results in classes where entry timing is exogenously randomized by the instructor versus classes where the participants are allowed to make their own choices about entry timing. Fifth, researchers could use post-disaster micro-lending to conduct actual field experiments on entry timing. For example, following the utter devastation of the 2004 Indian Ocean tsunami, De Mel, McKenzie, and Woodruff (2008, 2012a, 2012b) collaborated with the World Bank to run randomized experiments aimed at determining which types of micro-lending interventions are most effective for rebuilding industries that had been destroyed. Although their experimental design did not manipulate the timing of these micro-loans in order to exogenously randomize entry timing, it certainly could have done so, and future post-disaster micro-lending experiments could incorporate randomized delays into their research design. A sixth approach would take advantage of the fact that most researchers are employed at universities, and universities sometimes create new geographic markets by constructing new buildings (or even entire new campuses) that include spaces leased out to new businesses like restaurants, bookstores, convenience stores, laundromats, or vending machines. With the cooperation of a friendly university administration, the timing of these leases could be manipulated in order to exogenously randomize the entry timing of competing businesses within each newly constructed venue.

Seventh, rather than designing their own experiments, researchers might exploit natural experiments in which governments exogenously randomize entry timing in regulated industries. For example, in industries where a license is required to enter and where the total number of licenses is limited by law, demand for licenses may exceed the scarce supply. Although license auctions are often employed in such situations in order to equilibrate demand and supply, sometimes government agencies instead ration scarce licenses by means of a random lottery. Perhaps the largest and most famous license lotteries were the cellular telephone spectrum lotteries held by the U.S. Federal Communications Commission during the 1980's (before switching to spectrum auctions in the 1990's), but numerous smaller-scale license lotteries are held by local authorities. In various jurisdictions in the United States, for instance, random lotteries have been used to allocate licenses for commercial fishing and clam-digging businesses (Rhode Island and Scarborough, Maine), liquor stores and bars (Arizona, California, Florida and Montana), and medical marijuana dispensaries (Santa Ana, California and Clark County, Nevada). If the number of available licenses increases at a later time, then the losers in the initial lottery get a delayed second chance to enter – thereby, in effect, randomizing the entry timing of all firms that had entered the lottery in the first place.

In sum, this list of seven possible empirical approaches shows that, although it may not be easy to measure FMB, it is nevertheless certainly possible for a motivated, resourceful, and creative researcher to do so. Indeed, the authors of the present paper are currently engaged in a concurrent empirical research project that has already yielded direct FMB measurements via the license lottery method. Therefore, since the empirical challenges to measuring FMB are surmountable, it is useful to theorize predictions about the factors that cause FMA to diverge from FMB, in order to inform and guide this emerging empirical research.

Finally, even if it were truly impossible to measure FMB, it would still be important to theorize about FMB in order to make theory-grounded predictions about firms' entry timing decisions. After all, as we have discussed, one would naturally expect a firm's actual entry timing decisions to be based on its own unique firm-level FMB, rather than on the market-level concept of FMA. Toward this end, the present paper examines the main and interaction effects of network externalities in order to make predictions about which firms, under which conditions, have the greatest incentive for early entry into network-based industries.

2.2.3 Network Externalities as a Preemptive Mechanism

In any given empirical context, the specific biases that arise from conflating FMA with FMB may differ according to the specific preemptive mechanism by which early commitment may boost performance in that particular context. Many such preemptive mechanisms have been considered, on both the demand and supply sides (for a review, see Lieberman & Montgomery 1988). On the supply side, these mechanisms include technological leadership, patent races, scale economies, preemptive capacity expansion, and preemption of scarce resources. On the demand side, they also include customer loyalty, switching costs, information cascades, fads or bandwagon effects, and network externalities.

Among these mechanisms, network externalities are among the least understood yet also among the most important to the modern information-driven economy, where the infusion of information technology has the potential to unleash network externalities in virtually any industry. For these reasons, researchers have called for greater attention to the role of network externalities in shaping entry-timing decisions and the performance consequences of those decisions (Lieberman & Montgomery, 2013a). Accordingly, we respond to that call by using network externalities as the preemptive mechanism that benefits an early entrant in our model. A network externality refers to an increase in the utility that users of a product receive as the number of other users of the same product increases (Farrell & Saloner, 1986; Katz & Shapiro, 1985). Telecommunications networks are the most a classic example where the value one gets from using it depends on the number of other users (Katz & Shapiro, 1994).

Various economic models of network-based industries have been developed to study preemption, predation, compatibility effects, technology adoption, innovation and technology management, and product introductions (Farrell & Saloner, 1986; Katz & Shapiro, 1985, 1986, 1992; Shapiro & Varian, 1999; Tirole & Fudenberg, 1985). Several empirical studies have explored the importance of network externalities on technology adoption (Brynjolfsson & Kemerer, 1996; Schilling, 2002; Shankar & Bayus, 2003). The positive feedback loop that is generated with growing user often, but not always, base tips the market towards the dominant firm that becomes the industry standard and forms a winner-take-all market structure leading to “lock-in” (Arthur, 1989). This market evolution benefits an early mover that gets an effective “head start” on preemptively accumulating a user network, perhaps even serving as an entry deterrent or entry barrier (Katz & Shapiro, 1985, 1994; Lieberman, 2007; Lieberman & Montgomery, 1988; Suarez, Cusumano, & Fine, 1995). Such rapid accumulation of users would help the early mover establish itself as the standard, with the potential for increasing returns to scale (Arthur, 1989, 1994; Klemperer, 1987; Lieberman & Montgomery, 1988; Teece, 1986), as the resulting lock-in effect impedes later entrants from attracting customers.

However, more recent research suggests that this story is incomplete, and that factors other than the installed base can significantly influence the likelihood of lock-in and the resulting magnitude of any network-based first-mover advantage. For example, various authors argue that quality differences between products have a major influence over the extent of first-mover advantages in network-based industries (Liebowitz, 2002; Liebowitz & Margolis, 1994; Liebowitz & Margolis, 2001; MacCormack & Iansiti, 2009; Zhu & Iansiti, 2012). Likewise, Shankar and Bayus (2003) and Suarez (2005) examined how firms with smaller installed base outperformed their more popular rivals in video-game consoles and wireless technologies, concluding that network effects should be expressed not solely as a function of network size but also as a function of "network strength." Similarly, Evans (2003) observes various examples of disadvantaged early entrants in markets characterized by network externalities, such Apple in the PC market. Using software evaluation data from computer magazines, Liebowitz and Margolis (2001) empirically illustrate that, despite strong network externalities, early monopolists are frequently replaced by products of superior quality. In addition, Shapiro and Varian (1999) analyzed how Microsoft and Sony achieved leadership positions in new product markets despite late entry timing due to the self-fulfilling prophecy of persuading customers to expect that they would ultimately prevail. As mentioned earlier, our model adds to this list of caveats and moderators that limit the applicability of the original winner-take-all "lock-in" story by considering how the impact of network externalities is affected by both firm-level and market-level factors, such as rivalry intensity, market growth rate, and competitive advantage in complementary assets.

2.3 MODEL

2.3.1 Assumptions

Since entry-order advantages and network externalities are inherently dynamic phenomena, we use a dynamic model. For simplicity and tractability, we limit the model to two firms and two time periods, an initial period when the first mover enjoys a monopoly and a second period when the second firm enters the market and the two firms compete with imperfectly substitutable products. Consumers are assumed to be utility maximizers, resulting in inverse demand functions for each firm's product that reflect their imperfect substitutability. Each firm is assumed to make an irrevocable commitment to a particular level of output per period (i.e., its scale of production) at the time of its entry into the industry, and this choice of output level is assumed to maximize its own net present value (NPV), with no possibility of collusion, conditional upon the information available to the firm at the time of its output decision. Through consumers' utility-maximizing inverse-demand functions for each period, these output levels then determine the prices received by each firm in that time period. Our model assumes incompatibility between competing firms' products in the sense that all network externalities are firm-specific. It also does not allow for firms to gain "adoption insurance" by pre-announcing prices contingent on future sales in order to influence consumers' current purchase decisions (Katz & Shapiro, 1992), since such commitments are vanishingly rare in practice and their credibility would be questionable anyway.

In order to distinguish between first-mover advantages and first-mover benefits, we run the model under two scenarios about the entry timing of the two firms, which are denoted as firm *A* and firm *B*. In scenario *a*, firm *A* enters in the first period, followed by firm *B* in the second period. Conversely, in scenario *b*, firm *B* enters in the first period, followed by firm *A* in the second period. Without loss of generality, we take firm *A* as our "focal firm" and examine the first-mover advantages and benefits for firm *A*. Analyzing firm *A*'s first-mover advantages only requires scenario *a* (where A enters first); the first-mover advantage is captured by comparing firm *A*'s performance to firm *B*'s performance under scenario *a*. However, analyzing firm *A*'s first-mover benefits requires a comparison between both scenarios; the first-mover benefit is captured by comparing firm *A*'s performance under scenario *a* (where firm *A* enters first) to firm *A*'s performance under scenario *b* (where firm *B* enters first). For simplicity of notation and exposition, we will sometimes refer to the first mover as firm *F* and the second mover as firm *S*, with the understanding that *F*=*A* and *S*=*B* in scenario *a*, and that *F*=*B* and *S*=*A* in scenario *b*. For notational convenience, we also designate the scenario by defining a numerical dummy variable d_s that is either equal to 1 under scenario *s*=*a*, or equal to 0 under scenario *s*=*b*.

Table 2. 1 Definitions of parameters and endogenous variables

Exogenous Parameters		Endogenous Variables	
α	Discount factor	p	Price
β	Baseline marginal cost per unit	q	Quantity
γ	Rivalry intensity	c	Marginal cost
δ	Complementary asset advantage	m	Margin
ω	Network externality strength of industry	π	Profit
ρ	Demand growth rate	n	Net present value
σ	Demand uncertainty	Z	Demand shock

The left side of Table 2.1 shows the underlying exogenous parameters of our model represented by Greek letters, while the table's right side shows the model's endogenous variables represented as lower-case letters, and its random variables represented as upper-case letters; the sole exception to this notational convention is for firms' profits, which are designated by π, as is conventional in economic modeling. Also consistent with convention, we denote price by *p*, quantity by *q*, marginal unit cost by *c*, unit profit margin by *m*, and net present value by *n*. On the demand side, we denote the representative consumer's utility as *u*, product-specific willingness to pay as *w*, monetary endowment as ϵ, and unspent funds as *f*. The parameter $\omega \geq 0$ represents the industry-level network intensity parameter, with higher levels indicating a greater impact of a firm's prior-period installed base size on the current-period customer willingness to pay for its product. The parameter $\delta \in (-1,1)$ captures pre-existing differences in firms' complementary assets – i.e., resources that are independent of network size but still also affect customer WTP – with positive values of δ representing an advantage for firm *A* and a disadvantage for firm *B*, and negative values of δ representing an advantage for firm *B* and a disadvantage for firm *A*.

In order for our model to capture the classic entry-timing trade-off of preemption versus flexibility, two conditions must be satisfied: First, in order to ensure some benefit for preemption, the first mover must make some irrevocable (or at least difficult-to-change) commitment in the first period, before the second mover has an opportunity to make its own move. Second, in order to ensure some countervailing benefit for flexibility, there must be some relevant new information affecting the profitability of the firms' decisions that becomes known after the first mover has made its irrevocable commitment but before the second mover makes its own move, thereby giving the second mover an opportunity to make adjustments that the first mover cannot. In our model, the irrevocable commitment is the choice of output level upon entry (as in the classic leader-follower model of von Stackelberg, 1934), and the new information that only becomes known in the second period is an industry-wide demand shock, which represents either market uncertainty or a shift in customer needs – two of the four first-mover disadvantages considered by Lieberman and Montgomery (1988: 47-48). Specifically, we denote the demand shock as the random variable *Z*, which follows a symmetric Bernoulli distribution with mean of zero and becomes observable to the firms after the first firm enters but before the second firm enters. Since output choices are assumed to be irrevocable, this commitment to its output level gives firm *F* an opportunity to preempt market share; and since the demand shock occurs after firm *F*'s commitment but before firm *S*'s commitment, this timing gives firm *S*, but not firm *F*, an opportunity for flexibility to adjust to the shock. The decision sequence of the model is illustrated via the timeline in Figure 2.2.

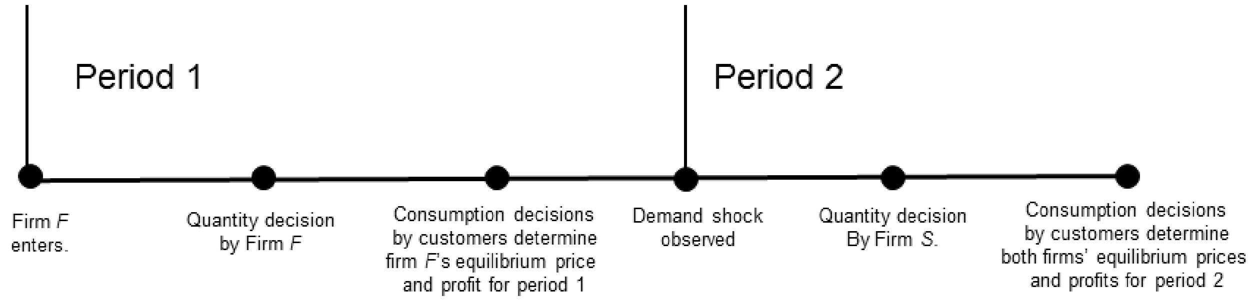

Figure 2. 2 Model timeline

The parameter $\sigma \geq 0$ denotes the standard deviation of the demand shock. The parameter ρ represents an exogenous industry growth factor – i.e., the portion of industry growth between the two periods that is independent of both the network effects and the demand shock. If we think of the two periods as being roughly equal in length of calendar time, then ρ could be interpreted as representing growth in the number of products sold per unit of calendar time (e.g., per day, month, or year). On the other hand, if we think of the number of products sold per unit of calendar time as being roughly constant, then ρ could be interpreted as representing the relative length of calendar time in the second period's duopoly phase of industry history in comparison to the first period's monopoly phase. Of course, it is also possible to interpret ρ as representing some combination of both the relative number of products sold per unit of calendar time in the two periods and the relative length of calendar time of the two periods.

The parameter $\gamma \in [0,1)$ represents the degree of substitutability between the competing firms' products, which in turn drives the intensity of rivalry between the firms, where the perfectly non-substitutable extreme of $\gamma = 0$ implies that the firms operate in separate monopolies with no rivalry between them, and the perfectly substitutable extreme of $\gamma \to 1$ approaches undifferentiated Bertrand competition. The parameter $\theta > 0$ represents the baseline willingness to pay. For simplicity, both firms $i \in \{F,S\}$ are assumed to have identical costs, given by $c_i = \beta\theta$, where the parameter $\beta \in [0,1]$ allows us to express the firms' marginal cost per unit as a fraction of consumers' baseline willingness to pay. We use the subscript $t \in \{1,2\}$ to index the two time periods, and the subscript $s \in \{a, b\}$ to index the two scenarios, so that the customer buys quantity $q_{F,t,s}$ at price $p_{F,t,s}$ from firm *F* (first mover – i.e., firm *A* in scenario a, or firm *B* in scenario b) and buys quantity $q_{S,t,s}$ at price $p_{S,t,s}$ from firm *S* (second mover – i.e., firm *B* in scenario a, or firm *A* in scenario b). These sales yield profits of $\pi_{i,t,s} = q_{i,t,s}(p_{i,t,s} - c_i)$ for firm *i* in time *t* under scenario s. Both firms are assumed to choose their output levels non-cooperatively, so as to maximize the conditional expected value of their own discounted net present value (NPV), i.e., conditional upon the information available to them at the time of their decision. These conditional expected NPV's are designated as $\mathrm{n}_{F,s} = \pi_{F,1,s} + \alpha\,\mathrm{E}(\pi_{F,2,s})$ for firm *F*, and as $\mathrm{n}_{S,s} = \alpha\,\mathrm{E}(\pi_{S,2,s}|Z) = \alpha\,\pi_{S,2,s}$ for firm *S*, where the parameter $\alpha \in (0,1]$ represents the discount factor applied to second-period profit relative to first-period profit.

2.3.2 Solution Overview

As detailed in the Appendix, the model is solved using backward induction, in order for firm *F* to have accurate expectations of the second-period results to serve as inputs for its first-period decision. So, we first derive firm *S*'s optimal output choice conditional upon both firm *F*'s prior output choice and the actual observed value of the demand shock *Z*. We substitute firm *S*'s optimal output into firm *F*'s expected NPV function, and we then maximize that function to derive firm *F*'s optimal output choice prior to observing the demand shock. We then substitute both firms' optimal output choices into their respective *ex ante* unconditional expected NPV functions and second-period profit functions, thereby giving us their equilibrium *ex ante* expected NPV and second-period profit functions, designated as $n_{i,s}^{**}$ and $\pi_{i,2,s}^{**}$ respectively. The exact analytical solutions for these two *ex-ante* expected outcome variables are provided in the Appendix. We can then conduct comparative-statics analysis on either of these outcome variables by differentiate these *ex ante* expected equilibrium outcomes with respect to various underlying parameters.[3]

To ensure meaningful results, we impose whatever constraints on the underlying parameters are necessary in order for the following conditions to hold true: (1) Both firms' chosen optimal quantity levels must be non-negative regardless of the realized value of the demand shock and must be maxima of their respective equilibrium NPV functions (i.e., second order conditions satisfied). (2) All profits earned by either firm in either period must be non-negative. (3) Both firms' *ex ante* expected equilibrium NPV's must be non-negative. We define the "valid region" for each scenario as the region of parameter space where all of these conditions are met under that scenario. When deriving FMA results, we limit our analysis to the valid region for scenario *a*. When deriving FMB results (and when deriving results about the FMA – FMB difference), we limit our analysis to the intersection of the valid regions for both scenarios *a* and *b*.

[3] Empirical studies of FMA focus only on performance during the competition period as their dependent variable, rather than using some NPV measure that would also incorporate results during the monopoly period. Therefore, to maintain consistency with empirical studies, this paper derives its propositions from comparative statics analysis of FMA and FMB measures defined in terms of firms' second-period profit functions $\pi_{i,2,s}^{**}$ rather than in terms of NPV, but the results are nearly identical either way. All of the reported second-period profit effects with an unambiguous sign also have the same sign when the effect is defined in terms of NPV. However, as indicated in the note under Table 3, one of the effects that has an ambiguous sign when defined in terms of second-period profit is unambiguously positive when defined in terms of NPV.

2.3.3 Derivation of Outcome Variables

The main outcome variables are FMA and FMB. Without loss of generality – since we allow for the only source of inter-firm asymmetry in our model, the complementary assets parameter δ, to be either positive or negative – we use firm *A* as our focal firm, and therefore calculate the FMA of firm *A* over firm *B* in scenario a. For our main results, we calculate FMA and FMB in terms of differentials in equilibrium *ex ante* expected second-period profits, rather than as differences in NPV. We do this in order to ensure consistency with empirical studies in FMA, which only consider performance differentials measured during time periods when the first mover and subsequent entrants actually compete with each other, without taking into account the first mover's performance during the earlier monopoly period (which would be required if FMA and FMB were defined in terms of NPV). Either way, the results are nearly identical.

