ABSTRACT

Title of dissertation: ESSAYS ON ORGANIZATIONAL CHOICE UNDER UNCERTAINTY

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Environmental uncertainty has been widely studied by organizational theorists and strategy scholars. In this dissertation, I aim to contribute towards a further understanding of the implications of environmental uncertainty on organizational choices.

I develop a general framework, across the two chapters, which links the effect of uncertainty on organizational choices, mediated by changes in the competitive landscape. In my two chapters, I look at different types of uncertainty namely, state uncertainty and effect uncertainty. I explore how these types of uncertainties impact the competitive landscape either by compressing performance difference between organizations and changing the viability of positions on the landscape respectively. As a consequence of the changing landscape, I study the strategic behavior response of organizations as they engage in risk-taking or repositioning.

I test my theoretical predictions across two interesting empirical constructs of Formula 1 car racing and the Consumer Electronics Show. Also, I also employ the use of a simulation model in my second chapter to supplement my empirical context.

ESSAYS ON ORGANIZATIONAL CHOICE UNDER UNCERTAINTY

by

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Dissertation submitted to the Faculty of the Graduate School of the
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Dedication

I dedicate this work to the two most important ladies in my life: My mother, Vijaya Lakshmi Sharma and my wife, Sangeetha Hariharan. Without their constant support, encouragement and perseverance, I could not achieved this.

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"It takes a village to raise a child." Similarly, a dissertation is a culmination of the effort of numerous individuals, each playing their part. I owe my gratitude to all the people who have made this dissertation possible and because of whom my graduate school experience has been one that I will cherish forever.

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It is impossible to remember all, and I apologize to those I've inadvertently left out.

Lastly, cheers to the Maryland's Men's Basketball Team who gave me numerous highs, a few heartbreaks, and restored sanity when it was most required.

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List of Abbreviations

β	beta
ϵ	epsilon
σ	sigma
FIA	Federation Internationale de l'Automobile
F-1	Formula One
WDC	World Drivers Championship
WCC	World Constructors Championship
CES	Consumer Electronics Show

Chapter 1: Introduction

Environmental uncertainty has been a central construct of organizational theorists and strategic management researchers for many decades (Beckman et al., 2004; Duncan, 1972; Knight, 1921; March and Simon, 1958; Pfeffer and Salancik, 1978; Thompson, 1967). My dissertation aims to add to our understanding of this construct by examining the effect of environmental uncertainty on competitive interactions between organizations, and the resulting behavioral and strategic choices, such as risk taking and repositioning, that organizations make. I explore two exogenous sources of uncertainty for a focal organization: first, random events which alter the state of the environment; and second, imperfect information about competitor organizations. Changes in the relative positions of organizations in the competitive landscape mediate the effect of these types of environmental uncertainty, caused by the above sources, on the strategic behavior and choices of the organizations. Across my two chapters, I explore changes in risk-taking and repositioning by organizations and how they are influenced by environmental uncertainty and the changing competitive landscape.

The seminal paper by Milliken (1987) defined environmental uncertainty as "an individual's perceived inability to predict something accurately." She suggested that the uncertainty construct should be disaggregated, and identified three types of perceived uncertainty about the environment. State uncertainty – the inability to predict the future state of the environment; effect uncertainty – the inability of decision makers to predict how environmental changes will impact their organizations; and response uncertainty – the inability of managers to identify potential organizational actions and their outcomes.

The characterization of environmental uncertainty in my first chapter directly overlays the phenomenon of state uncertainty, which negatively impacts the fit between organizational structure and environment. The well-established negative consequence of state uncertainty is a reduction in organizational performance (Andersen et al., 2007; Martin et al., 2015). I build upon this by arguing that reductions in performance across organizations are disparate in nature but systemic which compresses the performance distribution of organizations in the competitive landscape. At the organizational level, these changes in the distribution result in greater crowding by competitor organizations around the focal organizations. The implications of the increase in level of crowding are two-fold: first, it leads to an overall increase in risk-taking by organizations due greater competitive pressures and opportunities which result from increased crowding; second, it motivates the lower placed competitors to engage in greater risk-taking because crowding creates greater opportunities for them compared to higher placed competitors (Bothner et al., 2007).

The broad framework developed in the first chapter can be helpful in understanding the behavior of organizations as their environment, impacted by uncertainty, undergoes a change. The ongoing transition of the automobile industry, from gasoline based engines to alternative propulsion systems such as electric or hydrogen based, can serve as a case for examining the real world application of the framework. The development and increasing economic viability of alternative propulsion systems for automobiles, in a relatively short period, can be argued as an exogenous source of uncertainty in the operating environment for incumbent automakers, whose products are designed primarily to exploit the oil-based energy economy. This is state uncertainty because the future state of the environment is unclear. The underlying uncertainty, in this context, stems from incomplete information about the pace of change, future regulatory support, availability of supporting infrastructure, development of competing technologies and the suitable business models. As a result, consistent with my framework, automakers are investing in R&D and evaluation of alternative technologies which can be constituted as engaging in risk-taking. Additionally, the organizations placing the relatively large bets, accounting for size, are the smaller car companies like Tesla & Faraday Future and those from China, and not the typical industry leaders.

I test these ideas by examining risk taking in Formula 1 car racing both at the race level and at the driver level. I exploit uncertainty brought about by the incidence of rain during races and find that it reduces performance differentials between drivers, leading to increased risk-taking at the race level. Further, during conditions of uncertainty, lower performing drivers engage in greater risk taking compared to higher performing drivers. Therefore, engaging in increased risk-taking is a direct consequence of changes in the competitive landscape, in this case, the competitive crowding around organizations.

Even though the empirical context offers rich data, translating inferences from car racing to the broader business world has generalizability constraints because of the very specific nature of how these races are organized. For example information about how uncertainty impacts a potential competitor might not be known for a while in the real world compared to relatively instantaneously in my context because drivers can observe how other drivers respond. This could influence risk-taking. The primary reason behind risk-taking, according to my framework, is competition between the organizations. The predictions might not apply well in stable and slow moving industries where the competition is not intense. Finally, my empirical context does not focus upon survival concerns of organizations. It could be possible that such concerns might make lower performing organizations more risk averse considering that an unfavorable outcome from risk-taking can have a greater impact on their survival compared to higher performing organizations.

The second chapter in this dissertation explores the effects of uncertainty brought about by an organization's imperfect knowledge of a competitor's innovations and as well as the potential value of its innovations. The uncertainty stems from the unknown value of a competitor's innovation relative to its own. This type of uncertainty is similar to that of effect uncertainty where the lacuna of information plays a role when the focal organization seeks to reposition itself in the competitive landscape. Consistent with localized competition, organizations typically compete with organizations of similar size. Upon developing an innovation of potentially high value in relative terms, organizations might seek to reposition themselves, utilizing the changing relative value of its innovation versus others to occupy better positions in the landscape.

I explore this repositioning through a set of four factors, namely, agglomeration effects, demand highpoints, and gains and loss from innovation in conjunction with the unknown relative value of the innovation of the focal organization. While the effect of each factor is relatively straightforward in isolation, taken together, the outcomes are nonobvious considering the uncertainty. To overcome this and develop a set of predictions for the strategic choices made by organizations, I develop a simulation model for organizations of different sizes, and with differing probability and values of innovation. Organizations choose where to locate in a two-dimensional space with heterogeneous demands to maximize their expected demand. Beyond varied demand, collocated groups of organizations generate demand-agglomeration economies. While this encourages locating adjacent to other organizations, neighboring organizations also compete by taking demand from each other. Larger organizations take more from smaller ones, which discourages smaller organizations from locating adjacent to larger organizations. However, innovations enable organizations to capture even more of competitors' demand, encouraging organizations with innovations to locate near larger organizations more than they otherwise would.