So, FMA is calculated as the equilibrium *ex ante* expected second-period profit differential between firm *A* and firm *B* under scenario a – i.e., $FMA_{\pi} = \Delta\pi^{**}_{FMA} = \pi^{**}_{A,2,a} - \pi^{**}_{B,2,a}$. Likewise, FMB is calculated as the equilibrium *ex ante* expected second-period profit differential between scenario a and scenario b for firm A – i.e., $FMB_{\pi} = \Delta\pi^{**}_{FMB} = \pi^{**}_{A,2,a} - \pi^{**}_{A,2,b}$. Thus, FMA represents the performance differential between two different firms in a single entry-order scenario. By contrast, the first-mover benefit (FMB), represents the performance differential between two different entry-order scenarios for a single firm. In addition, we also calculated FMA – FMB in order to better examine the difference between the two constructs – i.e., $FMA_{\pi} - FMB_{\pi} = \Delta\pi^{**}_{FMA} - \Delta\pi^{**}_{FMB}$.

2.3.4 Derivation of Comparative Statics

To derive comparative statics results for each of the outcome variables described above, we calculate the outcome variable's first derivative with respect to each underlying model parameter for the main effects, and its cross-partial multiple derivative with respect to combinations of underlying model parameters for the interaction effects. As Equations 9 and 10 illustrate, the outcome variables described above are complicated mathematical expressions, and their derivatives are equally complicated. So, we cannot make interpretations or inferences about the signs of these comparative statics expressions analytically, i.e., by merely inspecting them. Therefore, we resort to numerical methods. Specifically, we use Mathematica (complete code is available from the authors upon request) to plot the signs of each comparative statics expression at over 78,000 combinations of possible values for the seven underlying model parameters (i.e., $\omega, \delta, \alpha, \rho, \gamma, \beta, \sigma$) across the entire valid region of the parameter space defined earlier (i.e., where the dynamic equilibrium solutions are valid). We base our comparative-statics results on any derivatives whose signs are consistent (either consistently positive or consistently negative) throughout this entire valid region.

2.4 Results

Comparative statics yields three categories of results: (1) effects of complementary assets advantage, including both main effects and interactions with other parameters, (3) interaction effects of network externalities with other parameters, and (3) effects of endogeneity of entry timing. We discuss each of these three categories in turn.

2.4.1 Effects of Complementary Assets Advantage

Our first result shows that heterogeneity in complementary assets drives a wedge between FMA and FMB, thereby making FMA a worse proxy for FMB at higher levels of asymmetry. FMA is only equal to FMB when the two firms are perfectly symmetric in their complementary assets (i.e., when δ is exactly zero). FMA exceeds FMB when the focal firm has superior complementary assets (i.e., when δ is positive), while FMB exceeds FMA when the focal firm's complementary assets are inferior (i.e., when δ is negative). Thus, empirical studies that use measures of FMA as a proxy for estimating FMB would be expected to have estimates that are biased upward when the first mover has an advantage in complementary resources, and biased downward when the first mover has a disadvantage in complementary resources. So, as indicated in the main effect column of Table 2.2, the FMA – FMB difference unambiguously increases as the focal firm's complementary assets improve (i.e., as δ increases). These results are driven more by the effect of complementary assets on FMA than by their effect on FMB. In particular, as shown in that same main effect column, increasing the complementary assets advantage parameter δ unambiguously raises FMA, yet its impact on FMB is ambiguous. So, we propose:

> ***Proposition P1:*** *FMA, as well as the difference between FMA and FMB, both increase as the strength of the focal firm's complementary assets increases, so that FMA exceeds FMB when the focal firm is at a competitive advantage over its rivals in the relative strength of their complementary assets, FMA and FMB are equivalent when the focal firm is at parity with its rivals in the strength of their complementary assets, and FMB exceeds FMA when the focal firm is at a competitive disadvantage relative to its rivals in the strength of their complementary assets. So, using FMA as a proxy for FMB is expected to generate upward-biased estimates when the first mover has an advantage in complementary assets, and downward-biased estimates when the first mover has a disadvantage in complementary assets.*

Table 2. 2 Main and interaction effects of non-network parameters on FMA and FMB

Outcome variable	Definition of outcome variable	Sign of main effect of: Comp. assets advantage (δ)	Demand uncertainty (σ)	Market growth (ρ)	Rivalry intensity (γ)	Sign of interaction effect of complementary assets advantage with: Demand uncertainty (δ x σ)	Market growth (δ x ρ)
FMA_π	$\Delta\pi^{**}_{FMA} = \pi^{**}_{A,a} - \pi^{**}_{B,a}$	+[P1]	–	A	A	+[P2]	+[P3]
FMB_π	$\Delta\pi^{**}_{FMB} = \pi^{**}_{A,a} - \pi^{**}_{A,b}$	A	–	A	A	–[P2]	A
$FMA_\pi - FMB_\pi$	$\Delta\pi^{**}_{FMA} - \Delta\pi^{**}_{FMB}$	+[P1]	A	A	A	+[P2]	+[P3]

+ = Positive effect – = Negative effect A = Ambiguous effect
(Superscripts on these symbols indicate which proposition, if any, expresses the given effect.)

Table 2.2's second main effect column shows that demand uncertainty, as one would naturally expect, has a negative main effect on both FMA and FMB. But much more interestingly, Table 2.2 also shows that demand uncertainty drives the ambiguity in the relationship between complementary assets and FMB. In particular, as shown in the δ x σ interaction effect column of Table 2.2, strengthening δ increases FMB when σ is low, but decreases FMB when σ is high, and this is true regardless of whether FMB is defined in terms of NPV or second-period profit. That is, having stronger complementary assets relative to those of rivals increases the relative profitability of moving earlier rather than later under low uncertainty, but decreases it under high uncertainty. The economic intuition behind this result is a bit complicated because complementary assets can be used in either one of two ways: First, they can be used by a first mover as a tool to preempt others – i.e., by making its early commitment more effective at blocking, deterring, or hindering later entrants. But second, they can also be used by a later entrant as a tool to overcome the preemptive moves of others – i.e., by letting it more effectively "catch up" to (or even surpass) the first mover and thereby overcome the first mover's blocking, deterring, or hindering barriers. When uncertainty is high, waiting to observe true market conditions (i.e., the level of the demand shock, in our model) before committing to a specific way of serving the market (i.e., the output level, in our model) can benefit performance greatly, in which case the "overcoming others' preemptive moves by catching up" usage of complementary assets as a later entrant outweighs their "preempting others" usage as a first mover. However, when uncertainty is low, there is little performance benefit from waiting until market uncertainties are resolved before committing to a specific way of serving the market, in which case the "overcoming others' preemptive moves by catching up" usage of complementary assets as a later entrant is insufficient to overcome their "preempting others" usage as a first mover.[4]

However, as indicated in that same δ x σ column of Table 2.2, note also that the δ x σ interaction has the opposite effect on FMA as on FMB – i.e., strengthening δ increases FMA more strongly when σ is high than when σ is low. That is, when a first mover's complementary assets get stronger relative to those of a later mover, the resulting increase in the superiority of its profit over that of the later mover is greater when uncertainty is high than when uncertainty is low. The economic intuition for this opposite result relies on two key differences between FMA and FMB: First, unlike FMB, FMA is driven just as much by decreases to the rival's performance as it is by increases to the focal firm's performance. Second, unlike in FMB, the focal firm in FMA is always the first mover, so the impact of the focal firm's complementary assets is always and only caused by the "preempting others" usage of those assets, rather than by the "overcoming others'

[4] Although this result is consistent with the argument by Teece (1986: 291-292) that complementary assets become more important over time, our result here is based on an entirely different theoretical logic.

preemptive moves by catching up" usage. The damage that the first mover's complementary assets preemptively inflict on a later entrant's performance is more severe when uncertainty is high than when uncertainty is low, for the same reason that an airstrike does more unintentional collateral damage to civilians when there is more uncertainty about the exact location of its legitimate intended military target. In our model, if the first mover could know the exact value of the demand shock before committing to its output level, then the intensity of its preemptive move would be proportionate to the observed demand shock, which would, on average, benefit the profitability of the late entrant. Greater uncertainty, however, makes the first mover's preemptive more disconnected from actual demand – i.e., more excessive when demand is low, and the more inadequate when demand is high – thereby forcing the later entrant to adjust its own behavior to compensate for these blind excesses by the first mover, which hurts the later entrant, on average.

Because the δ x σ interaction has the opposite effect on FMA (positive) as it does on FMB (negative), it therefore has an unambiguously positive effect on the FMA – FMB difference. That is, increasing uncertainty magnifies the wedge that asymmetry in complementary assets drives between FMA and FMB. So, when using FMA as an empirical proxy for estimating FMB, the positive bias that stronger complementary assets induces in the estimate is amplified by higher levels of uncertainty. Combining all of the results from the δ x σ column of Table 2.2, we propose:

> ***Proposition P2:*** *Increasing the strength of a firm's complementary assets increases its FMB when uncertainty is low, but decreases its FMB when uncertainty is high. However, increasing the strength of a firm's complementary assets increases FMA more strongly when uncertainty is high than when uncertainty is low. Consequently, the effects of a firm's advantage in complementary assets on the difference between FMA and its FMB are more positive when uncertainty is high than when uncertainty is low.*

As shown in the δ x ρ interaction effect column of Table 2.2, increasing the market growth rate unambiguously amplifies the positive effects of a firm's complementary assets advantage on its FMA, as well as on the FMA – FMB difference. So, the wedge that asymmetry in complementary assets drives between FMA and FMB is wider when the market grows more quickly. The economic intuition for this result can only be understood in light of the fact that complementary assets can either be used to bolster a firm's preemptive moves against later entrants or to help overcome the preemptive moves made by earlier entrants. In the trade-off between these two usages, faster market growth increases the benefits of making preemptive moves against later entrants, but faster market growth also reduces the effectiveness of complementary assets at overcoming the preemptive moves made by earlier entrants. The effect of complementary assets on FMA (where the focal firm always moves first) is purely a reflection of preemptive moves against later entrants, whereas the effect on FMB (which is a comparison between moving first or moving later) reflects a trade-off between preempting later entrants versus overcoming the preemption of earlier entrants. Thus, faster market growth amplifies the effect of complementary assets on FMA more than their effect on FMB. Consequently, when using FMA as an empirical proxy for estimating FMB, the positive bias that stronger complementary assets induces in the estimate is amplified by faster market growth. So, we propose:

> ***Proposition P3:*** *The effects of a firm's advantage in complementary assets on FMA, as well as on the difference between FMA and its FMB, are more positive when the market grows fast than when the market grows slowly.*

2.4.2 Effects of Network Externalities

Since network externalities have long been understood to benefit the first mover, Table 2.3 shows that the strength of network externalities has an unambiguously positive main effect on FMB (and FMA as well). However, our focus here is on two questions about when this effect is stronger or weaker: (1) Under what market conditions does the strength of network externalities provide a larger or smaller benefit to the first mover? (2) What firm-level characteristics increase the firm's relative incentive to enter early, compared to other firms (thereby possibly predicting actual entry timing decisions)?

Answering these questions requires examining the interaction effects of network externalities with other parameters on FMB. Table 2.3 shows three such network interaction effects.

Table 2. 3 Main and interaction effects of network externality strength on FMA and FMB

Outcome variable	Definition of outcome variable	Sign of main effect of network externality strength (ω)	Sign of interaction effect of network externality strength with: Comp. assets advantage (ω x δ)	Market growth (ω x ρ)	Comp. assets advantage & market growth (ω x δ x ρ)
FMA_π	$\Delta\pi^{**}_{FMA} = \pi^{**}_{A,a} - \pi^{**}_{B,a}$	+	+	A*	+
FMB_π	$\Delta\pi^{**}_{FMB} = \pi^{**}_{A,a} - \pi^{**}_{A,b}$	+	+[P4]	+[P4]	+[P4]
$FMA_\pi - FMB_\pi$	$\Delta\pi^{**}_{FMA} - \Delta\pi^{**}_{FMB}$	A	A	A	A

\+ = Positive effect – = Negative effect A = Ambiguous effect
(Superscripts on these symbols indicate which proposition, if any, expresses the given effect.)
* = Effect is unambiguously positive when FMA is defined in terms of NPV rather than in terms of second-period profit.

The first network interaction effect in Table 2.3 is between the strength of the industry's network externalities and the strength of the firm's complementary assets. As one might naturally expect from the very nature of the phrase "complementary assets," this interaction has a uniformly and unambiguously positive effect on FMB, indicating a synergistic complementarity. The second network interaction effect in Table 2.3 shows that the interaction of network externalities with market growth has a positive impact on FMB. In other words, network externalities are more favorable to first movers in high-growth industries than in low-growth industries. This result is interesting because previous research has argued that environments characterized by faster market evolution, such as high-growth markets, offer greater opportunity for followers to catch up with and even overtake the pioneers (Suarez & Lanzolla, 2007b). According to this logic, high growth provides more space in the market for late entrants to occupy, thereby increasing their survival chances and performance (Christensen, 1997; Suarez & Lanzolla, 2007b) . However, our results suggest that the effect of market growth on performance might be context-dependent, and in industries characterized by network effects, increased market growth actually helps the first movers more since it enhances the bandwagon effect – i.e., the installed base can attract a larger number of new adopters in industries with higher growth. Finally, the last network interaction effect in Table 2.3 indicates that the first two network interaction effects amplify and reinforce each other: When a firm's complementary assets advantage is stronger, market growth has an even greater effect on the relationship between network externalities and FMB.

Conversely, when market growth is greater, a firm's complementary assets advantage has an even stronger effect on the relationship between network externalities and FMB. Combining these results from Table 2.3, we propose:

> ***Proposition P4:*** *The positive effect of the industry's network externality strength on FMB is stronger when the market's growth rate increases **or** when the firm's complementary assets advantage increases, and it is even stronger still when the market's growth rate **and** the firm's complementary assets advantage **both** increase together. Thus, in an industry with stronger network externalities, a firm has a stronger incentive to enter early if it has an advantage in its complementary assets **or** if the market growth rate is high, and even stronger still if both of these are true.*

2.4.3 Effects of Endogeneity of Entry Timing

In order to determine the effect of endogeneity on observed FMA in our model, we must compare the model's FMA results when entry timing is determined exogenously from the corresponding FMA results when entry timing is determined endogenously. Generating the latter results require that we must examine a version of the model in which the firms' entry timing is endogenously determined. Fortunately, this is quite simple to do: We simply assume that entry timing is determined by the magnitude of the firms' respective FMB's. In other words, in the endogenous entry-order version of the model, the first mover is whichever firm benefits more from moving first. This is a very natural assumption because the firm with the highest FMB would profit the most to gain by entering first, and therefore the strongest incentive to do so. Specifically, the model's results indicate that the focal firm, A, has greater FMB than its rival, B, if and only if δ>0. So, in order to predict how endogeneity is likely to bias empirical measures of FMA when entry-order is endogenous (as it is in almost every real-world industry), we simply compare how the model's FMA results change when we move from the general case, where δ can assume any valid value, to the more restricted subset of parameter space where δ>0. These comparisons are shown in Table 2.4, where the first row shows the general case where entry timing can be exogenously determined, while the second row shows the δ>0 special case where entry timing is as if it were determined endogenously.

Table 2. 4 Effects of endogeneity on FMA

Outcome variable	Definition of outcome variable	Sign of level of outcome variable	Sign of main effect of market growth (ρ)
FMA_{π}	$\Delta\pi^{**}_{FMA} = \pi^{**}_{A,2,a} - \pi^{**}_{B,2,a}$	A[P5]	A[P5]
$FMA_{\pi,endog}$	$\Delta\pi^{**}_{FMA}\vert_{\delta>0}$	+[P5]	+[P5]

+ = Positive effect – = Negative effect A = Ambiguous effect
(Superscripts on these symbols indicate which proposition, if any, expresses the given effect.)

Table 2.4's first column of results shows that the sign of FMA depends upon whether entry timing is endogenous. When entry timing is determined endogenously (i.e., when δ>0), FMA is unambiguously positive, but this sign is ambiguous when entry timing can be exogenously determined. The economic intuition for this result is simply that FMA appears more positive in situations where the first entrant is the firm that would profit the most from entering first than in situations where the second entrant would have profited the most from entering first. The empirical implication is that we can expect endogeneity of entry timing to place an upward bias on observed measures of FMA, since such observations are inflated by combining both treatment effects and selection effects. Similarly, the second column of Table 2.4 shows that the sign of the main effect of market growth on FMA also depends upon whether entry timing is endogenous. When entry timing is determined endogenously (i.e., when $\delta>0$), increased market growth unambiguously increases FMA, but this effect is ambiguous when entry timing can be exogenously determined. So, we propose:

> ***Proposition P5:*** *Observed FMA, and the effect of market growth on observed FMA, are more likely to appear positive when entry timing is determined endogenously than when entry timing is exogenously determined.*

2.5 Discussion and Conclusion

This paper contributes to the literatures about the effects of both entry timing and network externalities on firm performance. First, its contribution to the entry timing literature is to highlight and pinpoint empirical biases expected to result from the mutually endogenous nature of the relationship between entry timing and firm performance among competitors who differ in the strength of their complementary assets. Specifically, this paper distinguishes the pure treatment-effect concept of FMB, which is counterfactual and therefore usually unobservable, from the empirical measure of FMA, which is observable but inextricably blends the treatment effect with selection effects. Whereas FMB represents only the effects of entry timing on future performance, FMA also includes the effects of anticipated future performance on entry timing, which can induce biases in industries with heterogeneous competitors because of how pre-existing differences in their complementary assets can affect the performance consequences of their entry-order decisions. When using FMA as an empirical proxy to measure FMB, measurement biases can arise due to the combination of both heterogeneity in competitors' complementary assets and endogeneity of entry-order decisions. This paper helps to excavate this problem by using a dynamic economic model to make specific predictions about what particular biases could arise from using FMA as an empirical proxy for FMB due to heterogeneity in competitors' complementary assets, and how observations of FMA may be influenced by the endogeneity of entry timing. Although several such biases are predicted by our model and stated as formal propositions here, perhaps the most notable of these is that a firm's FMA is expected to exceed its FMB when its complementary assets are superior to those of its rivals, but its FMB is expected to exceed its FMA when its complementary assets are inferior to those of its rivals.

In addition to the entry timing literature, this paper also contributes to research on network externalities by analyzing how competitive outcomes associated with entry timing in network-based industries can be affected by several important contingency factors, including the market growth rate and pre-existing heterogeneity in firms' complementary assets. Our results indicate that the positive impact of network externalities strength on FMA and FMB is stronger when either of these contingency factors increases, and even more so when both increase together.