This model of competition led repositioning lends itself well to the examination of choices by organizations in industries, such as the movie industry. The competition landscape in the movie industry is temporal in nature; because of cultural reasons certain times of the year and week experience higher demands than other times, thus representing the demand highpoints of the landscape. As such, we expect movies with valued innovations, such as those with a novel concept or sequel of a proven idea, to release during the temporal highpoints, such as the summer or the holiday season. This represents a repositioning, by the movie studios, to demand highpoints to exploit the novelty of their ideas. The above model can also be applied to the academic world where upon having a high-quality idea, the authors might seek to position their paper towards a higher quality journal, which typically gets higher attention, than the journals the authors would normally publish in. The underlying uncertainty in the above examples results from the lack of information about the relative value of novelty between movies releasing at similar times and between the quality of paper and expectations of the journal.

I test the predictions of the simulation model using empirical data from the trade show booths at the Consumer Electronics Show. The results indicate that upon having an innovation, organizations reposition themselves closer to positions of larger neighbors, who might have innovations of their own. Further, medium sized organizations reposition themselves more significantly than small or large organizations. Fewer repositioning choices constrain smaller organizations and thus exhibit lower levels of repositioning compared to the medium sized organization; while the largest organizations have little to gain from repositioning.

The model detailed in the second chapter, while clear in its predictions, has certain limitations in its applicability. The model applies well in the case of punctuated competition, where organizations compete in distinct cycles rather than continuously. Opportunities for repositioning involving a significant shift which might not be as common, as or relatively low cost in typical business environments. A few of the assumptions in the simulation model could be restrictive for the real world. In the model, I assume that organizations are randomly assigned an innovation, which is probably not the case, especially for the larger organizations which have significant resources. Additionally, I assume a normal distribution as far as size of organizations is concerned. This goes against the left skewed distribution normal observed in any industry. These restrictions negatively impact the generalizability of the model as far as broader uses of it in the real world.

The two chapters focus on two different types of uncertainty: state uncertainty and effect uncertainty. Both of them draw on a similar framework where uncertainty impacts the relative position of organizations in the competitive landscape, which then results in different strategic behaviors by the organizations. Together, the two chapters seek to demonstrate the changing competitive landscape as a mediating mechanism to connect uncertainty and resulting behavioral outcomes.

Chapter 2: Environmental Uncertainty & Competition: Organizational Risk Taking in Formula 1 Racing

2.1 Introduction

Managing uncertainty is one of the fundamental objectives of an organization (Thompson, 1967). To that effect, organizations attempt to reduce their experience of uncertainty by engaging in actions such as bringing changes to their social network (Beckman et al., 2004), altering board interlocks (Martin et al., 2015), or focusing their energies on a single technology (Toh and Kim, 2013). In essence, organizations choose alternatives with a lower variance in outcome during periods of environmental uncertainty. I argue, however, that the existing literature does not fully address the effect of the competitive interactions between organizations during periods of environmental uncertainty. In this paper, I add to our understanding of organizational behavior by arguing that, under conditions of competition and uncertainty, organizations can engage in risk-taking actions that add to, rather than reduce, their experience of uncertainty.

The amount of risk in a decision is directly dependent on the likelihood of adverse versus favorable outcomes and the magnitude of potential loss in the event of an adverse outcome (March and Shapira, 1992; Sitkin and Pablo, 1992). An organization is said to be taking a risk when the decision maker perceives variation in the distribution of possible outcomes, their likelihoods, and their subjective values (March and Shapira, 1987). The underlying idea is that risk involves an inherent variability, though well defined, in the outcome of a decision. Thus, an organization taking a risk in an uncertain environment, potentially adds to the variance of the outcome by compounding risk with environmental uncertainty, thereby increasing the risk associated with such a decision.

Uncertainty about the state of the environment can impact organizational decision-making generally, and specifically regarding the decisions on operational aspects of the organization (Milliken, 1987). Scholars have demonstrated that, on average, uncertainty reduces the performance of organizations, as uncertainty impacts the ability of organizations to make optimal decisions (Bowman, 1980; Bromiley, 1991; Martin et al., 2015). I argue, however, that these reductions in performance are discriminatory in nature since better-performing organizations face a higher decline in performance in absolute terms when compared to lower performing organizations.

The key to understanding the discriminatory reduction in performance is the degree of fit between the structure of the organization and the environment, and how that fit impacts the organizations performance. From the literature on organizational ecology, we know that organizations adapt their structure, aligning it with their environment, they typically operate within, to achieve greater exploitation and higher performance (Hannan and Freeman, 1977). Greater exploitation and resulting higher performance, however, is contingent on the environment remaining stable and aligned with the structure of the organization. Therefore, a shift in the environment as a result of environmental uncertainty negatively impacts the degree of fit between the structures of the organization (Andersen et al., 2007). This shift has a bigger impact on the performance of more organizations with a high initial level of fit, and consequently, they suffer a greater decline in fit compared to organizations with a lower initial level of fit. This, in turn, affects performance differentials between organizations: with a greater decline in fit for organizations having a higher initial level of fit, an overall contraction in performance differentials across organizations occurs.

The lowering of both the mean and the variance of performance across organizations has significant implications for competitive interactions and organizational behavior. The reduction in variance of performance implies that a focal organization now has more organizations performing at a comparable level to it, relative to normal environmental conditions. This contributes to an increase in competitive crowding around the focal organization (Sørensen, 1999; Podolny, 1993). An increase in crowding leads to greater risk-taking as organizations respond to either greater threats to their position in the hierarchy or increased opportunities for advancement (Bothner et al., 2007). Therefore, as environmental uncertainty alters the competitive landscape, I expect to observe an overall increase in risk-taking across organizations.

While an increase in crowding leads to greater risk-taking, uncertainty in the environment also affects the risk-taking behavior of the organizations heterogeneously, conditional on their position in the performance hierarchy. Higher performing organizations, due to a greater reduction in performance, experience higher crowding around them compared to organizations lower in the hierarchy. This would suggest that such organizations should take greater risks to protect their extant position. However, the higher levels of competition, in conjunction with the uncertain environment, lower the chance of successful outcomes from risk taking. This, coupled with the fact that organizations higher in the hierarchy have more to lose from an unsuccessful outcome, suppresses their propensity to take greater risk. In contrast, lower performing organizations not only experience relatively less crowding but also have less to lose and have a higher chance of achieving a successful outcome from risk taking. Therefore, I expect lower performing organizations to take more risk as uncertainty in the environment increases.

Empirically, I test my propositions in the context of Formula-1 car racing using data from the 1995 to 2015 seasons, drawing on a combination of race-level and lap-level information about each drivers performance. The study leverages a natural experiment: whether it rained during a race, which serves as a measure of uncertainty in the racing environment. Rain, by its very nature, is an exogenous and random independent variable that can help to identify the effects of uncertainty clearly. The empirical findings are consistent with my propositions, demonstrating that competitive effects during uncertainty account for why organizations engage in increased risk taking in such situations.

2.2 Theory & Hypothesis

Uncertainty has been a central concept in the organization theory literature, particularly among theories which seek to explain the nature of the relationship between organizations and their environments (Argote, 1982; Thompson, 1967). The characterization of uncertainty in management literature has its origin in Knight (1921) definition of uncertainty, where probabilities of possible future outcomes are unknown. Uncertainty manifests in difficulty predicting future outcomes (Beckman et al., 2004), or more precisely for organizational studies, perceived inability to make accurate predictions. An organization therefore experiences uncertainty because it perceives itself to be lacking sufficient information to predict accurately. This experience of uncertainty can occur in a variety of environmental dimensions including technology (Anderson and Tushman, 2001), politics (Henisz and Delios, 2001), and resource (Delacroix and Swaminathan, 1991).