2.6 Caveats, Limitations, and Opportunities for Future Research

The greatest challenge to applying our model's results, as mentioned in the introduction, is the inherent difficulty in measuring FMB empirically. Nevertheless, as we argued in the introduction, difficult does not mean impossible, and efforts to overcome this measurement obstacle are already underway in our concurrent empirical project, which has already yielded direct measures of FMB. Specifically, we identified seven methods by which FMB might be empirically measured – (1) improved instrumental-variables models using more accurate predictions of entry timing, (2) entry races where some firms suffer an unexpected exogenously-imposed delay, (3) stock-market event studies of firms that announce delays in their previously announced plans to pioneer new markets, (4) lab studies using industry simulations that allow for either exogenously- or endogenously-determined entry timing, (5) exogenously randomized delays in micro-lending to rebuild industries devastated by disaster, (6) exogenously randomized delays in leasing space to companies doing business in new geographic markets created by university building construction, and (7) exogenously randomized entry timing due to license lotteries in regulated industries. Future research may use any of these empirical strategies to measure differences between FMA and FMB, and to identify the conditions under which these two constructs have the greatest divergence from each other.

Although our model illuminates some previously overlooked aspects of the bidirectional relationship between entry timing and firm performance, its contributions in this area are incomplete. It considers only a single causal mechanism that favors early entry – namely, network externalities. It also considers only a single causal mechanism that favors later entry – namely, flexibility to respond to exogenous environmental shocks. As Lieberman and Montgomery (1988) highlight, there are numerous real-world mechanisms on both sides of this equation, such as switching costs, technological leadership, preemption through rare assets that favor early entry, and other such mechanisms as free-riding, incumbent of inertia as well as changes in consumer preferences that favor late entry. A more complete model of the biases induced by using FMA as a proxy for FMB would include all of these mechanisms. Due to the extraordinary complexities that such a model would involve, we leave its development for future research. In this regard, our model is just a first step toward understanding, and ultimately correcting for, the inherent biases in estimating a counterfactual concept that is not usually directly observable.

Although our model illuminates some previously overlooked aspects of the effects of network externalities on firm performance, its contributions in this area are also incomplete. Our paper's focus is on markets shaped by direct network externalities, but many new industries – especially those with platform-based business models, like online retailing, social media, and online search – may be more strongly influenced by indirect, rather than direct, network effects. Therefore, further research could incorporate both indirect and direct network effects as well as their interactions, thereby providing more insightful propositions in such settings.

Also, our model uses Stackelberg-style inflexibility in production output to capture commitment, which may be limiting for two reasons: First, from a theoretical perspective, this assumption forces the competing firms' moves to be strategic substitutes and does not allow for the possibility of moves (e.g., pricing decisions) that could be strategic complements. So, one avenue for future research would be to extend this model to account for the possibility of strategic complementarity as a robustness check on our results. Second, from an empirical perspective, the assumption of irrevocably inflexibility output decisions would be unrealistic in many industry settings where output can easily be adjusted. In such settings, other forms of commitment would be more appropriate, such as commitments to a particular brand identity, level of quality, or set of product characteristics, or irreversible investments in physical resources, intellectual property, or human capital. Future extensions or adaptations of the model could incorporate these alternative forms of commitment to investigate whether the particular form of commitment might have an impact on the results. On a related note, our paper also makes the assumption that all consumers share common preferences as represented by the same utility function. If, on the other hand, customers were treated as heterogeneous, then other forms of commitment by firms, such as endogenous heterogeneity in their choices about horizontal and/or vertical product differentiation, could also be incorporated into the model. Future research could explore the impact of customer heterogeneity on the model's results.

Appendix

Following Singh and Vives (1984), we use the following quadratic utility function for the representative consumer in our model during time period *t* under scenario *s*:

$$u_{t,s} = w_{F,t,s}\, q_{F,t,s} + w_{S,t,s}\, q_{S,t,s} - \frac{1}{2}(q_{F,t,s}^2 + 2\,\gamma\, q_{F,t,s}\, q_{S,t,s} + q_{S,t,s}^2) + f_{t,s} \quad \text{(A1)}$$

where $q_{F,t,s}$ and $q_{S,t,s}$ represent the quantities of products the customer buys from firms *F* (first mover) and *S* (second mover) respectively, and where $f_{t,s} = \epsilon_t - (p_{F,t,s}\, q_{F,t,s} + p_{S,t,s}\, q_{S,t,s})$ represents the unspent portion of the representative customer's endowment ϵ that remains left over to use for other purposes. Likewise, $w_{F,t,s}$ and $w_{S,t,s}$ represent the customer's willingness to pay for the products of firms *F* and *S* respectively, such that:

$$w_{F,t,s} = \theta(1 - \delta(-1)^{d_s})(1 + \rho + Z)^{t-1} + \omega\, q_{F,t-1,s} \quad \text{(A2)}$$

$$w_{S,t,s} = \theta(1 + \delta(-1)^{d_s})(1 + \rho + Z)^{t-1} + \omega\, q_{S,t-1,s} \quad \text{(A3)}$$

Of course, $q_{F,0,s} = 0$ since nothing is produced prior to the start of the industry in period 1, so the second term in Equation (A2) above vanishes in period 1. Likewise, $q_{S,1,s} = 0$ since *S* enters in the second period, so the second term in Equation (A3) above vanishes in period 2. The resulting utility-maximizing inverse demand functions for each firm are:

$$p_{F,1,s} = \theta(1 - \delta(-1)^{d_s}) - q_{F,1,s} \quad \text{(A4)}$$

$$p_{F,2,s} = \theta(1 + \rho + Z)(1 - \delta(-1)^{d_s}) - (1 - 2\omega)q_{F,1,s} - \gamma q_{S,2,s} \quad \text{(A5)}$$

$$p_{S,2,s} = \theta(1 + \rho + Z)(1 - \delta(-1)^{d_s}) - \gamma q_{F,1,s} - q_{S,2,s} \quad \text{(A6)}$$

Given output levels $q_{i,t,s}$ for each firm i ∈ {F,S} in each period t ∈ {1,2}, the consumption decisions represented by these inverse demand functions determine the market-clearing prices that equilibrate demand and supply for firm *F*'s product in the first period and for both firms' products in the second period. So, we substitute these inverse demand functions as the equilibrium prices into the profit functions for the relevant firms in each time period, as given by $\pi_{i,t,s} = q_{i,t,s}(p_{i,t,s} - c_i)$. For simplicity, both firms are assumed to have identical costs, $c_i = \beta\theta$, where the parameter $\beta \in [0,1]$ allows us to express the firms' marginal cost per unit produced as a fraction of consumers' baseline willingness to pay. In the period when each firm enters, it irrevocably chooses its quantity of output per period, designated as $q_{F,1,s}$ for firm *F*, and as $q_{S,2,s}$ for firm *S*. Each firm's output choice is assumed to maximize its conditional expected NPV (i.e., conditional upon information available to it at the time of its decision), designated as $\mathrm{n}_{F,s} = \pi_{F,1,s} + \alpha\, \mathrm{E}(\pi_{F,2,s})$ for firm *F*, and as $\mathrm{n}_{S,s} = \alpha\, \mathrm{E}(\pi_{S,2,s}|Z) = \alpha\, \pi_{S,2,s}$ for firm *S*, under discount factor, $\alpha \in (0,1]$.

The model is solved using backward induction, in order for firm *F* to have accurate expectations of the second-period results to serve as inputs for its first-period decision. So, we first derive firm *S*'s optimal output choice conditional upon firm *F*'s prior output choice, then substitute firm *S*'s optimal output into firm *F*'s NPV function, and we then maximize that function to derive firm F's optimal output choice. We then substitute both firms' optimal output choices into their respective *ex ante* unconditional expected NPV functions and second-period profit functions, thereby giving us their equilibrium *ex ante* expected NPV and second-period profit functions, designated as $\mathrm{n}_{i,s}^{**}$ and $\pi_{i,2,s}^{**}$ respectively. We then differentiate these *ex ante* expected equilibrium outcomes with respect to various parameters in order to derive our comparative-statics results.

Starting with the second stage in our backward-induction solution, firm *S* optimally chooses output level:

$$q_{S,2,s}^{*} = \frac{1}{2}\left(\theta[(1+\rho+Z)(1+\delta(-1)^{d_s}) - \beta] - \gamma q_{F,1,s}^{*}\right) \tag{A7}$$

conditional upon the demand shock *Z* and firm *F*'s prior choice of output level, $q_{F,1,s}^{*}$, which yields an NPV for firm *S* (also conditional upon *Z* and $q^*_{F,1,s}$) of $n^*_{S,s} = \alpha(q^*_{S,2,s})^2$. Substituting firm *S*'s optimal output from Equation 7 into firm *F*'s NPV function $\mathrm{n}_{F,s}$ and maximizing this resulting NPV yields an optimal output level for firm *F* of:

$$q^*_{F,1,s} = \frac{\theta\Big(2\big[1-\beta-\delta(-1)^{d_s}\big]+\alpha\Big((1+\rho)\big[2-\gamma-\delta(-1)^{d_s}(2+\gamma)\big]-\beta(2-\gamma)\Big)\Big)}{4+2\alpha(2-\gamma^2-4\omega)} \quad \text{(A8)}$$

Substituting both firms' optimal output levels into both firms' NPV functions and taking their *ex ante* unconditional expected values yields their equilibrium *ex ante* expected NPV's of:

$$n^{**}_{F,s} = \frac{\theta^2\Big(2\big[1-\beta-\delta(-1)^{d_s}\big]+\alpha\Big((1+\rho)\big[2-\gamma-\delta(-1)^{d_s}(2+\gamma)\big]-\beta(2-\gamma)\Big)\Big)^2}{8\big(2+\alpha(2-\gamma^2-4\omega)\big)} \quad \text{(A9)}$$

$$n^{**}_{S,s} = \frac{\alpha\theta^2}{8}\left(\left[\beta + \frac{\gamma\Big(2\big[1-\beta-\delta(-1)^{d_s}\big]+\alpha\Big[(1+\rho)\Big(2-\gamma-\delta(-1)^{d_s}(2+\gamma)\Big)-\beta(2-\gamma)\Big]\Big)}{4+2\alpha(2-\gamma^2-4\omega)} - (1+\rho-\sigma)(1+\delta(-1)^{d_s})\right]^2 + \left[\beta + \frac{\gamma\Big(2\big[1-\beta-\delta(-1)^{d_s}\big]+\alpha\Big[(1+\rho)\Big(2-\gamma-\delta(-1)^{d_s}(2+\gamma)\Big)-\beta(2-\gamma)\Big]\Big)}{4+2\alpha(2-\gamma^2-4\omega)} - (1+\rho+\sigma)(1+\delta(-1)^{d_s})\right]^2\right) \quad \text{(A10)}$$

Using the same substitution, the equilibrium *ex ante* expected values of the firms' second-period profits are given by:

$$\pi^{**}_{F,2,s} = \frac{\alpha\theta^2}{4\big(2+\alpha(2-\gamma^2-4\omega)\big)}\Big(2\big[1-\beta-\delta(-1)^{d_s}\big]+\alpha\Big[(1+\rho)\Big(2-\gamma-\delta(-1)^{d_s}(2+\gamma)\Big)-\beta(2-\gamma)\Big]\Big)\left[(1+\rho)\Big(2-\gamma-\delta(-1)^{d_s}(2+\gamma)\Big)-\beta(2-\gamma)-\frac{(2-\gamma^2-4\omega)\Big(2\big[1-\beta-\delta(-1)^{d_s}\big]+\alpha\Big[(1+\rho)\Big(2-\gamma-\delta(-1)^{d_s}(2+\gamma)\Big)-\beta(2-\gamma)\Big]\Big)}{2\big(2+\alpha(2-\gamma^2-4\omega)\big)}\right] \quad \text{(A11)}$$

$\pi_{S,2,s}^{**} =$

$$\frac{\theta^2}{8}\left(\left[\beta + \frac{\gamma\left(2\left[1-\beta-\delta(-1)^{d_s}\right]+\alpha\left[(1+\rho)\left(2-\gamma-\delta(-1)^{d_s}(2+\gamma)\right)-\beta(2-\gamma)\right]\right)}{4+2\alpha(2-\gamma^2-4\omega)} - (1+\rho-\sigma)(1+\delta(-1)^{d_s})\right]^2 + \left[\beta + \frac{\gamma\left(2\left[1-\beta-\delta(-1)^{d_s}\right]+\alpha\left[(1+\rho)\left(2-\gamma-\delta(-1)^{d_s}(2+\gamma)\right)-\beta(2-\gamma)\right]\right)}{4+2\alpha(2-\gamma^2-4\omega)} - (1+\rho+\sigma)(1+\delta(-1)^{d_s})\right]^2\right) \quad \text{(A12)}$$

CHAPTER 3. DOES MARKET RIVALRY INCREASE FIRST-MOVER ADVANTAGE? EVIDENCE FROM A UNIQUE NATURAL EXPERIMENT

3.1 Introduction

Research suggests that timing of entry into a new market is one of the key strategic decisions firms make, with implications for firm performance, growth, and even survival. Also framed as first-mover advantage (FMA), the subject has received significant attention from researchers in strategy, marketing and economics fields, with mixed and sometimes contradictory results (Fosfuri *et al.*, 2013; Lieberman & Montgomery, 2013; Zachary *et al.*, 2015). This ambiguity may reflect the fact that the timing of entry represents a classic preemption versus flexibility trade-off: On one hand, early entry allows a pioneer to preempt market space either on the supply side (e.g., scarce resources, supply sources, capacity, distribution channels, or market positions in geographic or product-attribute space) or on the demand side (e.g., by exploiting customer switching costs, brand equity, customer inertia, network externalities, herding or bandwagon effects). On the other hand, delayed entry allows a follower to benefit from retaining flexibility (e.g., making decisions after the resolution of environmental uncertainties, adapting better to shifts in technology or demand, or exploiting free-rider effects and incumbent inertia). Given the presence of such countervailing forces, it is perhaps unsurprising that research has yielded inconclusive results, with some studies finding benefits for early entry (Lambkin, 1988; Makadok, 1998; Urban *et al.*, 1986), while others find benefits for late entry (Cho *et al.*, 1998; Shamsie *et al.*, 2004; Shankar *et al.*, 1998).

However, in addition to this inherent trade-off, two other closely-linked issues – one methodological, and one substantive – may also be partly responsible for these ambiguous results.

3.1.1 The Methodological Issue of Endogenous Entry Order

On the methodological side, the most critical and frequently cited challenge has been the selection bias that results from an endogeneity problem. Entry timing choices are endogenous decisions (Boulding & Christen, 2003; Lieberman & Montgomery, 1988, 1998, 2013; Robinson *et al.*, 1992). Therefore, the observed statistical association of entry order with performance does not necessarily reflect the causal influence of entry order, but rather may reflect this treatment effect being confounded with a selection effect. In other words, some firms, by virtue of their unique set of resources and capabilities, stand to benefit more from pioneering a new market than other firms with different sets of resources and capabilities. If even a modicum of rationality governs entry timing decisions, then the firm that benefits most from pioneering a new market is more likely to be the one that enters earliest. So, the observed performance difference between that pioneer and its subsequent followers conflates two effects with each other – the treatment effect of entering early and the selection effect of having previously accumulated resources and capabilities that motivate early entry. Consequently, since the selection effect is expected to be positive as long as firms are at least somewhat performance-motivated, game-theoretic analysis has predicted that this blending of the treatment and selection effects exerts a strong upward bias on measures of FMA (Cirik & Makadok, 2017), thereby calling into question the validity of all existing FMA research. Indeed, if the selection effect were strong enough to overcome a negative treatment effect, it might even make a first-mover disadvantage appear as if it were a first-mover advantage.

Despite the clear threat that it poses to the validity of both empirical findings and managerial prescriptions in the FMA literature, the endogeneity issue has remained surprisingly underexplored, with only a few exceptions (Boulding & Christen, 2003; Moore *et al.*, 1991; Murthi *et al.*, 1996). Unfortunately, there are three fundamental problems with existing efforts to correct for this endogeneity problem: First, the biggest problem is that they do not measure the treatment effect directly. Rather, they rely on econometric techniques to make counterfactual inferences about what the performance of firms would have been if the order of entry had been different. Such econometric techniques are only as good as the accuracy of their predictions about firms' entry-order decisions. A model that poorly predicts entry order cannot make valid inferences about how the performance of firms would have differed if their entry order had been different. So, a healthy skepticism is warranted when using elaborate counterfactual econometric inferences as a substitute for simple but direct observations of an actual treatment effect. The second problem with existing efforts to correct for endogeneity is that they, like the FMA literature overall, have yielded conflicting results, with some studies (Moore *et al.*, 1991) finding that many effects of pioneering are weakened or even reversed by an endogeneity correction, while other studies (Murthi *et al.*, 1996) find that the effects of pioneering are robust to endogeneity correction. Third, these studies rely heavily on the PIMS database, which suffers from significant and well-known methodological drawbacks, such as survival bias as well as incorrect identification of pioneers due to self-reporting by the sample firms (Golder & Tellis, 1993; Lieberman & Montgomery, 1988, 1998). So, the results of research using PIMS data should be viewed with caution (Boulding & Christen, 2003, 2008). Due to these three problems, endogeneity remains a key unresolved methodological challenge in FMA research that undermines the validity of causal inferences and casts significant doubt on their interpretation. In short, researchers still do not know whether the first-mover advantages observed in prior studies are really the treatment effect of choosing to enter first, or are instead simply artifacts of inter-firm differences in resources that motivate some firms to enter first and others to delay entry.

So, one purpose of this paper is to address the methodological question: Do first movers still enjoy an advantage over later entrants when the firms themselves do not determine their order of entry? After all, the best way to fix the endogeneity problem is to eliminate it completely by designing a field experiment with exogenously randomized entry order of real firms into a real market (i.e., not an artificial laboratory setting). Such an approach controls for any heterogeneity between early and later entrants and isolates the pure treatment effect by preventing the selection effect from occurring in the first place. While this study does not create a new real-world market for the sole purpose of experimentally measuring entry-order effects, it takes the next-best approach of exploiting an extraordinary natural experiment that almost perfectly replicates the ideal experimental design. The legalization of marijuana in the state of Washington in 2014 provides that rare and unique experimental setting where the endogeneity problem is eliminated through randomized entry order. In 2014, the U.S. state of Washington authorized the opening of state-licensed recreational marijuana stores, with a fixed number of licenses allotted to each local jurisdiction. In the 75 jurisdictions where the number of applicants for these licenses exceeded the number of licenses available, the scarce licenses were allocated on a completely random basis through a double-blind lottery in April 2014. The retail stores that won the lottery began operating in July 2015 after going through a post-lottery screening. In December 2015, eighteen months after the initial batch of early entrants, the state increased the number of retail licenses by 66% in order to integrate the medical marijuana market into the recreational marijuana retailing market. All of these new licenses in the second batch of entrants were granted to unsuccessful applicants from the original April 2014 lottery (also called “Priority 1” group) – i.e., companies that had wanted to enter in the first batch but were prevented from doing so by the scarcity of licenses at that time. So, both the first and second batches consist of firms that were all equally ready and willing to enter from the start and had all passed the initial pre-lottery background screening. Only the random selection of the lottery determined which firms wound up in which batches. This randomized entry order provides a perfect natural experiment setting to test and directly draw causal inferences between the timing of entry and performance, due to the absence of any endogeneity concern. In addition, as explained in detail in a subsequent section, this natural experiment also offers other benefits by preventing several methodological problems that have been common in FMA empirical research, such as ambiguous market definition, incorrect identification of entry order, survivorship bias, and observations drawn from the wrong phase of the market life cycle.

3.1.2 The Substantive Issue of Market-Level Macro-Contingency Effects

In addition to fixing the methodological problem of endogeneity-induced selection bias, this study also answers the call by various authors for a more holistic contingency-based approach to understanding the contingency factors that may influence the strength of entry-order effects (Lee, 2008; Lieberman & Montgomery, 1998, 2013; Suarez & Lanzolla, 2007; Zachary *et al.*, 2015). While micro-firm level contingency factors have been extensively analyzed in the entry timing literature, macro-level factors have received significantly less attention (Fosfuri *et al.*, 2013; Suarez & Lanzolla, 2007). This is an important gap given the key performance implications associated with industry and macro-environmental factors in strategy research, so their omission from most FMA studies seems puzzling and has been considered as a fundamental reason behind the under-development of theory in this research stream (Lieberman & Montgomery, 2013; Suarez & Lanzolla, 2007; Zachary *et al.*, 2015).

In other words, while extensive research has examined what kind of *firms* may *capture* the greatest FMA, little research has examined what kind of *markets* may *offer* the greatest FMA. For example, do markets with greater competitive rivalry experience larger or smaller FMA? This latter question has, to date, only been addressed in game-theoretic models, with no empirical tests. Gal-Or (1985), for instance, suggests that one should expect increased competitive rivalry to reduce the magnitude of FMA, yet this prediction has not yet been tested empirically.

Interestingly, the present study's long-overdue test of this hypothesis finds exactly the opposite result. Specifically, this study's full-sample empirical analysis finds strong evidence that FMA is significantly enhanced with increases in rivalry intensity (where the latter is operationalized as the number of local competitors in the firm's jurisdiction), and that when this rivalry interaction effect is accounted for, there is no evidence for any direct effect of entry order at all. Split-sample supplementary analysis confirms that there is strong evidence for FMA in jurisdictions with large numbers of competitors, but no evidence for FMA in jurisdictions with small numbers of competitors.

This study's unusual double-blind randomization of entry order uniquely positions it to focus on macro-contingency factors, since the lottery natural experiment automatically levels the playing field in terms of firm-level micro-contingency factors, such as internal resources and capabilities. So, this paper focuses instead on how two key industry structure contingency factors

– namely, the intensity of market rivalry and the rate of market growth – could influence the magnitude of FMA in that market. If the study's methodology did not automatically control for micro-level factors by exogenizing entry order in this way, then it would suffer from the additional obstacle of distinguishing macro-level and micro-level factors from each other, which might be especially challenging in light of the likelihood that endogenous entry order could cause strong correlations between firm characteristics and market characteristics. In this regard, the substantive and methodological issues that this study addresses are inherently intertwined. Conversely, the recognition that inter-firm heterogeneity created an endogeneity problem for all prior FMA studies has virtually forced FMA researchers to focus careful attention on the micro-contingency factors reflected in this firm-level heterogeneity, to the neglect of more macro-level market factors.

The remainder of this paper is organized as follows: The literature overview section provides a review of research on entry timing and its effects on performance, including methodological challenges facing this research stream. The hypotheses section provides a set of predictions about possible macro-contingency effects on FMA. The empirical setting and research design section details the historical evolution and current status of marijuana industry in the state of Washington, as well as explaining the study's data, variables, and methods. The paper concludes by presenting the results, followed by a discussion of the study's limitations and possible future extensions.

3.2 LITERATURE OVERVIEW

Lieberman and Montgomery (1988) defined first-mover advantages as the benefits associated with being the first firm to enter a new market or commercialize a new product for an existing market and identified several mechanisms that can underlie first-mover advantages, such as technological leadership, preemption of scarce assets, customer switching costs, and network effects. Conversely, Lieberman and Montgomery (1988) also classified first-mover disadvantages that can provide benefits to late movers in four main areas – free riding on early movers' investments, resolution of technological and market uncertainty, shifts in technology or customer needs, and incumbent inertia. Not surprisingly, due to the simultaneous presence of such advantages and disadvantages, some researchers have provided evidence for superior performance of pioneers (Lambkin, 1988; Makadok, 1998; Urban *et al.*, 1986), while others have found evidence for superior performance of late entrants (Cho *et al.*, 1998; Christensen & Bower, 1996; Shamsie *et al.*, 2004; Shankar *et al.*, 1998). Indeed, even after decades of research, there is still no definitive consensus answer to the question of whether early or late entrants perform better**.** FMA research still faces numerous challenges particularly with regard to the methodological, definitional, and contextual issues all of which are argued to contribute to the conflicting findings, and thus delay both theoretical and empirical progress in the field (Fosfuri *et al.*, 2013; Lieberman & Montgomery, 2013; Suarez & Lanzolla, 2007; Zachary *et al.*, 2015).

3.2.1 Micro-Level and Macro-Level Contingency Effects

Consequently, in the absence of a clear main effect of entry timing on performance, researchers have adopted a micro-contingency based approach with a particular focus on differences among entrants in their firm-level resources and capabilities, such as complementary assets (Mitchell, 1991; Teece, 1986), knowledge-related assets (Li & Calantone, 1998), pre-entry experience (Klepper & Simons, 2000), as well as technological capabilities (Franco *et al.*, 2009; Lieberman, 2005). Teece (1986) suggested that firms with unique sets of complementary assets for new product commercialization can delay their entry, and still overtake market pioneers. In a similar vein, Mitchell (1991) emphasized the key role complementary assets play in providing the incumbent with higher survival and growth chances relative to newcomers. Li and Calantone (1998) empirically showed that early entrants outperform late movers specifically due to earlier and more effective access to consumer information. Klepper and Simons (2000) in their study of entry into the TV industry highlighted the importance of pre-entry experience and suggested that diversifying entrants from the radio industry with transferable experience into the TV industry survived longer than the de novo entrants. More recent research has looked at the impact of technological resources on entry timing related outcomes. Lieberman (2005) found that early moving firms had better survival chances in the Internet industry. Similarly, Franco *et al.* (2009) reported that the survival chances of early movers depend on the strength of their technological capabilities, and that early entry is recommended only for firms with strong technological resources.

Similarly, research on the advantages of *late* entrants has also focused on firm-level micro-contingency factors such as the relatedness and size of resources (Shamsie *et al.*, 2004), innovation capabilities (Shankar *et al.*, 1998), and speed capabilities (Hawk *et al.*, 2013), which have all been shown to improve performance advantages associated with delayed entry. Shankar *et al.* (1998) suggested that late movers with strong innovative capabilities can overtake early movers. Shamsie *et al.* (2004) in their study on the household electrical equipment market has found that the quality of the resource pool late movers draw from can help them effectively compete even in the presence of strong and successful pioneers. Finally, Hawk *et al.* (2013) illustrated how speed capabilities could provide firms with the option to delay their entry until uncertainty resolution without facing any pre-emption risk.

While firm-level contingencies have been heavily incorporated into entry timing studies, the potential influence of macro-level contingencies on the performance consequences of entry timing has surprisingly received very little attention (Fosfuri *et al.*, 2013; Suarez & Lanzolla, 2007). Although macro-contingency effects on FMA have occasionally been hypothesized in game-theoretic models (e.g., Amir & Stepanova, 2006; Gal-Or, 1985), none of these hypotheses have been tested empirically. Specifically, Gal-Or (1985) predicts that increasing market rivalry can reduce, or even reverse, FMA. The results presented here directly contradict this prediction.

3.2.2 Methodological Issues in FMA Research

Most FMA studies suffer from several methodological limitations that might underlie their inconsistent empirical results, as emphasized by various authors (Fosfuri *et al.*, 2013; Lieberman & Montgomery, 2013; Zachary *et al.*, 2015). Such limitations include endogeneity-induced selection bias, survival bias, definitional problems associated with the dependent variables, and imprecise identification of markets and players (Fosfuri *et al.*, 2013; Lieberman & Montgomery, 2013; Zachary *et al.*, 2015). This study's randomized natural experiment setting, in combination with the detailed and disaggregated monthly data provided by Washington State, entirely eliminates all of these methodological concerns. The remainder of this section discusses each of these methodological challenges and summarizes what progress has been made so far toward addressing each of them.

Among these methodological problems afflicting FMA research, endogeneity-induced selection bias has been noted as the most critical and most challenging one (Fosfuri *et al.*, 2013; Lieberman & Montgomery, 2013; Zachary *et al.*, 2015). Entry timing decisions are endogenous to each firm's unique collection of resources, such that some resources may enhance the performance benefits of early entry while different resources enhance the performance benefits of late entry (Boulding & Christen, 2003; Lieberman & Montgomery, 1988; Moore *et al.*, 1991; Robinson *et al.*, 1992). For example, Robinson *et al.* (1992) suggested that early-moving firms and late-moving firms differ in terms of their resources and capabilities. Similarly, Lieberman and Montgomery (1988) noted that early and late movers differ by their resource characteristics. Therefore, optimum entry timing for any firm will be dependent on the *ex-ante* nature of its resources, so that some firms are better off entering early and others late. Even if firms are only somewhat performance-motivated (i.e., not fully rational in this regard), then one still might reasonably expect firms' endogenous entry-order decisions to be at least moderately correlated with their pre-existing resource profiles. For instance, established firms with rare and valuable complementary assets or speed capabilities might delay their entry as such resources effectively provide them with the option to wait until the uncertainty resolves (Hawk *et al.*, 2013; Teece, 1986). In contrast, firms with relatively weaker strategic resource positions might be better off entering early in order to benefit from the first-mover advantages that will offset their initial weaknesses (Narasimhan & Zhang, 2000). Due to this potential resource heterogeneity between early and late moving firms, any observed relative performance difference between pioneers and followers does not necessarily reflect the direct causal impact of entry timing on performance. Rather, the performance differential may stem from systematic differences in the *ex-ante* resource and capability positions between the firms in both cohorts. Therefore, empirical investigations that do not adequately control for the effect of *ex ante* firm-level heterogeneity on endogenous entry order may produce biased results that wrongly attribute performance differences directly to the treatment effect of entry timing itself when they actually just reflect the selection effect of pre-existing resources that motivated those entry-timing decisions in the first place (Boulding & Christen, 2003; Lieberman & Montgomery, 1988; Moore *et al.*, 1991; Robinson *et al.*, 1992). That is, when entry order is endogenous, early movers and late movers are not appropriate counterfactuals for each other due to systematic differences in their resources and other characteristics, so differences in their performance do not capture a pure treatment effect. Thus, selection bias results from the correlation between the error term and the entry-order variable, due to the non-random endogenous assignment of pioneers and followers. Specifically, game-theoretic analysis has suggested that this endogeneity problem exerts an upward bias on FMA measures, since the selection effect is expected to be positive for performance-motivated firms (Cirik & Makadok, 2017).

So, endogeneity-induced selection bias has been a “Gordian knot” for FMA researchers. A few studies have made increasingly arduous efforts to untie this Gordian knot by applying ever more sophisticated econometric techniques intended to control for this endogeneity, with mixed and inconsistent results. Of course, one inherent limitation of this “untying” approach is that such econometric techniques can only be as accurate as their ability to predict entry order. Unfortunately, this predictive accuracy is likely to be poor since many of the firm-level characteristics driving inter-firm differences in entry-order choices may be unknown, or at least unobserved, and perhaps even unobservable. After all, despite the best efforts of FMA researchers who have pursued the micro-contingency approach, it seems likely that their results provide only a highly incomplete catalog of firm-level characteristics that drive entry order decisions. This predictive challenge further tangles and tightens the Gordian knot of endogeneity-induced selection bias, making it more difficult to untie via sophisticated econometrics.

The first attempt to untie the knot in this way was a study by Moore *et al.* (1991) suggesting that the results of endogenous and exogenous empirical analysis on entry timing remarkably differ in terms of both the sign of the coefficient of the entry timing variable as well as its statistical significance. However, the instrumental variable method employed in this paper assumes that the instrumental variables have no correlation with the unobserved effects, and the validity of this assumption could not be confirmed by the authors due to the cross-sectional nature of the data, as noted by Boulding and Christen (2003). By contrast, a second untying attempt by Murthi *et al.* (1996) found that pioneering improves performance outcomes even when potential endogeneity is considered by controlling for managerial capabilities, thereby providing support for FMA. However, their estimation approach assumes that all firm level resource and capabilities that can impact competitive outcomes are included in the regression equation (Boulding & Christen, 2003). Therefore, Boulding and Christen (2003) infer that both papers likely suffer from biased results, concluding that "*Existing analyses that control for unobserved firm differences in resources and skills yield results that can only be considered unbiased by assumption".* So, Boulding and Christen (2003) made their own attempt to untie this knot through even more sophisticated econometrics, leading them to conclude that entry timing decisions are endogenous, and that pioneering advantages dissipate over time, lasting around 12 to 14 years, with pioneers facing a cost disadvantage relative to their competitors after that period. However, their study relies on PIMS data, which suffers from several significant and well-known limitations, despite its frequent use in past research (Boulding & Christen, 2003, 2008, 2009; Lambkin, 1988; Parry & Bass, 1990; Robinson & Fornell, 1985).

Three major drawbacks associated with PIMS data use are incorrect identification of pioneers versus followers, survivorship bias, and its sole focus on mature markets (Golder & Tellis, 1993; Kerin *et al.*, 1992; Lieberman & Montgomery, 1988, 1998; Ramanujam & Venkatraman, 1984). First, PIMS data relies on self-reports provided by the firms themselves where they can self-identify themselves as pioneers, early follower or a late entrant. Self-reporting by a single informant can provide incorrect information particularly if the informant is new to the company especially for long standing product groups. This situation is exacerbated by the potential self-perception bias where dominant firms prefer to consider themselves as pioneers (Golder & Tellis, 1993)**.** Relatedly, PIMS data uses a relatively broad FMA definition stated as "one of the pioneers in first developing such products or services". Such strong potential sources of mismeasurement may explain why an astounding 52% of the firms in the PIMS dataset regard themselves as pioneers, including multiple competing firms within the same product categories (Buzzell & Gale, 1987; Golder & Tellis, 1993; Lieberman & Montgomery, 1988). Indeed, inaccurate identification of pioneers versus followers can be a problem for non-PIMS datasets as well, since it can be challenging to correctly identify the true start date of a new market or industry (Lieberman & Montgomery, 2013). The lack of methodological standards on how to define the start of a new industry could for example lead some researchers to classify a particular firm as a pioneer whereas others to classify the same firm as a follower, again leading to biased estimates.

Second, PIMS primarily contains data on divisions or strategic business units of well-established Fortune 500 companies in mature industries. So, regardless of their current performance at the time when the PIMS data was collected, these are all firms that were exceptionally successful at some point in time, or else they would never have reached the Fortune

500. So, using PIMS data to explain performance must necessarily, at least to some degree, amount to sampling on the dependent variable, which naturally leads to another selection bias that may further distort the magnitude and sustainability of FMA estimates (Day & Freeman, 1990; Golder & Tellis, 1993; Makadok, 1998).

Finally, PIMS data also suffers from survivorship bias. In FMA studies, if pioneers and followers differ in their survival rates, empirical analysis may yield biased results favoring pioneers since followers in general are considered to have higher survival rates than pioneers (Boulding & Christen, 2003; Golder & Tellis, 1993). Therefore, Boulding and Christen (2003) state that their empirical results should be approached with caution because *"The exclusion of pioneers that have failed may overstate the advantage of pioneers."* To empirically illustrate the limitations of PIMS data, Golder and Tellis (1993) conducted a study on 50 product markets where they identified the pioneers via the historical data, and have found that pioneers have lower success rates than those suggested by the studies using PIMS data. They concluded that PIMS data might potentially lead to biased estimations since only surviving firms are included in the sample, so firms that should be classified as followers might instead be misclassified as pioneers.

Survivorship bias is a profound issue in the entry timing literature that is not only limited to PIMS data, but rather applies to many, if not, most databases used in FMA research. Indeed, Lieberman and Montgomery (2013) call it the *"elephant in the closet"* – i.e., a hugely significant factor that has nevertheless been largely overlooked. Acknowledging data limitation as likely the most significant source of survivorship bias in entry timing studies, Dobrev and Gotsopoulos (2010) conclude that *"Yet even in well-designed and -executed studies, tracking down early entrants and recreating their complete histories poses a daunting task. Most such firms are small and obscure,* *their products often cumbersome and quixotic, and the records they leave behind incomplete."* They then go on to suggest that survivorship bias is the main reason why their results contradict those of Klepper (2002), which thereby provides a clear example of how much survivorship bias can distort research results.

All three of these problems with prior FMA research – i.e., questionable identification of pioneers versus followers, sampling on the dependent variable, and survivorship bias – only serve to further entangle the already drastically tangled Gordian knot of endogeneity-induced selection bias, because they make early movers and late movers even less valid counterfactuals for each other than they would otherwise be. In the classic Phyrgian legend, Alexander the Great grew so frustrated with the repeated failures of his increasingly strenuous efforts to untangle the Gordian knot that he eventually drew his sword and cut it. Similarly, FMA research has reached a point of diminishing returns in its efforts to untie the knot of endogeneity-induced selection bias, and the knot simply needs to be cut.

The most effective sword for cutting this particular knot is an experimental design where the entry order of a set of potential entrants is exogenously randomized, so that there would be no systematic differences between pioneers and followers. Then the counterfactual for the early entrants would be the late entrants, and vice versa, since random assignment would make both groups roughly equivalent (i.e., with no systematic differences, only random differences) in terms of both observable and unobservable characteristics, including their resource profiles. Such randomization thus allows for causal inference about the pure treatment effect without any spurious contamination by the confounding selection effect. In contrast to an endogenous entry-order scenario, where pioneers and followers are not valid counterfactuals for each other due to their systematic differences, randomized entry makes them valid counterfactuals for each other by ensuring that any *ex ante* differences between them are merely random and not systematic. Exogenously randomizing the entry-order treatment also eliminates the need to accurately predict firms' entry-order decisions, thereby rendering moot the question of whether the firm-level characteristics driving those decisions are observed, observable, or even knowable. There is no need to know why firms decide to enter early versus late when that decision is made for them. Fortunately, as explained later in this manuscript, the state of Washington's regulatory regime for its newly legalized recreational marijuana retailing industry provides the exact sword needed to cut this knot.