The underlying mechanisms that explain the effect of uncertainty on organizational performance can be broadly segregated into two streams of decision making and organizational fit with an environment. Uncertainty about the actual state of the environment can negatively impact decision making by organizations, in cases where the state of the environment is a critical factor in the decision, such as investment in new technology (Anderson and Tushman, 2001; Toh and Kim, 2013), or entry into a new market (Dowell and Killaly, 2009). For example, Dowell and

Killaly (2009) argue that resource variation in markets deters entry by new firms. In making the decision whether to commit resources to a market or a new technology, organizations must be able to make a reasonably accurate estimation of the attractiveness of the market or the potential of the technology (Cyert and March, 1963; Mitchell, 1989; Toh and Kim, 2013), and uncertainty impedes arriving at such a decision. Further, from the perspective of bounded rationality, managers have constraints in scanning and interpreting information (March and Simon, 1958). These limits are put under greater stress as the environment turns uncertain, compromising the ability of managers to take effective decisions. The diminished ability to make decisions that have a reasonable level of robustness in their outcomes during conditions of environmental uncertainty may adversely affect the performance of organizations.

From the perspective of fit, organizations strategically align their structure with the environment in which they operate to improve their fit. Environmental fit is a key factor determining organizational performance (Hannan and Freeman, 1977). Any change in the environment can negatively impact the fit, and thus, organizational performance. The greater the deviation from the expected environment, the greater the fall in performance. To avoid the reduction organizations need to adapt to the change in the environment (Andersen et al., 2007). Environmental uncertainty, therefore, negatively impacts organizational performance because it brings about a shift in the environment itself. Additionally, uncertainty about the environment makes it more difficult for organizations to adapt their structure. The first hypothesis, which concerns performance changes in organizations facing uncertainty, follows from the existing research on the mechanisms of decision making and structural fit.

> **Hypothesis 1:** As uncertainty in the environment increases, the performance of the organizations decrease.

The literature on organizational ecology conceptualizes organizations as strategically adapting to the environment to improve survival chances (Hannan and Freeman, 1977) and realize performance gains (Fiegenbaum et al., 1996). Organizations can choose to align their structure either with a broad or a narrow set of environments. Focusing on organizations within the same niche(s), one observes a distribution of organizations with varying degrees of fit. As a consequence, some organizations experience better performance as a result of their higher environmental fit. Such performance, however, is conditional on the environment being within the set of environmental states on which the organizations have modeled their fit. I label the set of such environmental states as the set of optimal states.

As the state of the environment changes due to uncertainty, the resulting state might deviate from the set of states for which the organization initially modeled its structures. A deviation in the environment state, therefore, negatively impacts the level of fit organizations have in the new environmental state. While the existing literature has focused on an average decline in fit for all organizations affected by the deviation, I argue that such a deviation causes a discriminatory reduction in fit for different organizations contingent on their initial level of fit.

Organizations with a higher initial level of fit suffer a greater decline in fit compared to those organizations with a lower initial level of fit. Let us consider a shift in the environment from an optimal state to a hypothetical non-optimal state, distant from the optimal state, in which all organizations have the same near-zero level of fit and thus, a near-zero level of performance. As a result, there is a greater decline in absolute fit for organizations having a higher degree of initial fit compared to organizations with a lower initial level of fit. Thus, for any given state of the environment lying between an optimal state and the distant hypothetical state, the effect would be similar in nature, but with lower reductions in fit. Figure 2.1, which is adapted from (Hannan and Freeman, 1977), provides a visual representation of the above argument. For any state, other than the optimal state, the organizations with higher fit suffer a greater decline due to an overall higher slope of their fit curve.

With the direct relationship between fit and performance, a deviation in the environment state has a negative effect on the performance of organizations (Hannan and Freeman, 1977; Andersen et al., 2007). Paralleling the unequal reductions in fit, organizations with a higher level of initial fit, when compared to those with a lower initial level of fit, suffer a greater decline in performance as a result of a change in the state of the environment. This unequal decline in performance leads to a reduction in the performance differentials between organizations in a non-optimal state.[1]

[1]It could be argued that organizations could adapt to the new state of the environment to avoid a decline in performance. I work with the assumption that organizational structures have high inertia and their pace of change is considerably slower than the pace of change of the environment.

Hypothesis 2: As uncertainty in the environment increases, the performance differentials between organizations decrease.

The concept of niche has been developed to model the structure of competition between organizations (Baum and Mezias, 1992; Greve, 2002; Hannan and Freeman, 1977). According to the concept, organizations within the niche compete primarily with others in the niche, giving rise to the idea of a localized competition (Baum and Mezias, 1992). Analogously, an organization typically competes with other organizations who reside in its performance neighborhood. Thus, higher performing organizations focus their competitive efforts on other higher performing organizations, and likewise, lower performing organizations focus their competitive efforts on other lower performing organizations. Reduction in performance differentials between organizations due to uncertainty modifies this localized structure of competition. Organizations from the neighborhood of lower performance are now competitive with those from the higher performance neighborhood due a greater decline in the performance of higher performing organizations. Further, lowering of performance differentials between organizations from different niches forces these performance neighborhoods to collapse and progressively move towards a single large performance neighborhood. Thus, an organization which initially only competed against and faced competition from organizations in its performance neighborhood, now potentially has to compete against organizations outside its performance neigh-

In the event organizations begin to adapt to the new environment, the effect would hold true till the organizations adapt their structures to the new state. Additionally, the environmental change could also be temporary in nature, and the environment reverts to the original state. In this case, the organizations do not attempt to even adapt to the new environmental state, resulting in declines in organizational performance.

borhood as well.

As the number of organizations in the performance neighborhood of any organization increases, it raises the number of competitors for the focal organization. This increase in the number of potential competitors contributes to competitive crowding around the focal organization (Eriksson, 1999; Bognanno, 2001). An organization experiences crowding from below when lower placed organizations challenge its position in the performance hierarchy. On the other hand, when an organization can potentially challenge higher placed competitors, it experiences crowding from above. Thus, an increase in crowding from below implies a higher risk of positional loss, and an increase in crowding from above connotes an improved opportunity to advance in the performance hierarchy. The level of crowding from below is therefore associated with the risk of loss, and the degree of crowding from above with the opportunity for gain (Bothner et al., 2007).

An increase in crowding is associated with greater risk-taking due to changes in opportunities and threats for the competing organizations. Research across different literature streams provide evidence that increased crowding leads to greater risk-taking. In the context of auctions, Kagel (1995) found that auctions with many bidders are likely to experience increased risky bids that result in an overpayment. At the individual level, Hvide and Kristiansen (2003) find that risk-taking is more likely when more individuals are competing in the system for a limited opportunity. Similarly, at the organizational level, risk taking has been linked to competition among organizations. Bolt and Tieman (2004) find that the intensity of rivalry in the banking industry pushed the participants into risky behavior. The next hypothesis focuses on the positive relationship between uncertainty and risk taking at the environmental level due to increased competitive crowding:

> **Hypothesis 3:** As uncertainty in the environment increases, the degree of risk taking increases.

In addition to expecting an increase in the average level of risk taking, it is important to evaluate possible heterogeneity in risk taking at the organizational level. As discussed earlier, the nature of competitive pressure due to crowding is different for organizations depending on their position in the performance hierarchy. As a result of a greater decline in performance of higher performing organizations, a greater incidence of crowding occurs as we ascend the performance hierarchy. Thus, higher performing organizations face greater crowding both from below and from above compared to lower performing organizations. Following Bothner et al. (2007), this unequal increase in crowding suggests a greater incidence of risk-taking by higher performing organizations compared to those placed lower in the performance hierarchy.

While a greater increase in crowding around organizations with higher performance prompts greater risk taking by them as the environment turns uncertain, factors such as the probability of an unsuccessful outcome and size of the loss in the case of an unsuccessful outcome are also important determinants of the propensity for risk-taking by organizations. The discriminatory decrease in performance of organizations across the hierarchy impacts the probability of success when engaging in risk taking. With the reduction in performance differentials due to uncertainty, higher performing organizations now compete against relatively better-performing competitors. This negatively impacts the probability of success when engaging in risky behavior while competing against them. For lower performing organizations, however, the opposite is true. Lower performance differentials improve a lower performing organizations chances of success when taking a risk compared to when the performance differentials are larger.

The second factor that affects the propensity for risk-taking by organizations is the possible size of the loss if the outcome is unsuccessful. An unsuccessful outcome can potentially lead to a greater penalty for the higher performing organizations by virtue of their higher standing in the performance hierarchy. For organizations lower in the performance order, an unsuccessful outcome has a limited negative effect because of their lower standing. Combining the effects of two factorsgreater probability of an undesirable outcome and greater loss in case of such an outcomewould logically lead higher performing organizations to be more conservative in taking risks compared to lower performing organizations, where both the probability of loss and the possible extent of that loss are lower.

To predict the propensity for risk-taking by various organizations across the performance hierarchy, one must take into consideration the two effects described above. While an increase in crowding would increase the propensity for risk-taking by higher performing organizations compared to lower performing organizations, as the extent of crowding becomes unequal, I posit that it is the lower performing organization who would have a higher propensity for risk-taking due to their lower loss and reduced cost of unsuccessful outcomes. While this prediction might seem inconsistent with what Boyle and Shapira (2012) have to say, it is not. I only hypothesize about the *increase* in propensity for risk-taking under uncertainty rather than actual risk-taking, which is what Boyle and Shapira (2012) focus on in their paper. My final hypothesis relates uncertainty and the risk-taking propensity of organizations across the performance hierarchy:

> **Hypothesis 4:** As uncertainty in the environment increases, lower performing organizations have a greater propensity for risk taking than higher performing organizations.

2.3 Data & Methods

2.3.1 Formula-1 Car Racing Series

To test my predictions, I examine how environmental uncertainty affects the degree of risk taking at the race level and the driver level in the Formula-1 (F-1) racing car series organized by the Federation Internationale de l'Automobile (FIA) from 1995 to 2015 F-1 seasons. I choose this empirical context for a number of reasons. First, unlike similar car racing series such as NASCAR, F-1 allows races to be run even during times of rain, which creates uncertainty for drivers as the weather changes from dry to wet. Second, rain, which by its very nature involves random assignment and random intensity, serves as an exogenous independent variable that allows for clear identification of environmental uncertainty. Third, the evolution of the relative position structure as each season progresses enables me to study changes in risky behavior across different conditions and for organizations at different performance levels. Fourth, although many factors might force a drivers race to end prematurely, the risk of crashing does depend in part on drivers behavior on the track. Finally, the availability of detailed lap-level data allows me to capture the performance of the drivers across multiple points in the race, and to empirically test the various mechanisms. Thus, using F-1 allows me to develop empirical measures of changes in environmental uncertainty, performance differentials across drivers, and risky conduct. The data comes at two levels of detail. While driver-level information for each race is available for all 371 races from 1995 to 2015, lap-level data such as timing and pit stop is available only for the 95 races from 2011 to 2015. The total number of driver-year observations is 7471. The data was obtained from multiple sources, including Formula1.com, wikepedia.com, fan forums, and magazines covering F-1.

2.3.2 Tournament Structure

An F-1 season consists of a series of races in a calendar year. The number of races per season has increased from about 16 in the 1990s to 17 in the 2000s to 19 in the 2010s, with the 2012 season having 20 races. Two world championships run in parallel throughout the season: the FIA Formula 1 World Drivers Championship (WDC) and FIA Formula 1 World Constructors Championship (WCC). The drivers contest the WDC, and the teams compete for the WCC. Around 22-24 drivers, who belong to any of the 11-12 teams participating in the season, participate in a given race. A team typically has more than two drivers, but only a maximum of two from each team can take part in a race. During a season, however, more than two drivers might represent a team; sometimes, due or injury or suspension, teams may field replacement drivers for a portion of the season. I drop all instances of drivers who participated in two or fewer races per season, for the simple reason that replacement drivers have no chance of winning a championship, and hence their incentive structure is different from that of regular drivers. The number of dropped observations is less than 1% of the total sample. The results, however, are robust to the inclusion of this 1%.

Drivers are awarded points depending upon their standing at the end of each race of the season. FIA, the organizers of the F-1 racing series, use the structure of the point system to promote competition and to make the races more exciting for the viewers. The points system, which has undergone a few changes, has largely remained the same regarding payoff structure for the competing drivers. The number of points accrued at each position and the number of drivers winning points, however, has changed several times over the seasons, which affects the degree of convexity of the payoff structure and the incentives drivers face at each position during the race. Since overtaking a competitor entails a significant cost in terms of planning, and/or potentially unfavorable outcomes such as spinning off the track or an accident, the non-linear point structure, by offering disproportionately more points for each improvement in standing in the race, incentivizes drivers to keep competing. Another element of the point system that promotes increased competitive behavior is the fact that not all drivers who finish the race are eligible for points. From the 1990s until 2002, only the top 6 drivers in a race were eligible to receive points, a number increased to the top 8 from 2003 to 2009, and after that, to the top 10 drivers in a race. The sum of the points obtained from standings in each race determine the standings of the drivers for the season. The standings of the teams are arrived at by summing the points obtained by the drivers of each team.

2.3.3 Drivers representing an organization

While F-1 allows for championships at both the team and driver levels, no prize money is allocated to drivers for winning a race or a season. The prize money is distributed to the teams depending on their standings at the end of the season. The teams and the drivers have a symbiotic relationship, providing the infrastructure and other related resources. The drivers are contracted by the teams to drive for them. For many reasons, however, they cannot be classified as a regular employee of the team, such as, say, a pit crew member. First, drivers cannot race independently in F-1, but need to be a part of a team. Second, drivers are paid in tens of millions of dollars[2] much like top level executives of organizations, and are the face of the teams they represent. Third, since each team can only field two drivers in the races, each driver is responsible for on average for half the earnings of the team through their prize money. Additionally, the two drivers compete against each other, and it

[2]Sebastian Vettel is the highest paid Formula 1 driver going into the 2016 F1 season with a record 3 year deal with Ferrari worth $150 million he is also one of the highest paid athlete/sportsmen in the world Source: www.totalsportek.com

is against the rules for teams to order a driver to drive in a way that benefits the other driver of the team. In addition to the prize money, drivers also bring money from sponsors to the team. Finally, even though the team personnel and the driver together decide on their race strategy, it the driver who is the final decision-maker on the track.

Following Boyle and Shapira (2012) who suggest that individuals who need to make nonroutine and high-stake decisions experience conditions faced by managers, I consider drivers equivalent to managers in the setup of F-1. The setting of the tournament context is similar to examples of executives trying to outperform each other for bigger bonuses, or business schools aiming to secure high positions for MBA rankings (Bothner et al., 2007). There is enough evidence from the context to suggest that drivers can be considered like managers of organizations. Therefore, for this study, I consider each driver as a manager and representative of his organization, not as an individual.

2.3.4 Rain Races in F-1

F-1 is different from other racing series, notably NASCAR, in that it allows races to proceed as scheduled even in the event of rain. Compared to a race in dry conditions, rain can alter the competitive landscape in an F-1 race in several ways. First, rain, by causing the track to be wet beyond a certain degree necessitates the use of more suitable rain tires for wet conditions, and can, therefore, require an unplanned pit stop to change the tires. Rain tires provide additional grip in wet conditions, but in dry conditions suffer from performance disadvantages in terms of speed and longevity. Pit stop management is an important part of the overall strategy of a driver coming into the race. An additional pit stop for changing the tires, typically lasting around 7 to 9 seconds, can force the driver to alter his strategy midway through a race, where the average separation between drivers is about 2-3 seconds. Thus, a pit stop impacts the standing of a driver in the race. Second, teams in F-1 design and tune up their cars to achieve the maximum amount of performance in dry conditions. When the race track is wet due to rain, these factors have less effect, leading to a reduction in the degree of fit the various cars have with the wet racing conditions. Thus, rain establishes a more level playing field wherein differences in performance across cars is minimized, and drivers become more competitive against each other. Mark Weber, an F-1 driver talking about rain races commented,"Generally, if you have a McLaren, a Ferrari or a Red Bull, then you like normal Grands Prix. If you have a Force India or a Williams, you want it to rain every race."[3]. Thus, rain brings multiple degrees of uncertainty, impacting reasons one and two described above. More importantly, teams or drivers cannot influence when it rains, making rain both a random and exogenous event.