3.3 HYPOTHESES

Although empirical research on FMA is abundant, conflicting results abound, with few empirical outcomes being validated in separate studies – i.e., few consistent regularities (Kalyanaram *et al.*, 1995; Suarez & Lanzolla, 2007). One of these few regularities is that FMA is associated more frequently with certain product types. In particular, research has shown that FMA is more likely in consumer goods industries (Kalyanaram *et al.*, 1995; Suarez & Lanzolla, 2007). Another well-known regularity in FMA studies is that the use of market share as a performance variable is more likely to lead to empirical results where a pioneering advantage is found (Lieberman & Montgomery, 2013). Since the dependent variable in this study is market share in a consumer goods market, one would naturally expect pioneering to have a positive direct effect on market share in this context, thereby suggesting the following prediction:

Hypothesis 1: *Pioneering firms earn higher market share.*

This study focuses on two market-level macro-contingency factors that may influence FMA – rivalry intensity and market growth rate. Industrial organization economics research has long considered a market's rivalry intensity and its growth rate as two of the central determinants of firm performance in that market (Bain, 1956; Demsetz, 1997). However, for each of these two market-level contingency factors, there are two directly opposing mechanisms by which they might affect the magnitude of first-mover advantage that the market offers. For each of these contingency factors, it is difficult to anticipate which of these two opposing mechanisms might be stronger, so both are hypothesized. The hypotheses about rivalry are designated with number 2, while those about market growth are designated with number 3. Within each of these, the hypotheses about mechanisms that diminish FMA are designated with letter a, while those about mechanisms that increase FMA are designated with letter b.

3.3.1 Market Rivalry

The Structure-Conduct-Performance (SCP) paradigm suggests that increased competition leads to the dissipation of profits and market share, due to either increased costs associated with acquiring scarce resources or the costs and price discounts necessary for a firm to defend its strategic position (Scherer & Ross, 1990). Yet in the entry timing literature, there has been very little attention to the potential effect of rivalry intensity on FMA. One notable exception, a game-theoretic model by Gal-Or (1985), suggests that greater rivalry intensity might be expected to decrease FMA. Specifically, that model indicates that FMA diminishes when switching from an accommodative regime where firms' choices are strategic substitutes with downward-sloping reaction functions (e.g., Cournot-style output competition) to an aggressive regime where firms' choices are strategic complements with upward-sloping reaction functions (e.g., Bertrand-style price competition). In other words, in markets characterized by higher levels of rivalry, pioneers get challenged more aggressively by each other and by followers, and are therefore less able to establish a secure beachhead by capturing and maintaining dominance in the market. This reduced market power of pioneers allows followers to compete more effectively. This logic suggests the following prediction:

Hypothesis 2a: *Higher rivalry intensity in a market reduces FMA in market share.*

On the other hand, greater market rivalry may benefit pioneers in the long run by motivating them to develop stronger competencies in order to survive and thrive in the more competitive environment. This "competition breeds competence" logic has figured prominently in studies of organizational learning (Barnett *et al.*, 1994; Barney & Zajac, 1994; Levinthal & Myatt, 1994). Similarly, corporate entrepreneurship studies indicate that increased competition leads firms to undertake more entrepreneurial actions such as exploration and firm renewal (Zahra, 1993; Zahra & Covin, 1995). In highly competitive environments, firms may also be more alert to threats, due to the need for constant monitoring of competitors' actions and customer needs (Jaworski & Kohli, 1993; Narver & Slater, 1990), which may make them less vulnerable to incumbent inertia (Schilling & Steensma, 2001). Conversely, industrial economics research on the "quiet life" hypothesis[5] confirms that weaker rivalry breeds complacency, and that the resulting inefficiencies in low-rivalry markets represent far greater public welfare losses than conventional "welfare triangle" concerns (Berger & Hannan, 1998; Koetter *et al.*, 2012). Similarly, a study by Baggs and de Bettignies (2007) on Canadian firms suggests that firms in markets with more intense rivalry undertake more cost reduction and quality improvement efforts. So, pioneering firms that have

[5] Hicks (1935: 8) quipped, "The best of all monopoly profits is a quiet life."

been “hardened” by highly competitive markets may pose a greater challenge for followers to overcome because they “set the bar higher” in a variety of ways. For example, hardened pioneers in very competitive markets may defend more aggressively against newcomers’ efforts to steal customers, or may possess capabilities that are so superior that it would be prohibitively expensive for newcomers to match them, or may leave fewer unserved market niches for newcomers to pursue. This logic suggests the following prediction:

Hypothesis 2b: *Higher rivalry intensity in a market increases FMA in market share.*

To be clear, we are not suggesting that rivalry intensity would positively improve performance measures like market share and profitability. Rather, we argue that while increased rivalry intensity on the whole would reduce performance for all firms, but that this reduction would be less pronounced for the pioneers than the followers.

3.3.2 Market Growth

As suggested by Suarez and Lanzolla (2007), speed of market evolution acts as an enabler or disabler on isolating mechanisms, and thus should be involved as an important contextual contingency in empirical models. Specifically, faster-moving environments like high-growth markets offer more opportunity for followers to catch up with or even overtake the pioneers. Following Gomez *et al.* (2016), the market growth rate serves as a proxy of speed of market evolution in this paper. High-growth markets provide more space for late entrants to penetrate since faster growth provides greater resources for newcomers for entry, thereby offering more opportunity for survival and profit (Christensen, 1997; Gomez *et al.*, 2016; Suarez & Lanzolla, 2007). For example, a newcomer to a stagnant or slow-growth industry may have no option other than targeting customers of incumbent firms, whereas a newcomer to a high-growth industry where many customers are new to the market can more easily attract sufficient demand without targeting incumbents' existing customers. This might also be a reason why pioneering advantages are more commonly in found in mature markets where speed of growth is slow (Gomez *et al.*, 2016; Utterback, 1994). Accordingly, these arguments suggest the following prediction:

Hypothesis 3a: *Faster market growth reduces FMA in market share.*

While it seems intuitive that a new entrant would prefer to compete in a high-growth rather than low-growth market, it may not be certain whether pioneers or followers would be better able to exploit this newly created growth space. Indeed, there are at least two major reasons why new customers might be attracted more to the pioneering firms and their products. First, consumer research indicates that entry order can dramatically affect customers' learning, judgment, and preferences in ways that bias them to favor pioneers over later entrants (Carpenter & Nakamoto, 1989; Kardes & Kalyanaram, 1992). Second, in new and emerging markets where potential customers are not very familiar with the new product, significant information asymmetry exists between the buyers and sellers, so consumers rely on word of mouth as a way to alleviate the severity of information asymmetry which ultimately guides their purchase decisions (Chen & Xie, 2008; Chevalier & Mayzlin, 2006; Zhu & Zhang, 2010).[6] In particular, online reviews and ratings have – by reinventing "word of mouth" (WOM) for the digital age – become critical sources of information in terms of product and service quality for potential customers, thereby significantly influencing purchase decisions by reducing information asymmetry and alleviating transaction hazards (Ba & Pavlou, 2002; Chevalier & Mayzlin, 2006; Senecal & Nantel, 2004; Zhu & Zhang,

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[6] For example, in this study's empirical context, marijuana legalization attracted many new consumers into the market who had no prior experience with the product, due to either legal concerns or security concerns, resulting in information asymmetry.

2010). Commercial market research surveys yield similar results. For example, a survey by search marketing company BrightLocal found that 88 percent of consumers find online reviews as trustworthy as personal suggestions.[7] So, positive experiences of early customers can create a herding or bandwagon effect, where new potential customers are more willing to purchase from the early entrants, since the risk and search costs associated with purchasing from them might be decreased. Therefore, market growth might actually benefit the early movers more than the late movers, as long as the early movers are able to form a positive perception in the minds of their consumers which potentially leads to the development of a positive feedback loop, similar to network effects. Accordingly, these arguments suggest the following prediction:

Hypothesis 3b: *Faster market growth increases FMA in market share.*

3.4 EMPIRICAL SETTING AND RESEARCH DESIGN

3.4.1 Marijuana Industry in the U.S.

Marijuana is obtained from the processing of the cannabis plant, and used for both recreational and medical purposes. It is the most consumed illicit drug in the world according to the United Nations' 2012 *Global Drug Report*.[8] Under Federal law, marijuana is a Schedule 1 drug with *"a high potential for abuse, no accepted medicinal value in treatment in the United States, and evidence that there is a general lack of accepted safety for its use even under medical supervision"* (U.S. Drug Enforcement Administration 2011).[9] While marijuana is illegal at the Federal level with regard to its sale and distribution, lax enforcement and limited policing resources at the Federal level have opened an opportunity for *de facto* legalization at the state level.

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[7] https://www.brightlocal.com/learn/local-consumer-review-survey-2014/
[8] https://www.unodc.org/documents/data-and-analysis/WDR2012/WDR_2012_web_small.pdf
[9] https://www.dea.gov/docs/marijuana_position_2011.pdf

Specifically, the 2014 passage of the Rohrabacher-Farr amendment has prohibited the U.S. Department of Justice from spending money to prevent states *"from implementing their own State laws that authorize the use, distribution, possession, or cultivation of medical marijuana."*[10] So, marijuana has been allowed for medicinal use in 29 states across the U.S.[11] Proponents of marijuana legalization claim that decriminalization of marijuana would result in high tax revenues, reduction in organized crime, freeing law-enforcement as well as prison resources and lowering their costs.[12] In 2014, two states, Washington and Colorado, legalized the production, processing and retail sales of marijuana for recreational (i.e., non-medical) use.

3.4.2 Legal Status of Marijuana in the State of Washington

Washington State passed Initiative 692 in November 1998, which legalized the use and production of cannabis for patients having a medical certificate and suffering from debilitating health conditions such as HIV, cancer, and multiple sclerosis.[13] In November 2012, Washington State passed Initiative 502 with a majority popular vote that made recreational cannabis use legal and gave the Washington State Liquor Control Board (later renamed the Washington State Liquor and Cannabis Board, or WSLCB) authority to regulate the licensing, production, processing, sales as well as taxing activities.[14] The board is also responsible for setting the standards for testing, packaging, and labeling of marijuana products. Legalization of recreational marijuana gave the start of a new commercial industry. The initiative allowed Washington residents to apply for and

[10] https://www.congress.gov/bill/113th-congress/house-bill/83/text?overview=closed
[11] http://www.ncsl.org/research/health/state-medical-marijuana-laws.aspx
[12] http://norml.org/component/zoo/category/rethinking-the-consequences-of-decriminalizing-marijuana
[13] http://www.wsipp.wa.gov/ReportFile/1555/Wsipp_Medical-Marijuana-Access-and-Regulations-in-Washington-State_Full-Report.pdf
[14] http://lcb.wa.gov/mj2015/fact-sheet

become business owners in the recreational marijuana industry. Each jurisdiction (county or local) was allocated a maximum number of licenses for recreational marijuana retailing. Retail license applications were accepted during December 2013. Basic application requirements included being at least 21 year of age, being a resident of Washington for the previous three months, and successfully passing a criminal background check.[15] For jurisdictions where the number of applications exceeded the number of the retail licenses allotted, licenses were assigned to applicants by means of a double-blind random lottery held in April 2014. The details of the lottery procedure will be explained in the next section. Retail licenses were begun to be issued early 2014 for the lottery winners who successfully passed additional post-lottery screening, and the first sales began in July 2014.[16] In early 2016, WSLCB announced and implemented a 66% increase in the number of retail licenses, with losing applicants from the first-batch lottery being given top priority in assignment of second-batch licenses. A timeline of these events is shown in Table 3.1.

Table 3. 1 Timeline of Events in Washington State Marijuana Market

Date	**Event**
November 1998	Legalization of medical marijuana through Initiative 692
November 2012	Legalization of recreational marijuana through Initiative 502
December 2013	Recreational marijuana retailer license applications accepted
April 2014	Completion of lottery process to rank-order retail applications in each jurisdiction
July 2014	Start of first retail sales
October 2015	Start of applications for second-batch retail licenses
January 2016	Public announcement of 222 second-batch retail licensees
July 2016	Deadline for unlicensed medical marijuana dispensaries to cease operations.

[15] https://lcb.wa.gov/pressreleases/liquor-control-board-approves-lottery-process-retail-marijuana-stores
[16] WSLCB also provides licenses for producers and processors. Within the vertical chain, processors are responsible for growing and selling marijuana, marijuana plant, as well as seeds to the processors.

3.4.3 Lottery to Select First Batch Entrants

The Washington State Liquor and Cannabis Board determined a total retail license limit of 334 retailers distributed over 122 jurisdictions in 2013 after an extensive market analysis, with licenses assigned to jurisdictions in proportion to their populations. For sparsely-populated areas, these jurisdictions were entire counties, but most were local or municipal jurisdictions. The board received over 2,000 initial applications, of which 1,174 were included in the lottery after prescreening of the applicants. For jurisdictions where number of applicants exceeded the number of licenses available (e.g., 191 applications for Seattle's 21 licenses), the board allocated those scarce licenses via a lottery.[17] The double-blind lottery process was designed by Washington State University's Social and Economic Research Center in collaboration with Kraght-Snell, a Seattle-based accounting firm that serves Washington Lottery. Kraght-Snell assigned a random number to each applicant, and sent these numbers to Washington State University's Social and Economic Research Center without providing any identifying information about the applicants. The center then randomly created a ranked list of these random numbers, and sent them back to Kraght-Snell for decoding. The lottery results were verified by an officer of the Washington State Treasurer's Office. The lottery process took place in April 2014.[18] Being selected as a successful applicant after the lottery did not guarantee the issue of a license, since the successful applicants had to go through a phone interview, criminal history check, independent assessment of the chosen retail location (which could not be within 1,000 feet of a school, or any other area specified in Initiative 502 as areas where children congregate), and were required to submit business plans.

[17] http://lcb.wa.gov/pressreleases/lottery-results-marijuana-retail-stores-available-wslcb-website
[18] http://lcb.wa.gov/pressreleases/lottery-results-marijuana-retail-stores-available-wslcb-website

When an applicant who won the lottery in a given jurisdiction failed this post-lottery review process, that applicant is removed from the list and WSLCB moved to the next applicant on the ranking list in that particular jurisdiction. The agency began issuing licenses in July 2014, which also marks the start period of first retail sales in the State of Washington.

3.4.4 Second Batch Entrants

The medical marijuana industry in the Washington State had been unregulated from its inception, without any monitoring and clear guiding procedures provided by state agencies. In order to restructure the medical marijuana industry to ensure better service for patients and tax collection, Senate Bill 5052 was signed in April 2015, authorizing the integration of the medical and recreational marijuana industries. Accordingly, existing medical dispensaries were given the option to apply for recreational licenses or end their sales operations by July 2016. WSLCB began to accept new license applications in October 2015. In January 2016, the board has announced that it would increase the number of retailers by 222 which was determined after an extensive market analysis. In total, the board received over 2,300 applications.[19] The new licenses were granted on a priority basis with the board setting three priority levels. Applicants in the Priority 1 Group were those who had applied for a retailing license before July 2014 – i.e., applicants who had lost at random in the first-batch lottery – and either managed or were employed by a medical marijuana collective garden prior to January 2013, hold state and local business licenses, and paid taxes and fees.[20] All second-batch licenses were received by Priority 1 applicants. Second batch retailers began to enter the market in January 2016 after successfully passing the licensing process. Both

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[19] http://lcb.wa.gov/pressreleases/lcb-to-increase-number-of-retail-mj-stores
[20] http://lcb.wa.gov/pressreleases/lcb-to-increase-number-of-retail-mj-stores

the former medical dispensaries that were granted the retailing licenses as members of the batch 2 group as well as existing recreational marijuana retailers from the batch 1 group had to apply for a medical marijuana endorsement in order to sell medical marijuana products. Medically endorsed retailers are also responsible for hiring medical consultants at their store and keeping a database of patients.[21] As of March 2017, around 80% of active retailers had a medical endorsement, yet medical sales were estimated to constitute only 17% of total 2016 sales and only 12% of total customers (Walsh, 2016).

3.4.5 Industry Definition

Various types of industries have been featured in FMA studies. Helfat and Lieberman (2002) developed a taxonomy of four separate groups: new to the world industry (i.e., fundamentally a new product or service), new product market niche, different geographic location, and established product market. The empirical context in this study would more appropriately fall into the intersection of different geographic location and new product setting since Washington was only the second state after Colorado to allow retailing of marijuana products. The intermediate markets between the producers, processers and retailers are clearly defined and separated by law. In order to avoid the monopoly-like structure in the marijuana retailing market, Washington State Liquor and Cannabis Board does not allow retailers to hold processor or producer licenses in addition to their retail licenses. So, retailers must purchase their products from processors rather than develop and manufacture them on their own.

[21] http://lcb.wa.gov/mjlicense/add-medical-mj-endorsement-to-an-existing-retail-license

3.4.6 Preemptive Mechanisms Underlying FMA

Lieberman and Montgomery (1988) identify three main categories of preemptive mechanisms – technological leadership, preemption of scarce resources, and demand-side frictions like buyer switching costs. So, consider the relevance of each of these three mechanisms, in turn, as potential sources of FMA in our particular empirical context of cannabis retailers. First, although there are certainly some contexts where technological leadership has played an important role for sustaining FMA in retailing (e.g., Wal-Mart's early adoption of advanced information technology and telecommunication systems for sophisticated inventory management), this preemptive mechanism is irrelevant to our empirical context because the same technologies are equally available to all recreational marijuana stores.

The second possible mechanism is preemption of scarce resources. The main scarce resource that a Washington state marijuana retailer can preempt is the store's geographic location, which leaves less attractive locations for the follower firms, and thereby limits their competitiveness (Kerin *et al.*, 1992; Lieberman & Montgomery, 1988). Indeed, location is one of the most frequently mentioned factors in online reviews of Washington marijuana stores, both on cannabis-focused review websites like Leafly and Weedmaps, and also on more general-purpose review websites like Yelp. In Washington's recreational marijuana retailing industry, prime geographic locations are both scarcer and more important than for other types of retailers. The heightened importance of location for marijuana retailers is due to two legal restrictions on their advertising that severely limit their ability to attract customers to obscure locations – (1) a prohibition from advertising through mainstream media, such as radio or television commercials or signs on public transit, which makes it difficult to attract customers who do not visually notice the store itself, and (2) a limitation on the size of any sign to approximately one square meter (1600 square inches), which severely limits the distance at which customers can visually notice the store.[22] Due to these restrictions, having a prime high-visibility location in a high-traffic areas is far more important for a recreational marijuana store than for other kinds of retailers. In terms of scarcity, recreational marijuana stores are required by law to locate at least 1000 feet away from any areas where children congregate, such as schools, parks, recreation centers, churches, or playgrounds, and WSLCB must approve all store locations. The 1000-foot rule more severely constrains stores in densely-populated urban jurisdictions, where there are fewer locations that satisfy these constraints than in more suburban or rural locations. Furthermore, due to the controversial nature of these businesses, both state regulators and shopping-center landlords can be subject to intense “not in my backyard” (NIMBY) lobbying from local community groups or from other nearby businesses, which may motivate them to disapprove recreational marijuana retailers from using locations that would otherwise be readily available to other types of retailers. Since the number of attractive locations are limited, first-movers are more likely to occupy those spaces leaving less attractive options for the late-movers. The combination of both the heightened importance of locations (due to advertising restrictions) and the heightened scarcity of locations (due to the 1000-foot rule and NIMBY lobbying) makes preemption of high-visibility locations in high-traffic areas an important source of both first-mover advantage[23] and differentiation.[24]

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[22] For comparison, a typical U.S. highway billboard is over 62 square meters, or 62 times the maximum area allowed. As another comparison, this maximum area allowed is only 23% larger than a standard “Do Not Enter” sign for multi-lane roads in the U.S.