Rain taking place over the entire duration of the race can have a different impact compared to rain that occurs only at the start of, or during a part of, the race. Rainfall throughout a race minimizes the chances of an additional pit stop needing to be made for the purpose of changing into wet tires since the cars use wet

[3]Source: www.nytimes.com "Wet or Dry? Rain on the Grand Prix Parade Is a Thrill Factor"

tires from the start. Further complexities arise when it rains either before the start of the race, such that the track is already wet when the race starts, or when it rains during a portion of the race. Drivers and their teams need to take into account when the track is wet or dry enough to change from dry tires to wet tires or vice versa. A wrongly-timed or additional pit stop can greatly impact the standing of the driver in the race. Additionally, being on the wrong set of tires can impact both a drivers ability to compete and capacity to stay on the track.

Another factor that adds a layer of uncertainty is the intensity of rain and the behavior of the track. Drivers must constantly evaluate the condition of segments of the race track to determine how fast they can go without losing control of their car. If a driver drives faster than the conditions allow, he risks spinning off the track or even crashing. If he drives slower than the conditions permit, he may be overtaken by other drivers. Thus, being able to figure out the maximum possible speed in a given condition and driving as close to that speed as possible is important for succeeding in a rain race. Rain brings a great of deal of uncertainty to a drivers strategy and on-track performance, and as a result, rain races are considered more exciting and are a favorite with F-1 viewers[4].

Rain thus offers an elegant exogenous variable with a random assignment that impacts the degree of uncertainty in the racing environment. For the purpose of this study, any race is considered to be a rain-affected race that has a wet track at any

[4]In an analysis of user rating by a fansite of the 100 races from 2008-2013, 17 of the 21 wet races from that period appeared in the top 50.

time during the race. Thus, races in which rain occurs before the start of the race, causing a wet track at the commencement of the race, are considered wet races in the sample. Out of the 371 total races from 1995 to 2015, the number of rain races was 61; while from 2011 to 2015, there were 12 rain races out of a total of 95.

2.3.5 Analysis

Re-stating the predictions in the context of F-1 racing, the main hypothesis suggests that there will be more crashes in the rain affected races. The onset of environmental uncertainty will reduce the performance differentials between the drivers, thereby increasing competition between the higher and lower performing drivers. Further, at the driver level, as drivers lower in the standings become more competitive with higher performing drivers, I expect increased risk taking and a higher incidence of crashes as they begin to compete with the better-performing drivers. To test my predictions and the underlying mechanisms, I run my analysis at both the race level and the driver level. Of the dependent and independent variables listed below, some are used in model specifications either at the race or the driver level, while others are used in specifications at both levels.

Predictions for the impact of uncertainty on reduction in performance differentials between competitors, and the resulting increase in risk at the aggregate level are tested at the race level. The model specifications take the following form:

$$(\text{Std. Dev. of Driver Speeds})_{r,t} = \beta_0 + \beta_1 \text{Rain}_{r,t} + \beta_2 (\text{Race Level Controls})_{r,t} + \epsilon_{r,t} \text{ — } (1)$$

The subscript ‘r’ is the race indicator of the season ‘t’ for the panel dataset from year 2011 to 2015. $\epsilon_{i,t}$ is the error term of the model. Lap level data for time taken and pit stop information is only available from 2011 onwards.

(Number of Crashes in the Race)$_{r,t} = \beta_0 + \beta_1$Rain$_{r,t} + \beta_2$(Race Level Controls)$_{r,t}$ + $\epsilon_{i,t}$ — (2)

The subscript ‘r’ is the race indicator of the season ‘t’ for the panel dataset from year 1995 to 2015. $\epsilon_{i,t}$ is the error term of the model.

To examine the effect of performance of the competitors and uncertainty at the driver level, I estimte the following logistic regression specification:

ln(p$_{d,r,t}$ / (1 - p$_{d,r,t}$)) = β_0 + β_1(Season Standing)$_{d,r,t}$ + β_2Rain$_{d,r,t}$ + Rain * β_3(Driver Level Controls)$_{d,r,t}$ + β_4(Race Level Controls)$_{d,r,t}$ + β_5(Circuit Level Controls)$_{d,r,t}$ + $\epsilon_{d,r,t}$ — (3)

As in the previous equations, the subscript ‘r’ is the race indicator of the season ‘t’ while ‘d’ is the driver indicator.

2.3.5.1 Dependent Variables

Risk Taking: I measure driver risk taking by the number of spin-offs or crashes in which they take part. A driver can expose himself to spinning off the track or crashing when he attempts to overtake other drivers. Overtaking is considered to be difficult in F-1[5], but drivers resort to overtaking to advance their standing in the race. Overtaking is made difficult due to narrow racing lines (the part of the race track where drivers normally drive), which makes it possible only on the straight portions of the track or when entering a corner. While trying to overtake another driver on the straightway, a driver can get close to the other car and experience a loss of grip due to turbulence from the car in front of him, potentially causing a crash. Having a noticeably faster car helps in overtaking on the straightaway. While trying to overtake another driver on the corner, drivers typically aim to outbreak the other drivers by braking as late as possible to force the opponent off the racing line and to try and take the inside lane. If the driver outbreaks less than required, he might have less space for making the corner and the inside front wheel might go off the track. If the driver outbreaks more than required, he risks a chance of slipping off the track due to having a higher speed at the corner. Overtaking from the outside has potential hazards of driving over debris, which can cause the driver to lose control and crash into a barrier. I mark all instances when a drivers race ends due to crashing into a barrier or spinning off the track as 1 and 0, respectively.

Overtaking becomes even riskier when the track is wet due to rain. Rain takes away the advantages of higher grip from cars having a better aerodynamic design, which can result in greater performance parity among the cars. The relative absence of performance difference makes it even more challenging to overtake on the straight section of the race track; besides, drivers must contend with the spray coming from

[5] Overtaking is relatively rare in F-1. Overtaking is always closely monitored by the officials and any driver, driving dangerously attracts instant penalty.

the tires of the car in front of them. Uncertainty about the condition of the track makes outbreaking more difficult to execute because the driver is unsure what speed is required to successfully negotiate the corner. Changes in track conditions sometimes push drivers to make an unscheduled pit stop to change tires, causing them to drop in race standings and sometimes attempt a risky overtake to advance their position.

Mean Performance of Drivers in a Race: I use data from 2011 to 2015, which includes lap level information such as lap time and laps when a pit stop was taken, to calculate the average performance of the drivers in the race. Using lap timing data and the length of the track, I get the speed of each driver for each of the laps he completes in the race. To get average performance at the race level, I take the average of all lap speeds for all the drivers in a given race. There are two factors which might have a downward bias on speed in a rain race: additional pit stops and safety car deployments. To account for the possible higher number of pit stops taken in rain races, I drop all the laps in which a pit stop was made by a driver. The deployment of the safety car also impacts the lap timing of the drivers, as the speed of the drivers is constrained by the speed of the safety car. To make sure that the measure for average performance is not biased because the safety car is deployed more in rain races, I also drop all the laps during which a safety car was on track. The speed of the driver is calculated in miles/hr.

Performance Differential between Drivers: To measure performance differentials between drivers, I make use of lap level information as described above.

I calculate the speed of the driver for each lap he completes in a race. I drop observations for laps in which a pit stop was made, or the deployment of a safety car affected it. I then get the standard deviation of all lap speeds of all drivers in a given race to arrive at the performance differential between drivers in a race.

2.3.5.2 Independent Variables

Season Standing of the Driver: Season standing captures the current position of the driver. Taking into account points earned for all the races held in the season before the start of the focal race. Drivers before their first start in the season have no standing. Therefore, all observations of the first race of the season and that of the first appearance in the season are dropped. Season standing of a driver can influence his propensity for risky behavior. Drivers who are high in the season standings aim to keep their position to aid their chances of winning the drivers championship and their teams chances of winning the constructors championship. Additionally, in dry races, drivers higher in the season standings typically face competition only from drivers close to them in the standings, since differences in car performance do not allow drivers lower in the standings to compete effectively with drivers with better cars. Thus, in dry races I expect risk-taking to be concentrated among drivers higher in the season standings. This risk-taking, however, is projected to change in a rain-affected race, where rain reduces performance differentials between drivers. In a rain race, lower performing drivers can compete more efficiently with higher performing drivers; I expect an increase in risk taking by the lower performing drivers, leading to similar levels of risk taking for drivers across the standing.

Champion Decided: The primary motivation behind a driver taking risk stems from the desire to win. The drivers championship represents the ultimate goal for any driver participating in the season. Winning a championship can bestow non-pecuniary benefits such as fame and recognition that are important to individuals (Sauer, 2007), apart from monetary incentives resulting from bonuses and better contract terms in the future. A driver winning the drivers championship can negatively impact the motivation of the other drivers aiming to win the championship . I expect risk taking by drivers to come down in races after the champion has already been decided. A season being decided represents a substantial lowering in competitive pressure on the drivers. Post-champion being decided, with lower competitive pressures, I expect drivers to turn risk averse in uncertain environments, in agreement with existing theory.

Driver Controls: A drivers innate tendency to take a risk during a race can affect the number of crashes in which he is involved. Research from the psychology literature indicates that such tendencies can be influenced by the underlying personality of the driver, such as a penchant for sensation-seeking (Rolison and Scherman, 2003). For testing hypothesis 4, which examines risk-taking at the driver level, I control for individual drivers to allow for intercepts to vary by the individuals style of driving, temperament, and attitude toward risk. Using a fixed effects specification constrains the estimates to reflect the consequences of within-driver changes in covariate values on the odds of crashing.

The number of crashes a driver is involved in speaks to the innate tendency of the driver to take a risk. I control for the aggregate number of crashes a driver has experienced in the current season before the start of any race. This number is updated after every race in a season. Having controlled for individual driver tendencies, every subsequent crash a driver is a part of should force the driver to be more careful and learn from the incidents. Experiencing a crash causes the driver to slide down in the season standings, and also exposes him to possible injury or even death. Thus, I expect the number of prior crashes to negatively affect the probability of crashes after controlling for driver fixed effects.

Other driver characteristics I control for are driver age, and driver experience, in terms of the number of races a driver has participated in. I expect both experience and age to lower the probability of crashing. Additional experience helps to fine tune a drivers skill and prepares him to better negotiate uncertainty. Older drivers tend to be more mature compared to younger drivers, and studies have tied risk taking to youth (Kweon and Kockelman, 2001; Vroom and Pahl, 1971).

I also adjust for a drivers position on the starting grid. Drivers participate in multiple stages of qualifying to determine the order in which they line up for the start of the race. The driver with the fastest timing in the qualifying gets to line up at the top of the grid, with the inside track giving him a starting advantage. Drivers starting from further behind may need to take additional risk to advance their standing in the race. I expect increased risk taking by drivers as their starting position slides down the grid.

Team Controls: In F-1, each driver, belongs to a team since independent drivers are not allowed to participate. While there are championships for the drivers as well as the constructors, only the constructors win prize money at the end of the season. The drivers are contracted by the teams much like soccer teams contract their players. The teams invest money and resources into improving the cars and setting up the support staff for the drivers. Teams also decide on race strategies with their drivers. Needless to say, teams play a major role in their drivers' performance. A driver can also take a risk either to maintain the standing of the team or try to improve it. To control for unobserved traits of the teams, I use fixed effects for each of the teams. I also control for the current season standing of the drivers teams to capture the effect of the performance of the team on driver crashes.

Race Controls: F-1 holds races across a variety of tracks around in the world in different conditions. The circuit in Monza, Italy has been in use since the 1950s. Singapore, on the other hand, has a street circuit, and the race is held under lights. The designs of the various races vary considerably, offering different opportunities for overtaking and taking advantages of a faster car. The specifics of the track can impact the risk-taking behavior of the drivers. I control for individual track level effects in my specifications.

I control for three related variables at the race level: The number of turns in the track, the length of the track, and the total distance of the race. The drivers can experience up to 3.5G of force while negotiating a turn as they reduce their speed from 185 miles/hr to about 60 miles/hr within 3 seconds[6]. Negotiating a turn takes an enormous amount of physical toll on the body, especially on the neck. Track with more and sharper turns exhaust a driver more quickly, leading to a potential crash. On the other hand, longer races allow drivers more time to compete without being forced to rush into a risky decision. Longer races also help spread out the field, which reduces competitive interactions between the drivers, thereby lowering the chances of a crash.

The length of the race track, on the other hand, has the opposite effect. Longer tracks allow for more space and thereby drive down congestion. Shorter tracks, on the other hand, pit drivers more closely, increasing the chances of a crash. Increased congestion can take maneuvering space away from a driver trying to avoid a crash. Short tracks also place increased demands on the drivers body since the driver has to negotiate turns with reduced time intervals. Another factor that can increase congestion is the number of drivers participating in the race. The number of drivers in a race can vary due to the number of teams competing in the season, driver disqualification, or the failure of some drivers to qualify for the race. The greater the number of drivers participating in a race. The more competition an individual driver faces. Besides, more drivers mean less space on the track for each driver,

[6] "The vast loadings that Formula One cars are capable of creating, anything up to a sustained 3.5 g of cornering force, for example, means drivers have to be enormously strong to be able to last for full race distances". Source: www.formula1.com

which increases the chances of a crash.

Temporal Controls: In addition to the driver, constructor, round, and race level controls, I account for changes in the points structure, the number of competing teams, rule changes from season to season, and changes in technology across season by means of time fixed effects. Since the F-1 season begins and ends in the same calendar year, I use calendar years to control for temporal changes across seasons. Within a season, I also control for the order in which a particular race is held, i.e. the round.

2.4 Results

The empirical analysis as described earlier is carried out both at the aggregate level, which is the race, and at the organization level, which pertains to the driver. The lap level data is available only between 2011 and 2015; therefore, the analysis using performance-related measures such as mean and standard deviation of performance is based on this sub-sample. For the rest of the other analysis, I use the full dataset from 1995 to 2015.

Table 2.1 contains the summary statistics from 1995 to 2015, covering a total of 371 races of which 16.4% were rain affected. This is greater than the 12.6% of races affected by rain in the smaller sample of 95 races from 2011 to 2015, descriptive statistics of which are provided in Table 2.2. Table 2.2 shows the distribution of wet and dry races across the various seasons in the sample data. From Table 2.3, the number of driver starts ending in a crash in the final sample is 11.2%. This is greater than 9.7% in the actual sample, without the removal of first round races, which typically have a lower crash rate.

Table 2.4 provides the correlation measures between variables in the smaller sample, whereas Table 2.5 provide the correlation statistics for the larger sample. As expected, the correlations between age and driver experience are quite high. To avoid issues of multicollinearity, I use driver experience in terms of races to capture the effect of these variables. The correlation between season standing of the driver and rank of the team is positive by construction since team rank is a direct result of the performance of the drivers on the team. I use mean adjusted variables to reduce the effect of high correlation. The variable inflation factor is less than 10. A similar process is followed for grid position and driver standing. The results of the main variables are robust to the inclusion of these variables.