[23] https://mjbizmagazine.com/landing-right-retail-location/

[24] http://www.adweek.com/brand-marketing/pot-retailers-are-overhauling-their-shops-to-make-them-more-sleek-and-sophisticated/

Lieberman and Montgomery's third category of preemption mechanisms is demand-side frictions, such as customer loyalty, switching costs, or network externalities. In recreational marijuana retailing, customer loyalty has become an important factor because of the special services provided by store employees. The legalization of recreational marijuana has brought into the market a large group of customers who had little or no prior personal experience with the product when it was illegal, either due to concerns about getting caught, or due to concerns about the potential dangers of associating with drug traffickers. At the same time, legalization has also brought into the market an enormous new variety of brands and product types, including a vast array of edibles and concentrates. One industry report about Washington state notes that "the proliferation of specific strains... easily number into the hundreds" and that the top ten cannabis strains account for only 20% of sales (Walsh, 2016: 20). This combination of inexperienced newcomers on the demand side, along with dizzying product proliferation on the supply side, has triggered demand for expert guidance at the point of sale. Consequently, retailers employ expert "bud-tenders" whose main responsibility is, in sommelier-like fashion, to provide information and advice to customers about what particular products they might prefer, and to build effective relations with them.[25] Due to their early entry, pioneering firms are more likely to be a customer's first point of contact with the legal cannabis market, and thereby enjoy greater preemptive benefits from providing such services. Specifically, these special services help build customer loyalty, as well as motivating customers to refer their friends, provide positive word-of-mouth, and write enthusiastic online reviews, all of which can contribute to generating a positive-feedback bandwagon effect similar to network externalities. Indeed, many reviews on online review

[25] https://www.leafly.com/news/industry/how-to-get-hired-to-work-in-the-medical-cannabis-industry-part-2

websites such as Yelp, Leafly, and Weedmaps highlight the importance of customer service and the knowledge level of bud-tenders as prime factors influencing buyers' purchase decisions. Similar effects have been observed in many other industries. For example, Kardes *et al.* (1993) show that pioneers gain significant advantage over the followers through their positive influence on their decision-making process. Similarly, Alpert and Kamins (1995) show that pioneers outperform followers since they can form more positive perceptions in the minds of the consumers.

3.4.7 Meeting Methodological Challenges

In addition to handling the endogeneity issue via the lottery's exogenous randomization of entry order, the empirical context of this industry also fixes other methodological problems discussed earlier, such as survivorship bias, ambiguous market definition, and incorrect identification of entry order. Survivorship bias in particular is considered a critical but largely neglected methodological issue that arises due to the misidentification of early and late entrants and consequently leads to biased results (Boulding & Christen, 2008; Golder & Tellis, 1993; Lieberman & Montgomery, 2013). Fortunately, none of these issues are a concern in this experimental setting, where state regulations provide a clear market definition and precise start date, and where public records of the Washington State Liquor and Cannabis Board (WSLCB) identify the exact entry order of the market players, thereby ensuring a clean separation of the pioneers from the followers and involve all market players from the start. Therefore, unlike previous studies that were vulnerable to methodological limitations and thus yielded potentially biased results, this paper offers clean, unbiased results due to the elimination of such methodological limitations. Also, many previous empirical papers focusing on FMA have used data limited to firms that enter in the early phases of market evolution process (Robinson, 1988;

Robinson & Min, 2002). Yet significant entry often occurs after the early phases of the product lifecycle (Agarwal & Bayus, 2002), so researchers suggest that empirical studies should extend into the maturity phase where sales peak and then level off, in order to capture the reduced role of isolating mechanisms as predictors of FMA during the maturity phase (Suarez & Lanzolla, 2007). So, this paper covers all phases of the product life cycle up to the maturity phase, rather than just the early phases, in order to provide a more complete picture of how entry timing affects the evolution of competition.

3.4.8 Data Description

WSLCB provides regularly updated comprehensive information on each retailer's name, license number, address, medical endorsement status, monthly sales and taxes. WSLCB also provides the ranked-ordered results of the lottery by jurisdiction, as well as the names of the jurisdictions that did not require a lottery. A total of 75 jurisdictions required a lottery, while 47 did not. In 11 of the 75 jurisdictions that required a lottery, no retailer entry occurred during the analysis period. Figure 3.1 lists the number of jurisdictions where a lottery was held, by county.

County	Lottery Jurisdictions	County	Lottery Jurisdictions	County	Lottery Jurisdictions
Asotin	1	Jefferson	2	Snohomish	6
Benton	2	King	11	Spokane	3
Chelan	1	Kitsap	3	Thurston	5
Clallam	3	Kittitas	2	Walla Walla	1
Clark	3	Lewis	1	Whatcom	2
Cowlitz	2	Mason	1	Whitman	1
Douglas	2	Pacific	1	Yakima	2
Grant	1	Pierce	2		
Grays Harbor	4	Skagit	3		

Figure 3. 1 Number of jurisdictions in each county where a lottery was held

The panel data was developed using the monthly retail sales figures by license number provided regularly by WSLCB. The dataset covers a total of thirty-six months between July 2014 (the start date of retail sales in the State of Washington) and June 2017. Matching the licensee numbers on the monthly sales data with those in the lottery results by jurisdiction identified batch 1 retailers (pioneers) in lottery jurisdictions. Batch 2 retailers (followers) began entering the market in January 2016, 18 months after the start of retail marijuana sales in the state.

For the purpose of measuring both a firm's market share and a market's characteristics like rivalry intensity and growth rate, markets were defined at the jurisdiction level, since the lotteries were held at that geographic level. Initial raw data included 6,607 firm-month observations. In order to be included in the analysis, a jurisdiction was required to have at least one firm which was licensed through lottery (a pioneer from batch 1) and at least one firm which entered through the new market regulations as a Priority 1 Group member (a follower from batch 2 – i.e., those who lost in the lottery). Accordingly, 25 jurisdictions which only had batch 1 firms were removed from the sample. The first month in each jurisdiction where there is at least one pioneer from batch 1 and one follower from batch 2 is coded as month 1, the second as month 2, etc. The analysis includes only observations after inter-batch competition began in each jurisdiction with the entry of its first batch 2 retailer, yielding 3,604 firm-month observations from 39 jurisdictions.

However, the dataset was trimmed still further by eliminating the first four months of observations for each follower. Although the pioneers in a market are always, by definition, older than followers, it is important to allow enough time for the followers to at least have a reasonable chance of catching up to the pioneers. Given the inertia in retail customers' shopping habits, it would certainly be unfair to compare the market share of a newly-opened store in its first month of operation to the market share of a store that had been operating for a year or more. So, it is common practice in FMA studies to exclude the early “launch” phase of a follower’s history from the analysis, and to focus instead on the period after the follower’s growth has stabilized. For example, Shamsie *et al.* (2004) exclude the first two years of data for followers in household electrical equipment manufacturing. Of course, the sales cycle and the product life cycle for electrical equipment are much longer than for marijuana retailing, so a shorter launch phase is appropriate here. Growth patterns in marijuana retailers’ revenues show that an average newly opened store experienced an initial hyper-growth period of double-digit monthly growth rates during its first four months, before settling down to a more normal growth rate. Therefore, the first four months of observations were excluded, so the analysis covered the period beginning with the fourth month data of each follower (batch 2) retailer. So, the final dataset includes 275 firms – 136 pioneers from batch 1 and 139 followers from batch 2 – with 2,457 firm-month observations from 39 jurisdictions in 21 out of the state’s 39 counties. A total of 20 firms have exited the market, but only 17 of those exits occurred during our analysis period after inter-batch competition began (9 from Batch 1, and 8 from Batch 2), and these exits were spread across 12 jurisdictions. Since this number of exits is relatively small, survivorship bias is not a meaningful problem. To control for location-specific effects, the data also includes zip code level census data on demographic characteristics such as household income and median age from ESRI, a geographic information provider.

The data period covers all product lifecycle stages starting with the introduction stage in July 2014 up to the beginning of the maturity stage. Figure 3.2 shows the number of entrants in each month, and Figure 3.3 shows the monthly total statewide sales. As shown in these figures, both aggregate revenues and the number of new entrants have stabilized, particularly in the last 6-7 months. In addition to market saturation within the state's own domestic market, revenues of Washington retailers – especially near the border with Oregon, which legalized recreational marijuana two years later – have also been leveling off due to a decline in "cannabis tourism" from outside the state. As more states – e.g., Oregon and Alaska in 2014, Delaware in 2015, California, Illinois, Maine, Massachusetts, and Nevada in 2016, and Vermont in 2017 – join the national trend towards recreational marijuana legalization (or at least decriminalization), fewer cannabis tourists travel to Washington from these states, and these newly legalizing states also give Washington more competition for cannabis-motivated travelers from states that have not yet legalized. For all of these reasons, even though the Washington recreational marijuana retailing industry is only three years old at the end of the dataset, it has already entered the maturity phase.

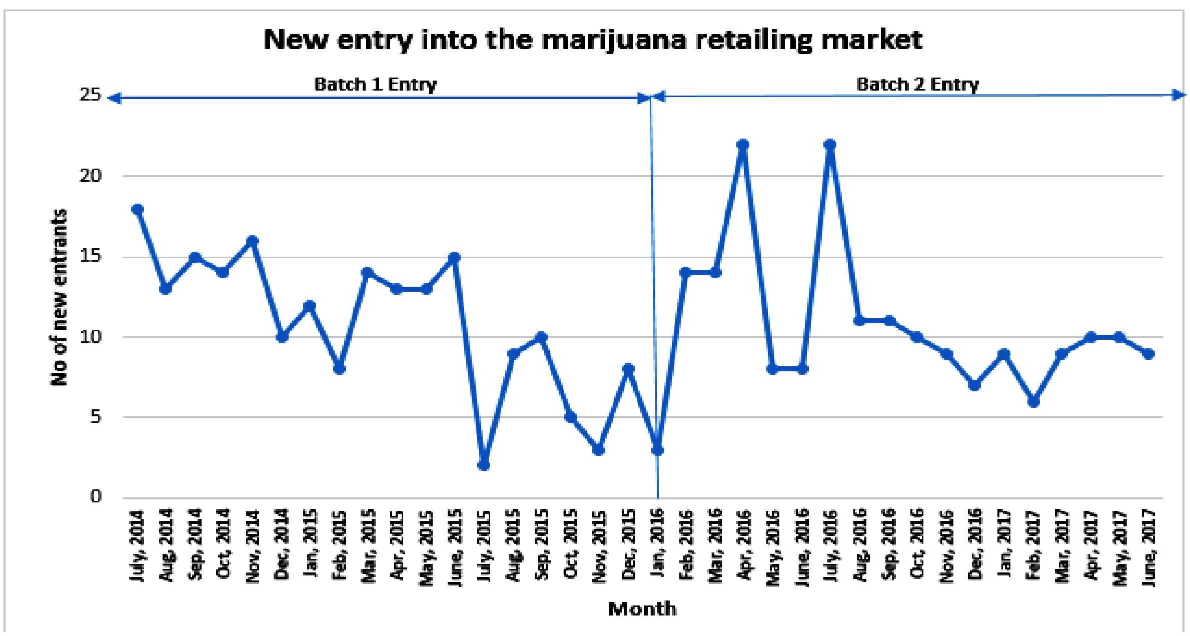

Figure 3. 2 Monthly number of new entrants into the Washington Retail Marijuana Market

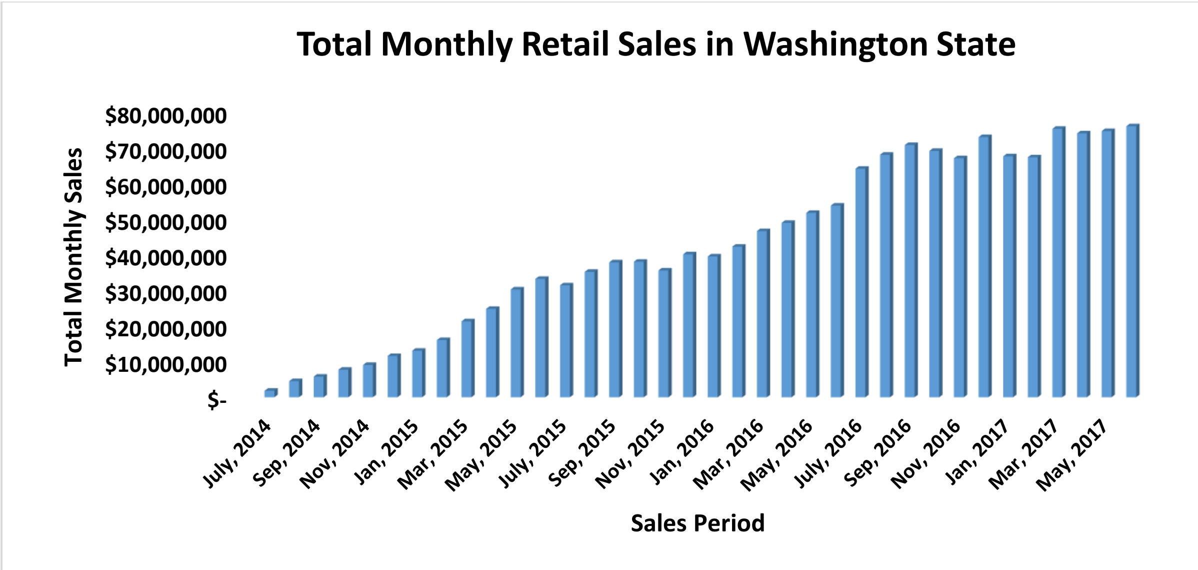

Figure 3. 3 Monthly Total Marijuana Retail Sales in the State of Washington

3.4.9 Dependent Variable

Market share remains the most frequently used performance measure in entry timing studies (Lieberman & Montgomery, 2013). Accordingly, the dependent variable in this study is the monthly natural logarithm of *market share* of the firms by jurisdiction. The natural logarithm adjusts the market share to deal with the left-skewness in the data, bringing it much closer to a normal distribution. Using the logged market share as a dependent variable also implies that our focus is on relative market shares, and we use jurisdiction level fixed effects to make the effects of independent variables on logged market share comparable across different jurisdictions.

3.4.10 Independent Variables

The sample consists of two batches as mentioned. Batch 1 contains the firms that were randomly selected by the lottery (pioneers), whereas Batch 2 contains those firms that were not successful in the lottery but gained the right to enter in the second entry period starting in January

2016 (followers). The *Pioneer* dummy variable that identifies these two cohorts of firms has a value of 1 for any batch 1 firm, and 0 for any batch 2 firm, and this independent variable provides the means for testing Hypothesis 1.

To construct a measure of rivalry intensity, we first calculate the Herfindahl index measure of market concentration for each jurisdiction in each month. The Herfindahl index has a theoretical lower limit of 0 in the case of perfect competition between infinitely many equal-sized competitors, and a theoretical upper limit of 1 in the case of a monopoly, so it is really the opposite of a rivalry intensity measure. Therefore, in order to facilitate its interpretation as a measure of rivalry intensity, the Herfindahl index was reversed by subtracting it from 1 (i.e., to equal 0 in the monopoly case and 1 in the perfect competition case). Consistent with previous research (Adner & Kapoor, 2010; Vissa & Chacar, 2009; Zott & Amit, 2008), this reverse Herfindahl was then mean-centered in order to reduce collinearity between its interaction effect and its main effect. Mean centering is a commonly applied standard and valid procedure to reduce the correlation between independent variables and their interaction effects (Aiken *et al.*, 1991). The resulting rivalry intensity measure is designated as *RI*. Consistent with previous studies (Christensen, 1997; Gomez *et al.*, 2016; Suarez & Lanzolla, 2007), the market growth rate, designated as *Grow*, is measured as the percentage increase in a jurisdiction's total sales over the previous month (lagged by one month in the regressions). Although main effects for *RI* and *Grow* are not hypothesized, they are still included in the regressions as control variables. To test hypotheses 2 and 3 about potential moderating effects on FMA, *Pioneer*RI* and *Pioneer*Grow* interactions are included.

Several other control variables are included in the regression models because they can potentially affect market share: The *medical endorsement* dummy variable equals 1 for retailers that are medically endorsed, and 0 for those that are not. It is time-variant, taking the value of 0 prior to approval of a retailer's medical endorsement, and 1 thereafter. Since customer demographic characteristics can impact purchase behavior, census data at the zip code level for *median household income* and *median population age* are also included. Because markets may differ according to their size, the prior month's total sales for each jurisdiction is included in the regressions as a control for *market size*. Finally, the regression models also include both jurisdiction-level and month-level fixed effects to account for unobserved effects of location and time periods.

3.4.11 Descriptive Statistics

Descriptive statistics and correlations are provided in Table 3.2. A close look at the correlation magnitudes show that there should not be any concern for multicollinearity. This is also confirmed by variance inflation factor (VIF) analyses for all of this study's regression models, where VIF's of all variables are below 3.15 with a mean VIF of 1.96, well below the suggested limit of 10.

Table 3. 2 Correlation Table

Variables	Mean	S.D.	Correlations 1	2	3	4	5	6	7	8	9	10
1. Log (Market share) (t)	-2.558	1.410	1.000									
2. Pioneer	0.589	0.492	0.101	1.000								
3. Rivalry intensity (t)	0.000	0.145	-0.571	0.028	1.000							
4. Pioneer x Rivalry intensity (t)	0.014	0.108	-0.376	0.016	0.740	1.000						
5. Market growth rate (t-1)	0.038	0.083	0.053	0.047	-0.011	0.005	1.000					
6. Pioneer x Market growth rate (t-1)	0.022	0.066	0.061	0.233	0.011	0.008	0.782	1.000				
7. Medical endorsement	0.601	0.492	0.054	-0.101	-0.004	0.020	-0.143	-0.163	1.000			
8. Market Size (t-1)	31.586	29.404	-0.577	0.006	0.685	0.512	-0.011	0.001	0.006	1.000		
9.Median population age	37.470	5.169	-0.013	-0.020	-0.167	-0.130	0.003	-0.009	0.039	-0.046	1.000	
10.Median annual income level	5.510	1.566	-0.222	0.030	0.164	0.169	0.013	0.018	0.012	0.031	0.342	1.000

N=2,457 firm-month observations

Census median annual income level values are measured in tens of thousands of dollars per person.

3.4.12 Estimation Procedures

Since the natural experiment eliminates endogeneity concerns, all regressions are estimated by the method of pooled ordinary least squares (OLS), with standard errors clustered at the firm level to account for potential heteroskedasticity and autocorrelation issues. As mentioned earlier, the analysis omits the first four months of observations for any follower (batch 2) firm, as this is a reasonable amount of time for the late entrants' revenue growth to stabilize after the hyper-growth of the initial launch period, and thus limits the analysis to an appropriate period to assess the comparative performance between the two batches of retailers. The empirical specification is:

$$MS_{i,t} = \beta_0 + \beta_1 Pioneer_i + \beta_2 RI_{i,t} + \beta_3 Pioneer_i RI_{i,t} + \beta_4 Grow_{i,t-1} + \beta_5 Pioneer_i Grow_{i,t-1} + \beta_6 X_{i,t} + \beta_7 K_i + \beta_8 T_t + u_{i,t}$$

where $MS_{i,t}$ is logged market share of firm *i* at time t, the $Pioneer_i$, $RI_{i,t}$, and $Grow_{i,t-1}$ variables are as previously defined in the Independent Variables section above, $X_{i,t}$ is the vector of control variables, K_i is the vector of time-invariant jurisdiction dummies, T_t is the vector of time-period dummies, and $u_{i,t}$ is the error term.