To test whether the baseline hypothesis, i.e. Hypothesis 1, holds in my empirical data, I examine the effect of rain on mean performance by drivers at the race level. Table 2.6 contains results from the estimation. Models 1 - 3 are specifications containing only the control variables while model 4 is the full specification model. Model 4 allows us to examine the effect of round and various circuit parameters on the performance of drivers. Model 6 controls for both round and circuit characteristics and is a more restrictive version of Model 4. The coefficient for *rain* is highly significant and negative in nature, which strongly suggests that uncertainty does, in fact, lead to a reduction in mean performance of competitors at the system level, which here is the race, lending support to hypothesis 1. The reduction of approximately 11.9 Miles per hour represents a decline of around 9.6% in average speed of the drivers. While the coefficient for the *number of drivers* in the race is insignificantly different from zero, the sign follows expectations. The coefficients for *round*, *circuit* and *race length* as well as the numbers of turns are all significant at various levels with expected signs. Longer circuits typically have longer straights, which contribute to higher speeds and also give more space to drivers to drive with less congestion. An increasing number of turns do force drivers to slow down, often reducing their speed.

I test the effect of uncertainty on performance differentials across organizations, and across various specifications, in Table 2.7. Similar to Table 2.6, models 1 - 3 are control only, while model 4 is the full specification model. Model 6 has fixed effects for both round and circuit characteristics. The significant and negative coefficient of *rain* in models 4, 5, and 6 allow me to reject the null hypothesis and claim support for hypothesis 2. Rain forces drivers to lower their speed to safe levels. Since the faster drivers typically drive at a much higher speed compared to the safe speed in the rain, they have to lower their speed by a larger amount than the slower drivers. Longer circuits provide more space to the drivers to allow more separation. The effect of the number of *turns* in the circuit is highly significant and negative; this is expected since turns act as speed barriers, and having a greater number of them impede the cars from reaching higher speeds and lower the separation between drivers.

The support for the baseline hypothesis 1 and hypothesis 2 together provide us the evidence that during uncertainty organizations have reduced performance on average with the difference in their performance shrinking. Finally, to test the effect of uncertainty on risk taking, I run specifications, results of which are presented in Table 2.8. Models 1 - 3 are the specifications with all controls. The significant and positive coefficient of *rain* across models 4 - 7 suggests increased risk taking in an uncertain environment by organizations, thereby lending support to hypothesis 3. The signs of coefficients of *number of drivers*, *circuit length* and *race length* all are according to expectations. The coefficient for race length is significant and suggests that longer races do help in spreading out the field and not pushing drivers to take risky decisions.

The coefficients of *Champion decided* and *Rain * Champion Decided* merit a detailed discussion. The signs of both these set of coefficients are negative in nature and are in line with expectations that drivers have less motivation and competition after a championship is decided. While determining a champion effects all drivers in general, it significantly affects the behavior of drivers who were in the running for the championship. Estimating the results of the same models on a sub-sample containing the top 50% drivers shows a more significant result. The coefficient of *Rain x Champion Decided* represents risk-taking in the rain affected races where the championship has been decided compared to rain affected races before the championship has been decided. The negative coefficient suggests that even in the rain affected races drivers turn risk averse once the championship has been decided, in line with the existing theory that predicts conservative behavior in uncertain environments. The coefficient turns significant using a sub-sample of only the top-half of the drivers.

Hypothesis 4 compares risk taking by higher and lower performing organizations. To test hypothesis 4, I run model specifications, the results of which are presented in Table 2.9. The models contain the interaction effect of *rain* with the *season standing* as well as with the control variables. Model 5 and 6 help us examine the effects of position in the hierarchy and uncertainty on risk taking. The coefficient of *season standing* is significant and negative in nature, suggesting that in non-rain races, higher performing drivers take more risk. This is expected since there is a high correlation between season standing and standing in individual races. Drivers earn points only when they finish in the top half, and therefore drivers have a greater incentive to take a risk when they are in contention for points. Additionally, lower performing drivers are not able to compete with higher performing drivers in dry conditions and therefore are rarely in contention for points, which accounts for their low-risk taking. While it might be argued that lower performing drivers have nothing to lose and everything to gain from taking a risk, being involved in a crash does have its negative effects. Not only are there chances of injury and possible loss of participation in future races, but the reputation of a driver might also suffer, hampering his chances of a getting a better contract in the future. The coefficient for *rain* ran along expected lines and was similar to its effect on the results discussed above.

The coefficient for the interaction variable *season standing * rain* is significant and positive. This suggests that as conditions change to rain, lower performing drivers take more risk than higher performing drivers, providing support to hypothesis 4 which states that lower performing organizations take more risk as uncertainty increases. The coefficients of some of the control variable demand attention. The coefficient for *grid*, which represents the starting position at the time of the race, is positive for dry races but reduces for rain affect races, suggesting that during rain races the starting grid position does not matter as much. A better comparison between the coefficients of the variables in dry- and rain-affected races can be made in Table 2.10, which is discussed in the robustness section.

2.4.1 Robustness Checks

I evaluate a variety of alternative specifications to test whether the empirical results are robust to different setups. I test for robustness of the results for hypothesis 3 by using negative binomial models in addition to OLS specification. I get consistent results for the same. To test the robustness of results for hypothesis 4 in Table 2.9, I test a different set of models in addition to the variation in models as described above. To examine how risk taking varies with performance level, I split the sample by rain, and use indicators of the season standing of drivers according to their position in the top, second, third, or last quarter instead of individual standings. The results are presented in Table 2.10. Models 1 - 4 use observations only from the dry races while models 5 - 8 use observations from the rain affected races.

We can observe that the coefficient of indicators for the third and last quarter are significant for dry races, suggesting that drivers in the lower half of the standing take less risk than those in the top half of the standing. This difference in risk taking goes away in the case of rain affected races where risk-taking is similar across the driver standing in various quarters. This result strongly suggests that as a result of the reduction in performance differential between drivers, the drivers are competing with drivers across the performance spectrum rather than competing with drivers in their performance neighborhood. This can also be seen in Figure 2.3, where during rain races, there is perceptually no difference in risk taking between higher and lower performing drivers when compared to the curve of the dry races.

Comparing the coefficients of control variables across the two sub-samples highlights the difference in the effect of the various variables as the environment changes. While drivers starting behind in grid position take more risks in dry races, grid position does not seem to matter in rain races. Additionally, the effect of the prior number of crashes in the season does not seem to have an effect on the risk-taking behavior of drivers in rain races, suggesting the influence of reduction in performance differentials on the risk taking of drivers. The lower performing drivers sense an opportunity to compete better, and thus, possibly disregard their earlier instances of crashes. Finally, the effect of the race length, which in dry races allows for creations of separation on the track between drivers, goes away in rain races, indicating the loss in advantage for faster cars in rain races. The coefficients of other variables such as *age, team performance*, and *champion decided* seem to be in line with expectations.

As I described earlier, braking in F1 plays a major role in that drivers attempt to overtake each other by outbreaking their competitors. Brakes of the cars work under tremendous stress as cars decelerate from nearly 200 miles per hour to 60 miles per hour in under 3 seconds. Drivers have to be careful how they use their brakes, as a failure can lead to a premature end to their participation in the race. As a result, I use the amount of brake failure as an alternate dependent variable. The results are similar in nature to what I obtained earlier.

2.4.2 Addressing the confounding effect of rain

Legitimate concerns can arise due to the incidence of rain as a proxy for environmental uncertainty, with crashes being a measure for risk taking. It can be argued that it is the bad conditions as a result of rain, and not competition, which contributes to increased risk taking by drivers. I provide a couple of pieces of empirical evidence showing that it is primarily the increase in competitive crowding that inspires increased risk taking by drivers. As explained earlier, winning the championship is the primary objective of any driver in the competition. When a championship winner has been decided, the other drivers, who could have won the championship, have less of an incentive to continue competing, which would be reflected in a lower incidence of risk-taking. The consistent negative coefficient of *champion decided* across the models provides a general evidence to that effect.

The coefficient of *champion decided * rain* in Table 2.9 provides further evidence that drivers turn cautious in the rain and take less risk once a championship has been decided. One point of note here is that the championship being decided has much less significance to drivers in the lower half of the performance hierarchy than in the upper half. This is the primary reason behind the low significance level of these coefficients. I run the same analysis as in Table 2.9 with only the top-half and top-quarter of performing drivers in the sample. The effect is consistent and statistically significant and provides evidence that the increased risk-taking is a result of increased crowding and not the result of rain. Table 2.8 provides additional evidence of the same. Rain does have an effect on the number of crashes once the season has been decided. A similar inferences can be drawn from Figure 2.3 in which the effect of rain on risk taking is dissimilar across the position standing after accounting for individual driver effects.