3.5 RESULTS

This section first presents results from regression analyses on the full sample. As discussed below, these full-sample results indicated a need to divide the sample in order to better understand the effect of market rivalry. So, the full-sample analysis is followed by subsample analyses focusing on either high-rivalry or low-rivalry markets.

3.5.1 Full Sample Analysis

Table 3.3 shows the results of full-sample regression models with robust standard errors. In the baseline model, Model 1, the *Pioneer* variable indicates a strong FMA (β=0.369, p<0.01), consistent with Hypothesis 1. In Model 2, FMA main effect remains (β=0.370, p<0.01) with the inclusion of the interaction between the *Pioneer* and *RI* variables, which is strongly positive and significant (β=1.345, p=0.04) indicating that pioneering advantage is stronger in markets characterized by higher rivalry, consistent with Hypothesis 2b but contradicting Hypothesis 2a. In other words, market pioneers achieve higher market share in more rivalrous markets.

Model 3 includes the interaction between *Pioneer* and *Grow*. As with Model 1, the *Pioneer* main effect is significant. (β=0.352, p<0.01) The interaction effect between *Pioneer* and *Grow* is positive but fairly insignificant (β=0.657, p=0.125). However, in the full model, Model 4, where both interaction effects are included, the interaction between the *Pioneer* and *Grow* is positive and marginally significant (β=0.72, p=0.09), thereby providing some modest support for Hypothesis 3b but contradicting Hypothesis 3a. Here again, the change in significance is due to an increase in the coefficient itself, since its standard error remains virtually unchanged between Models 3 and 4. Note also that the earlier results from Model 2 all still remain intact in the full model, Model 4: The FMA main effect again remains in Model 4 (β=0.351, p<0.01), as it did in Model 2, and the interaction between *Pioneer* and *RI* remains significant (β=1.356, p=0.04). Overall, these results indicate that market structure does affect FMA, since these market-level macro-contingency effects matter: FMA is substantially stronger in markets with higher rivalry, and may be modestly stronger in markets with higher growth rates.

Table 3. 3 Full Sample Analysis (Pooled OLS)

	Dependent Variable: Log (Market Share)			
	Model 1	Model 2	Model 3	Model 4
Pioneer	0.369***	0.370***	0.352***	0.352***
	(0.111)	(0.110)	(0.116)	(0.115)
Rivalry intensity	-0.855	-1.730	-0.823	-1.702
	(0.957)	(1.184)	(0.961)	(1.187)
Pioneer*Rivalry intensity		1.345**		1.356**
		(0.664)		(0.665)
Market growth rate (t-1)	0.324	0.299	-0.089	-0.157
	(0.171)	(0.165)	(0.286)	(0.280)
Pioneer*Market growth rate (t-1)			0.657	0.726*
			(0.427)	(0.427)
Median age	-0.041**	-0.038*	-0.041**	-0.038*
	(0.019)	(0.019)	(0.019)	(0.019)
Income	0.005	-0.004	0.005	-0.004
	(0.054)	(0.056)	(0.055)	(0.056)
Medical endorsement	0.350**	0.333**	0.352**	0.335**
	(0.166)	(0.168)	(0.167)	(0.168)
Market size (t-1)	-0.006	-0.004	-0.006	-0.004
	(0.007)	(0.007)	(0.007)	(0.007)
Constant	0.288	0.278	0.306	0.297
	(0.890)	(0.895)	(0.887)	(0.892)
Jurisdiction Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
F-Statistic	33.32***	22.44***	28.06***	22.13***
N	2,457	2,457	2,457	2,457
Adjusted R-Squared	0.471	0.475	0.471	0.476

(Robust standard errors, clustered at firm level, are shown in parentheses.)

Table 3. 4 Subsample Analysis (Pooled OLS)

	Dependent Variable: Log Market Share			
	Subsample 1 (low rivalry jurisdictions)		Subsample 2 (high rivalry jurisdictions)	
	A	B	A	B
Pioneer	0.219	0.217	0.481***	0.481***
	(0.156)	(0.155)	(0.171)	(0.171)
Rivalry intensity		-0.932		-1.867
		(0.844)		(4.931)
Market growth rate (t-1)	0.496**	0.510**	-0.173	-0.161
	(0.218)	(0.218)	(0.341)	(0.356)
Median age	-0.017	-0.017	-0.048	-0.048
	(0.026)	(0.026)	(0.027)	(0.027)
Income	-0.038	-0.038	0.012	0.012
	(0.126)	(0.126)	(0.066)	(0.066)
Medical endorsement	0.335	0.331	0.346	0.346
	(0.207)	(0.208)	(0.244)	(0.246)
Market size (t-1)	-0.050***	-0.048***	0.0142	0.014
	(0.017)	(0.016)	(0.013)	(0.013)
Constant	-0.083	-0.297	-2.211	-2.049
	(0.980)	(0.983)	(0.838)	(0.908)
Jurisdiction Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
F-Statistic	16.81***	17.1***	7.06***	7.39***
N	1177	1177	1280	1280
Adjusted R-Squared	0.318	0.319	0.302	0.302

(Robust standard errors, clustered at firm level, are shown in parentheses.)

3.5.2 Subsample Analysis

As mentioned in the prior section, the strong interaction effect between *Pioneer* and *RI* in the full-sample results indicates a possibility that FMA may not be significant in low-rivalry markets. So, these findings prompted additional subsample analyses in which the dataset was split into two groups of markets: those with higher versus lower rivalry intensity. In order to ensure that both subsamples would have roughly the same number of observations (and therefore roughly the same statistical power), the cut-off point for the reverse Herfindahl (rivalry intensity) was 0.85, so that any jurisdiction with lower rivalry intensity than that belongs to the lower rivalry group, designated as Subsample 1 with 1177 observations, and any jurisdiction with higher rivalry intensity belongs to the higher rivalry group, designated as Subsample 2 with 1280 observations. Results of these subsample analyses are reported in Table 3.4.

As seen in Table 3.4, two regression models were estimated for each subsample, labeled as models A and B, where the rivalry intensity variable is omitted from Model A but included in Model B. In both models for the low-rivalry Subsample 1, the coefficient for the *Pioneer* variable is insignificant (β =0.219, and p=0.162 for model A, while β=0.217, and p=0.165 for Model B). However, in both models for the high-rivalry Subsample 2, the coefficient for the *Pioneer* variable is positive and highly significant (β=0.481, and $p<0.01$ for both models). These results contrast the strong FMA in high-rivalry markets versus negligible FMA in low-rivalry markets, contrary to the "beachhead" logic of Gal-Or (1985), but consistent with the "competition breeds competence" logic of the "quiet life" hypothesis (Hicks, 1935: 8).

3.5.3 Alternative Rivalry Intensity Measure

As a robustness check, I have repeated the main analysis using an alternative rivalry intensity measure, the *average market share* in a jurisdiction. *Average market share* in each jurisdiction is calculated as *100/number of competitors.* Accordingly, the higher the average market share, the lower the rivalry intensity in a jurisdiction. This additional analysis also provides similar results consistent with the main analysis. As seen in Model 1 and Model 2 of Table 3.5, *Pioneering* is positive and significant (β =0.576, and $p<0.01$), and Pioneer*Average market share interaction effect is negative and significant (β =-0.016 and $p<0.05$). This indicates that as average market share in a market goes up indicating lower rivalry intensity, the positive effect of pioneering on market share goes down.

3.5.4 Onset of Maturity

As an additional robustness check, I have used alternative months as the start of the onset of the maturity phase, March-April-May 2017. Again, the results are consistent with the main analysis. As shown in Model 1 of Table 3.6 that covers the data till the end of May 2017, the *Pioneer* variable (β =0.345, and $p<0.01$), along with *Pioneer*Rivalry intensity* variable (β =1.549, and $p<0.05$) is positive and significant. In Model 2 which covers the period till April 2017, again the *Pioneer* variable (β =0.379, and $p<0.01$), along with *Pioneer*Rivalry intensity* variable (β =1.655, and $p<0.05$) is positive and significant. In the final model, Model 3, which covers the period till March 2017, I obtain again similar results where the Pioneer variable (β =0.399, and $p<0.01$), along with *Pioneer*Rivalry intensity* variable (β =1.751, and $p<0.05$) is positive and significant.

Table 3. 5 Full Sample Analysis with Alternative Rivalry Intensity Measure (Pooled OLS)

	Dependent Variable: Log (Market Share)
	Model 1
Pioneer	0.576***
	(0.168)
Rivalry Intensity (average market share_100/number of competitors)	0.064**
	(0.0266)
Pioneer*Rivalry intensity	-0.016**
	(0.007)
Market growth rate (t-1)	-0.016
	(0.271)
Pioneer * Market growth rate	0.692*
	(0.417)
Median age	-0.039**
	(0.019)
Income	-0.002
	(0.055)
Medical endorsement	0.325*
	(0.167)
Market size (t-1)	-0.008
	(0.007)
Constant	-1.511
	(1.207)
Jurisdiction Fixed Effects	Yes
Time Fixed Effects	Yes
F-Statistic	26.3***
N	2,457
Adjusted R-Squared	0.466

(Robust standard errors, clustered at firm level, are shown in parentheses.)

Table 3. 6 Full Sample Analysis with Alternative Onset of Maturity Dates (Pooled OLS)

	Dependent Variable: Log (Market Share)		
	Model 1	Model 2	Model 3
Pioneer	0.345***	0.379***	0.399***
	(0.115)	(0.115)	(0.113)
Rivalry Intensity	-2.062*	-2.154*	-2.171*
	(1.198)	(1.188)	(1.169)
Pioneer*Rivalry intensity	1.549**	1.655**	1.751***
	(0.676)	(0.673)	(0.67)
Market growth rate (t-1)	-0.145	0.0494	-0.294
	(0.266)	(0.276)	(0.369)
Pioneer * Market growth rate	0.596	0.382	0.611
	(0.411)	(0.422)	(0.526)
Median age	-0.0386**	-0.0341*	-0.031*
	(0.0190)	(0.0183)	(0.018)
Income	-0.00614	-0.0108	-0.0197
	(0.0541)	(0.0527)	(0.052)
Medical endorsement	0.314**	0.233*	0.176
	(0.158)	(0.138)	(0.123)
Market size (t-1)	-0.00164	-0.000659	0.00297
	(0.00685)	(0.00603)	(0.008)
Constant	0.246	0.873	-0.004
	(0.882)	-0.857	0.847
Jurisdiction Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
F-Statistic	23.63***	23.04***	22.95***
N	2,200	1,950	1,707
Adjusted R-Squared	0.482	0.501	0.523

3.6 DISCUSSION

Two intertwined weaknesses of prior FMA research motivated this study – endogeneity-induced selection bias, and neglect of market-level macro-contingency factors. These two problems are like two locked boxes that each contain the other's key. On one hand, endogeneity-induced selection bias is only a problem due to heterogeneity in firms' incentives to enter markets earlier versus later (i.e., there would be no such selection bias if all firms were identical in their entry-timing incentives), so this problem has virtually forced FMA researchers to take a micro-contingency approach focused on untangling the impact of firm-level characteristics on FMA, to the neglect of market-level macro-contingencies. On the other hand, endogeneity of entry order also means that a firm's unique characteristics may motivate it to enter earlier in some markets but later in others, depending upon the specific characteristics of the market. Therefore, micro-level firm characteristics and macro-level market characteristics may be highly correlated, making them difficult to disentangle from each other in empirical settings where entry order is endogenous, as is almost always true in real-world industries. So, these two weaknesses together, and especially in combination with other common weaknesses of FMA research (e.g., survivorship bias, difficulties in identifying pioneers versus followers, sampling on the dependent variable), present a Gordian knot to FMA researchers, and the project of trying to untangle that knot has been a lengthy exercise in frustration and confusion.

The present paper exploits the unique natural experiment of the Washington State marijuana retailing license lottery to cut this Gordian knot and fix all of these weaknesses simultaneously, albeit at the expense of producing results with very limited generalizability beyond this one industry. This special empirical context handles all major methodological concerns, including endogeneity-induced selection bias, survivorship bias, misidentification of pioneers, misidentification of market entry dates, and sampling on the dependent variable – all while also providing the first direct measures of market-level macro-contingency effects on FMA. Specifically, the results indicate that markets with high rivalry offer significantly larger FMA, and markets high growth rate may also offer some boost to FMA. Overall, the results highlight the importance of full consideration of both market structure and methodological concerns in better understanding entry timing decisions and their effect on performance outcomes.

3.6.1 Limitations and Extensions

This paper has certain limitations. First, its generalizability is highly limited, due to its narrow focus on a unique natural experiment affecting a specific industry in a specific location at a specific time. The empirical setting is the marijuana retailing industry, an emerging industry which might have significantly different characteristics from other industries. In addition, certain regulations that needs to be followed by the retailers limit their flexibility in terms of their range of competitive actions. For example, retailers are not allowed to produce and process and their own products as a rule of regulations. Such regulations rarely exist in other industries. Because of this, the results may not be generalizable for other settings. Nevertheless, limited generality is a reasonable price to pay in exchange for this study's elimination of all the methodological problems that have bedeviled FMA research for decades, including endogeneity-induced selection bias, survivorship bias, challenges to identifying pioneers versus followers, sampling on the dependent variable, and data from the wrong phase of the market life cycle. As a result of eliminating these methodological concerns, what this study lacks in terms of generality it more than compensates for in terms of accuracy. After all, research design always necessarily involves making trade-offs between accuracy, generality, and simplicity (Weick, 1979: 35-42). Second, this study uses market share as a performance metric. Despite its frequent use in entry timing studies, market share suffers from certain limitations, such as the possibility that it may provide upwardly biased measures of FMA. Future studies could provide more insights using other performance measures.

Finally, the Washington cannabis natural experiment offers several opportunities for extending this study in a variety of different directions. For example, although the focus of the present paper is market-level macro-contingency factors, the Washington recreational marijuana retailing setting offers an opportunity to take the study of micro-contingency factors to a whole new level of detail by augmenting the existing dataset with some moderate amount of additional data collection, and thereby make contributions to a variety of different research literatures (e.g., spatial economics, marketing, or entrepreneurship) depending upon the nature of the added data. As a potential contribution to spatial economics research, the precise geographic location of each store could be linked to fine-grained information about the surrounding traffic patterns or the store's proximity to nearby businesses of various types or to other landmarks, in order to draw granular inferences about the impact of location choices on the magnitude of FMA. Similarly, as a potential contribution to marketing research, additional data about each store's marketing choices (e.g., pricing, advertising, product offerings, store layout and décor, service quality) might shed light how marketing strategies affect FMA. Likewise, as a potential contribution to entrepreneurship research, since the names and addresses of each store owner can be found in public records, data collected via surveys, archival sources, or social media about each individual entrepreneur's characteristics (e.g., education, professional experiences, social networks, family history, and other background factors) could be used for studying the question of what kinds of entrepreneurs generate the greatest FMA – an entirely new research question for the field of entrepreneurship. A different type of extension would be to compare this study's results from Washington's exogenous entry-order setting to the corresponding results from a state that did not use a lottery system for cannabis licensing – i.e., where entry order was endogenous – in order to directly estimate the magnitude of selection bias resulting from endogenous entry order.

CHAPTER 4. SUSTAINABILITY OF PIONEERING ADVANTAGE

4.1 Introduction

The link between entry timing into a market space and firm performance has long been considered an important research question that has attracted attention from researchers representing various fields including marketing, economics, and strategy. While several researchers have looked at the potential contingency factors on the relationship between entry timing and performance outcomes, the duration or sustainability of such an advantage received little attention. This is surprising because entry timing is considered one of the four major profit generating mechanisms that can potentially underlie sustainable competitive advantage (Makadok, 2011). The few papers that looked at (Boulding & Christen, 2003; Robinson, 1988; Robinson and Fornell, 1985) relied on PIMS data yielding potentially biased empirical outcomes since PIMS data suffers from well-known significant methodological drawbacks such as survival bias as well as incorrect identification of pioneers due to self-reporting by the sample firms (Lieberman & Montgomery, 1988, 1998; Golder & Tellis, 1993).

In this essay, I examine how long pioneering advantage is sustained taking advantage of the natural experiment design offered by the marijuana retailing industry data coming from Washington State. Using this dataset allows me to effectively address the endogeneity issue due to the natural experiment design with randomized entry where heterogeneity among firms could be effectively accounted for. In June 2014, Washington State legalized the opening of recreational marijuana stores where the early entrants were determined on a completely random basis through a double-blind lottery process performed in April 2014. Later in December 2015, 18 months after the early entry, Washington State has decided to expand its license program adding 222 new retail licensing caps. All these new licenses were granted to applicants who lost in the April 2014 lottery, also called Priority 1 group. This randomized entry order provides me with a unique opportunity to test the sustainability of entry timing associated performance benefits directly without any endogeneity concerns. Using monthly cross-sectional data analysis shows that pioneering advantage on average is sustained for four quarters.

4.2 Literature Review

4.2.1 Entry Timing

Entry timing is considered one of the key strategic decisions firms have to make and has been shown to have strong implications on firm performance accordingly. Also termed as first-mover advantages (FMA) in the literature, the subject has received significant attention from researchers in strategy, marketing and economics fields. Despite years of research into the subject, the field is still unable to provide robust answers on how firms should approach the entry-timing decision processes. Part of this stems from fact that the classic commitment vs pre-emption trade-off is at the heart of the FMA concept. While early entry can allow the pioneer to pre-empt the market space in various alternative ways such as holding control over scarce assets, generation of switching costs etc., early commitment also makes the pioneer more vulnerable to the potentially costly mistakes which are hard to reverse. Research on entry timing has produced either mixed or contradictory results. Indeed, there is still not a consensus among management scholars as to whether early or late entry is more advantageous. While some research emphasizes the positive effects of pioneering on firm performance (Yip 1982; Urban et al. 1986; Lambkin 1988; Lieberman 1989; Makadok 1998) other research suggests that early entry does not automatically translate into sustainable competitive advantage and that there are also performance benefits that firms can derive by late entry (Christensen and Bower 1996, Christensen 1997, Cho, Kim, and Rhee 1998, Shankar, Carpenter, and Krishnamurthi 1998).

4.2.2 Sustainability of Pioneering Advantage

While performance implications of entry timing have been extensively investigated in the literature, the duration of entry timing linked performance advantages surprisingly has been rarely examined. This is an important gap in the literature since entry timing is considered one of the major profit generating mechanisms (Makadok, 1998), and thus it is crucial to gain insights on the endurance of performance benefits stemming purely from entry timing choice. The main consensus within the entry timing research stream is that performance benefits pioneers derive from early entry do not last forever since the strength of preemption-based mechanisms that underlie pioneering advantage (such as preemption of scarce assets, switching costs, buyer's choice under uncertainty etc.) decline over time (Brown & Lattin, 1994; Robinson and Fornell 1985; Robinson, 1988; Lieberman & Montgomery, 2013). Additionally, presence of flexibility -based mechanisms (such as incumbent inertia, free rider effects, shifts in consumer preferences etc.) can potentially accelerate this decline. Robinson and Fornell (1985) and Robinson (1988) show that pioneers' market share advantages in mature markets decay in a gradual fashion. Consistent with that, Brown and Lattin (1994) reveal that pioneers lose at least a part of their advantage over time. Kalyamaran et al (1995) report a similar finding that the entry timing associated performance outcomes decline in the long run in consumer goods industries. While the main focus of these papers has been on detecting as to whether there is a decline in performance advantages enjoyed by the pioneers, they do not measure how long the positive effect of pioneering on performance lasts until it fully evaporates. In addition, they also suffer from certain limitations such being limited to using a single year of cross-sectional data (Brown & Lattin, 1994), using PIMS data (Robinson and Fornell, 1985, Robinson, 1988) or focusing on mature markets (Kalyamaran et al, 1995) which can produce biased results. More recently, Boulding & Christen (2003) show that the profit benefits generated by early entry is sustained for around 12-14 years. Their results also reveal that beyond that period, pioneers experience a cost disadvantage relative to the followers. However, this paper also uses PIMS dataset which suffers from various well-known limitations which could easily bias the results. However, their study relies on PIMS data which suffers from significant and well-known limitations despite its frequent use in past research (Robinson & Fornell, 1985; Lambkin, 1988; Parry & Bass, 1990; Boulding & Christen, 2003, 2008, 2009). Two major drawbacks associated with PIMS data use are incorrect identification of pioneers and followers and survival bias (Lieberman & Montgomery, 1988, 1998; Golder & Tellis, 1993). First, PIMS data uses self-reports provided by the firms where they can self-identify themselves as pioneers, early follower or a late entrant which might be incorrect, and thus significantly limit the accuracy of the data (Lieberman & Montgomery, 1988; Kerin et al., 1992; Golder & Tellis, 1993). Self-reporting by a single informant can provide incorrect information particularly if the informant is new to the company in particular for long standing product groups. This situation is exacerbated by the potential self-perception bias where dominant firms prefer to consider themselves as pioneers (Golder & Tellis, 1993)**.** Relatedly, PIMS data uses a relatively broad FMA definition stated as “one of the pioneers in first developing such products or services”. Such strong potential sources of misspecification perhaps could explain why 52% of the firms in the PIMS dataset regard themselves as pioneers, and that also includes multiple competing firms within the same product categories (Buzzell &

Gale 1987; Lieberman & Montgomery 1988; Golder & Tellis, 1993). Second, PIMS data contains data on well-established Fortune 500 companies in mature industries which leads to selectivity bias exaggerating the magnitude as well as the sustainability of entry timing related performance metrics (Day & Freeman 1993; Golder and Tellis 1993; Makadok 1998). Finally, PIMS data also suffers from the survival bias. In the FMA context, the possibility that pioneers and followers differ in their survival rates, empirical analysis will yield biased results favoring pioneers since followers in general are considered to have higher survival rates than pioneers (Day & Freeman 1990; Golder & Tellis, 1993; Boulding & Christen). Therefore, Boulding & Christen (2003) state that their empirical results should be approached with caution as in their words *"The exclusion of pioneers that have failed may overstate the advantage of pioneers".* To illustrate the limitations of PIMS data, Golder & Tellis (1993) conducted a study on 50 product markets where they identified the pioneers via the historical data, and have found that pioneers have lower success rates than those suggested by the studies using PIMS data. Authors concluded that use of PIMS data might potentially lead to biased estimations since only surviving firms are included in the sample and thus firms which should be classified as followers could be misclassified as pioneers. The consequence of the survival bias problem is that the advantage of moving first may be systematically overestimated.

4.2.3 Endogeneity in Entry Timing Research

Another important limitation of these papers is the fact that they cannot sufficiently control for the endogenous nature of entry timing decisions. Since entry timing decisions are endogenous to the unique resource and capability collections of the firms, entry-timing performance related outcomes are strongly tied to the resource characteristic of these firms (Lieberman & Montgomery, 1988; Moore et al., 1991; Robinson et al., 1992, Murthi et al., 1996; Boulding & Christen, 2003). Robinson et al. (1992) suggested that early-moving firms and late-moving firms differ in terms of their resources and capabilities. Similarly, Lieberman & Montgomery (1988) stated early and late movers differ by their resource characteristics. Therefore, optimum entry timing for any firm will be dependent on the ex-ante nature of its resources where some firms are better off entering early and others late as an outcome of the unique resource and capability bundles they possess (Lieberman & Montgomery, 1988, 1998; Robinson et al., 1992). For example, established firms with rare and valuable complementary assets or speed capabilities might delay their entry as such resources effectively provide them with the option to wait until the uncertainty resolves (Hawk et al., 2014; Teece, 1986). In contrast, Narashiram & Zhang (2001) noted that firms with relatively weaker positions are better off entering early in order to take advantage of first-mover advantages that will offset their disadvantaged position in terms of their resource profile. Due to the presence of the potential resource heterogeneity that distinguishes early and late moving firms, any relative performance difference empirically found between the pioneer and followers does not necessarily reflect the direct causal impact of entry timing on performance. Rather the performance differential as suggested in the examples above stems from the differences in the ex-ante resource and capability positions between the firms in both cohorts. Therefore, empirical investigations that do not take ex-ante firm-level heterogeneity into account might produce biased results that wrongly attribute positive/negative performance outcomes directly to entry timing (Boulding & Christen 2003; Lieberman & Montgomery 1988, 1998: Robinson et al. 1992). The source of endogeneity here, the selection bias, results from the correlation between the error term and the entry order variable due to the non-random assignment of pioneers and followers.

The most effective solution to this issue would be a randomized experiment design which would allow for the examination of propositions from a counterfactual. In such a setting where the entry order is randomized among the potential entrants, the firms in the pioneer group and follower group would be interchangeable where the counterfactual for the group receiving the treatment (entry order) would be the other group that did not receive it. In other words, the counterfactual for the early entrants would be the late entrants since both groups are equivalent in terms of their both observable and unobservable characteristics including their resource profiles due to random assignment. Such randomization allows for making precise causal inferences without any contamination. Therefore, any between-group differences on the dependent variable could safely be attributed to the treatment effect (order of entry) without any spurious correlation or confounding concern. In contrast, however, as mentioned before, the presence of resource heterogeneity that exists among the followers and pioneers in non-randomized experimental settings results in systematical difference between the pioneers and follower groups. That significantly blurs the empirical analysis making it challenging to draw causal inferences since the appropriate counterfactual in such settings cannot be generated.

4.3 Research Setting

4.3.1 Marijuana Industry in the US.

Cannabis or marijuana is a product obtained from processing Cannabis plant and used for both recreational and medical purposes. Cannabis is regarded as the most consumed illicit drug in the world according to the United Nations' 2012 *Global Drug Report*.[26] According to federal law, cannabis is a Schedule 1 drug with “a high potential for abuse, no accepted medicinal value in

[26] https://www.unodc.org/documents/data-and-analysis/WDR2012/WDR_2012_web_small.pdf

treatment in the United States, and evidence that there is a general lack of accepted safety for its use even under medical supervision" (U.S. Drug Enforcement Administration 2013).[27] While not legal at the federal level with regard to its sale and distribution, marijuana has been allowed for medicinal use in twenty-nine states across the US. In 2014, two states, Washington and Colorado, have legalized the production, processing and retail sales of marijuana.

4.3.2 Marijuana Retailing Industry in Washington State

Washington State passed Initiative 692 in November 1998 that legalizes the use and production of cannabis for patients having a medical certificate and suffering from debilitating health conditions such as HIV, cancer, and multiple sclerosis.[28] In November 2012, Washington State passed Initiative 502 with a majority popular vote that made recreational cannabis use legal. Washington State Liquor Control Board regulates the licensing, production, processing, sales as well as taxing activities.[29] The board is also responsible for setting the standards for testing, packaging as well as labeling of the marijuana products. Retail license applications were accepted during December 2013. Retail licenses were begun to be issued early 2014, and the first sales began in July 2014. WSLCB also provides licenses for producers and processors. Within the vertical chain, processors are responsible for growing and selling marijuana, marijuana plant, as well as seeds to the processors. Processors are responsible for processing marijuana raw materials, packaging and labeling both marijuana and marijuana infused products for the ultimate purpose of

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[27] https://www.dea.gov/docs/marijuana_position_2011.pdf
[28] http://www.wsipp.wa.gov/ReportFile/1555/Wsipp_Medical-Marijuana-Access-and-Regulations-in-Washington-State_Full-Report.pdf
[29] http://lcb.wa.gov/mj2015/fact-sheet

sale to the retailers. While a licensed processor can also hold a producer license, and vice versa, a retailer can hold neither a producer nor a processor license.

4.3.3 Lottery

Washington State has determined a total license cap of 334 distributed over 122 jurisdictions. The WSLCB calculated the total number of retailers allowed per city and county based upon population and total jurisdiction. In total, there were 1,175 applicants. For areas where number of applicants exceeded the number of slots available, the WSLCB has organized a lottery. For instance, Seattle received 191 applications for 21 slots available. 75 jurisdictions required a lottery. Applicants in these jurisdictions were ranked through an independent double-blind lottery process that took in April 21-25, 2014.[30] The lottery process was designed by Washington State University and Kraght-Snell, a Seattle-based firm that cooperates with the Washington State Lottery. Winning the lottery however has not guaranteed the issue of the license since the winners had to go through a phone interview, declaration to the local authorities, independent assessment of the chosen retail location and submit business plans. When an applicant who won the lottery in a given jurisdiction fails the following licensing process, that applicant is removed from the list and WSLCB moves to the next applicant high on the ranking list of that particular jurisdiction.

4.3.4 Second Batch

Medical marijuana industry in the Washington State has been unregulated from its inception without any monitoring and clear guiding procedures provided by the state agencies. In order to restructure the medical marijuana industry in a formal manner and ensure better service

[30] http://lcb.wa.gov/pressreleases/lottery-results-marijuana-retail-stores-available-wslcb-website

for patients & tax collection, Senate Bill 5052 was signed in April 2015 which suggested medical marijuana industry be integrated into the marijuana retailing industry[31]. Accordingly, existing medical dispensaries were given the option to apply for retail licensing or end their sales operations by July 2016. In order to ensure smooth integration of medical marijuana provision system into the legal retailing system, WSLCB has begun to accept new licensing application in October 2015. In January 2016, the board has announced that it would increase the number of retail stores by 222 determined after an extensive market analysis. In total, the board received over 2,300 applications. The new licenses were granted on a priority basis with the board setting three priority levels. Applicants in the Priority 1 Group were those who applied for a marijuana retailing license before July 1, 2014 (applicants who were not licensed through the lottery), either managed or were employed by a collective garden prior to January 2013, hold a state and local business licenses, and pay taxes and fees. All new licenses were received by Priority 1 applicants. The second batch members began to enter the market in January 2016 after successfully going through the licensing process. Both former medical dispensaries that were granted the retailing license as well as existing marijuana retailers had to apply for a medical marijuana endorsement which would allow them to sell medical marijuana products. Medically endorsed retailers are also responsible for hiring medical consultants at their store and keeping a database of customers.

4.3.5 Data Description

WSLCB website provides regularly updated comprehensive information on the names, license numbers, addresses, medical endorsement status, as well as the monthly sales and tax

[31] http://lcb.wa.gov/pressreleases/lcb-to-increase-number-of-retail-mj-stores

information by each licensed marijuana retailer. The ranked-ordered results of the lottery by jurisdiction as well as the names of the jurisdictions that did not require a lottery were posted on the public records section of the website In the State of Washington, 75 jurisdictions required a lottery and 47 did not. In 8 of the 75 jurisdictions that required a lottery, no retailer entry was found and recorded during our analysis period. The dataset was developed using the monthly retail sales and tax figures by license number provided regularly on the WSLCB website. The dataset covers a total of 36 months between July 2014 (the start date of retail sales in the State of Washington) and June 2017. Matching the licensee numbers on the monthly sales data with those in the lottery results by jurisdiction allowed us to distinguish between pioneers that entered via lottery and followers without lottery. Followers began entering the market in January 2017, 18 months after the start of the marijuana sales in the state. Out of 390 entrants, 48 were from the jurisdictions which did not require a lottery. These entrants that were not determined by random draw were excluded from the dataset.

The analysis was conducted at the jurisdiction level. As a pre-condition prior to the analysis, we applied the criteria of involving jurisdiction markets in which there is at least one firm which was licensed through lottery (pioneer) and at least one firm which entered through the new medical marijuana market regulations as a Priority 1 Group member (follower). Out of a total 288 firms, 148 were pioneers, and 140 were followers based in 39 jurisdictions in 21 out of the state's 39 counties. I also collected zip code level data such as income and median age through the ESRI website, an international geographic information provider company based in California. The dataset covers all product lifecycle stages starting with the introduction stage in July 2014 up to the beginning of the maturity stage.

4.3.6 Independent and Dependent Variables

The dependent variable in this study is the monthly *logged market share* of the firms by county. Despite its limitations, market share measure has been among the most frequently used performance metrics in the entry timing studies (Lieberman & Montgomery, 2013). Our sample consists of two batches as mentioned. *Pioneer* group contains the firms that were randomly picked by the lottery whereas *follower* group contains those firms that were not successful in the lottery but gained the right to enter in the second entry period with the start date of January 2016. I use a binary variable to identify these two cohorts of firms where *pioneers take the* value of 1, and followers 0. *Rivalry intensity* is captured via market concentration. Market concentration was measured by the use of Herfindahl index with the below formula:

$$H_{c,t} = \sum_{i=1}^{N} s_{i,c,t}$$

Where the market concentration *H* in county *c* in month t with *N* competitors is calculated as the sum of all market shares *s* by firm *I* in county *c* in month *t*. Since higher value of index is inversely proportional to the rivalry intensity, we subtract the index value from 1. Thus, the lower the market concentration in a given county, the more intense the rivalry is. In order to capture the *speed of the market evolution*, I use market growth at the county level on a monthly basis as a proxy. For *medical endorsement*, I use a binary variable that takes the value of 1 for the retailers that are medically endorsed, and 0 for those that are not. For those medically endorsed stores, the dummy value is time-variant that takes the value of 0 until the month of medical endorsement, and takes 1 in the month of and after the endorsement.

4.3.7 Control Variables

I include several control variables that can potentially affect the monthly market share performance of the retailers at the county level including jurisdiction level market size, and zip code level median income as well as median age. Finally, I also include jurisdiction level and month level fixed effects to account for the location and time effects respectively.

4.3.8 Estimation

In the empirical analysis, I use cross-sectional OLS methods with robust standard errors taking advantage of the natural experiment setting with randomized entry order. Standard errors are clustered at the firm level in order to eliminate potential concerns on heteroscedasticity and autocorrelation issues. Cross-sectional analysis would provide detailed insights on the evolution of competition and resulting performance differences between market pioneers and followers. The analysis is carried out at the quarterly level where each quarter contains three months. In total, the dataset contains five quarters (fifteen months).

where $MS_{i,t}$ is logged market share of firm *i* at time *t*, the $Pioneer_i$, $RI_{i,t}$, and $Grow_{i,t-1}$ variables are as previously defined in the Independent Variables section above, $X_{i,t}$ is the vector of control variables, K_i is the vector of time-invariant jurisdiction dummies, T_t is the vector of time-period dummies, and $u_{i,t}$ is the error term.

The empirical specification is shown below:

$$MS_{i,t} = \beta_0 + \beta_1 Pioneer_i + \beta_2 RI_{i,t} + \beta_3 Grow_{i,t-1} + \beta_4 X_{i,t} + \beta_5 K_i + \beta_6 T_t + u_{i,t}$$

Where

$MS_{i,t}$ represents the logged market share of firm i at time t, $Pioneer_i$ is the firm-level binary variable which equals one if the firm is a pioneer (lottery winner). $RI_{i,t}$ represents the level of rivalry intensity at time t, $Grow_{i,t-1}$refers to the level of market growth in a given jurisdiction. $X_{i,t}$ is the vector of control variables, K_i is the vector of time-invariant jurisdiction dummies, T_t is the vector of time-period dummies, and $u_{i,t}$ is the error term

4.3.9 Results

Analysis results show a gradual decline in terms magnitude and overall significance of pioneering advantage. Models Quarter 1 - Quarter 4 show that there is a very strong and positive pioneering effect on market share performance in the first four quarters of inter-batch competition ($p<0.01$). In quarter five, however, this effect becomes insignificant ($p>0.1$) indicating that the pioneering advantage in the marijuana retailing industry in Washington State lasts only four quarters.

4.4 Conclusion

Taking advantage of the unique dataset coming from the marijuana retailing industry in Washington State, this paper aims at measuring how long the pioneering advantage is sustained in this market. Monthly cross-sectional analysis shows that pioneering advantage lasts for four quarters. The fact that pioneering advantage in Washington State marijuana retailing industry is very short-lived suggests that preemption-based mechanisms present in this market that can potentially underlie pioneering advantage are easily overcome by the followers. Such preemptive mechanisms specific to this market include preemption of premium retailing locations, retailer brand loyalty through budtenders (customer service agents), and information availability through online reviews that can favor pioneers.

Table 4. 1 Cross-Sectional (Monthly) Analysis (Pooled OLS)

			Dependent Variable: Log (Market Share)		
	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Quarter 5
Pioneer	1.062***	0.865***	0.658***	0.445***	0.248
	(0.119)	(0.132)	(0.135)	(0.153)	(0.162)
Rivalry intensity	0.580	-0.414	3.758	-0.318	6.503
	(1.239)	(1.878)	(4.806)	(2.447)	(5.750)
Market growth rate (t-1)	0.824*	0.533**	0.363	0.0440	-0.893
	(0.439)	(0.258)	(0.352)	(0.242)	(0.754)
Median age	-0.0296	-0.0228	-0.0397**	-0.0617**	-0.0484*
	(0.0183)	(0.0186)	(0.0188)	(0.0276)	(0.0257)
Income	0.0438	-0.00855	-0.0200	0.0277	0.0166
	(0.0536)	(0.0532)	(0.0587)	(0.0652)	(0.0770)
Medical endorsement	0.0117	0.0924	0.245	0.437	0.787**
	(0.141)	(0.155)	(0.146)	(0.252)	(0.384)
Market size (t-1)	-0.00113	-0.000457	-0.0178	0.0000559	0.000284
	(0.00387)	(0.00671)	(0.0120)	(0.0102)	(0.0149)
Constant	-1.043	-1.027	0.651	0.348	2.945
	(0.739)	(0.825)	(1.319)	(1.076)	(2.144)
Jurisdiction Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-Statistic	22.42	14.49	18.25	18.59	25.76
N	604	669	712	710	621
Adjusted R-squared	0.665	0.515	0.466	0.375	0.324

(Robust standard errors, clustered at firm level, are shown in parentheses.)

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