2.5 Discussion

In this study, I investigate how uncertainty and competition affect risk taking by organizations. I argue that uncertainty not only reduces the mean performance of organizations but that higher and lower performing organizations experience differential amounts of performance reduction, with higher performing organizations experiencing greater declines. This leads to an increase in competitive crowding around organizations, which in turn encourages organizations to engage in greater risk taking. The extent of risk-taking is expected to differ for higher and lower performing organizations, with higher performing organizations taking less risk. Consistent with these expectations, my results indicate that, on average, greater risk occurs in uncertain environments; and differentiating among organizations, that lower performing organizations take more risk than higher performing ones.

The findings have important implications. First, the findings show that there is a contraction in performance differentials across organizations as uncertainty increases. The fact that better performing organizations lose their traditional advantage over competitors in uncertain environments should be concerning to the market leaders. On the other hand, market challengers can view uncertainty as an opportunity to compete and challenge the market leaders. The creation of a more level playing field has consequences for competitive interactions between organizations. As organizations compete with others, settling on a stable strategy becomes difficult and puts a strain on the cognitive resources of managers.

Second, the evidence for increased risk taking during uncertainty has important implications for managerial decision making. Organizations commonly engage in risk taking to make up for performance shortfalls (Lehman and Hahn, 2013) or to keep up with their peers. An important consideration, however, is the cost of risk taking and the potential consequences of unfavorable outcomes. Risk taking typically pushes organizations to undertake activities outside their normal purview. While activities such as investment in new technology and entry into new markets are important for growth and survival, engaging in such activities as a quick reaction to the sudden emergence of an opportunity or threat can have potentially negative consequences. Uncertainty creates an opportunity to engage in risk taking for potential gains but is accompanied by a high probability of an unfavorable outcome. Managers must be cognizant of such tradeoffs when responding to uncertainty.

Finally, this study has important implications for organizational adaptation and fit. With environments regularly buffeted by technological and political change, followed by periods of uncertainty, managers of lower performing organizations should leverage these periods of uncertainty to become more competitive with better-established rivals. However, they must also learn to capitalize on such opportunities by holding onto the gains made during the period of uncertainty once the environment stabilizes. Higher performing organizations need to be adaptive to avoid being challenged by lower performing organizations during a period of environmental uncertainty. This brings us to the core concept of organizational fit. Having the ability to adapt to changing environmental conditions is essential for both the short term and long term performance of an organization (Lengnick-Hall and E., 2005)). What starts as a temporary disadvantage and advantage for both high and low performing organizations, can become more sustained depending upon their ability to adapt and reconfigure their fit with the environment.

Table 2.1: Summary Statistics of Races from 1995 to 2015

Statistic	N	Mean	St. Dev.	Min	Max
Crashes	371	2.491	2.357	0	13
Rain	371	0.164	0.371	0	1
Year	371	2,005.334	6.074	1,995	2,015
Champion Decided	371	0.075	0.265	0	1
Round	371	9.375	5.170	1	20
Num Drivers	371	21.752	1.533	18	26
Circuit Length	371	3.133	0.514	2.075	4.356
Race Distance	371	189.451	15.242	106.861	226.891
Turns	371	16.221	2.858	9	25

Table 2.2: Summary Statistics of Races from 2011 to 2015

Statistic	N	Mean	St. Dev.	Min	Max
Crashes	95	1.516	1.590	0	6
Rain	95	0.126	0.334	0	1
Std. Dev Speed	95	3.590	0.813	1.450	5.425
Average Speed (M/hr)	95	116.852	12.829	85.581	144.571
Year	95	2,012.979	1.422	2,011	2,015
Champion Decided	95	0.105	0.309	0	1
Round	95	10.021	5.541	1	20
Num Drivers	95	22.295	1.630	18	24
Circuit Length	95	3.238	0.491	2.075	4.356
Race Distance	95	189.164	7.431	158.898	193.415
Turns	95	16.947	3.227	9	25

Table 2.3: Summary Statistics of Driver Level Observations

Statistic	N	Mean	St. Dev.	Min	Max
Crashes	7,471	0.112	0.315	0	1
Season Standing	7,471	11.540	6.565	1	27
Rain Race	7,471	0.174	0.379	0	1
Prior Crashes	7,471	0.954	1.133	0	8
Grid Position	7,471	11.289	6.347	0	26
Driver Age	7,471	28.556	4.596	17.492	43.893
Driver Exp	7,471	81.111	69.008	1	325
Year	7,471	2,005.383	6.103	1,995	2,015
Team Rank	7,471	5.929	3.169	1	13
Champion Decided	7,471	0.077	0.267	0	1
Round	7,471	9.828	4.887	2	20
Num Drivers	7,471	21.849	1.515	18	26
Length	7,471	3.126	0.527	2.075	4.356
Race Dist	7,471	189.466	15.522	106.861	226.891
Turns	7,471	16.255	2.938	9	25

Table 2.4: Correlation Matrix of Race Level Variables from 1995 to 2015

	Variables	1	2	3	4	5	6	7	8	9
1	Crashes	1								
2	Rain	0.291	1							
3	Year	-0.353	-0.064	1						
4	Champion Decided	-0.103	-0.072	0.05	1					
5	Round	-0.069	0.01	0.095	0.398	1				
6	Num Drivers	0.156	0.077	-0.056	-0.107	-0.074	1			
7	Circuit Length	-0.113	0.065	0.152	0.091	0.204	-0.007	1		
8	Race Distance	-0.172	-0.025	0.001	0.015	0.098	0.002	0.365	1	
9	Turns	0.009	0.05	0.167	0.028	0.116	0.04	0.193	-0.053	1

Table 2.5: Correlation Matrix of Driver Level Variables from 1995 to 2015

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Crashes	1														
2	Season Standing	0.045	1													
3	Rain Race	0.107	0.01	1												
4	Prior Crashes	0.051	0.174	0.023	1											
5	Grid Position	0.06	0.72	0.013	0.1	1										
6	Driver Age	-0.015	-0.123	0.002	-0.011	-0.101	1									
7	Driver Exp	-0.076	-0.355	-0.016	-0.125	-0.309	0.771	1								
8	Year	-0.119	-0.003	-0.067	-0.228	0.007	-0.076	0.193	1							
9	Team Rank	0.06	0.853	0.011	0.112	0.739	-0.137	-0.352	0.002	1						
10	Champion Decided	-0.036	0	-0.076	0.103	-0.012	-0.003	0.036	0.054	-0.014	1					
11	Round	-0.017	0.024	-0.021	0.4	-0.011	0.019	0.08	0.107	-0.008	0.401	1				
12	Num Drivers	0.027	0.108	0.089	-0.034	0.116	0.046	-0.049	-0.016	0.117	-0.108	-0.072	1			
13	Length	-0.04	0.012	0.072	0.086	0.003	-0.006	0.039	0.153	0	0.093	0.256	0	1		
14	Race Dist	-0.067	0.004	-0.022	0.05	-0.001	0.007	0.009	0.002	0	0.012	0.107	0.007	0.372	1	
15	Turns	0.004	0.006	0.046	-0.017	0.005	-0.003	0.036	0.169	0.006	0.029	0.114	0.056	0.195	-0.056	1

Table 2.6: Effect of Uncertainty on Mean Performance in Races

	Dependent variable:					
	Average Performance of Teams in Race (Avg Speed (M per hr))					
	(1)	(2)	(3)	(4)	(5)	(6)
Drivers in Race	−0.145	−1.504	−1.479	−0.856	0.596	−0.261
	(2.552)	(1.399)	(1.351)	(1.184)	(1.052)	(0.944)
Circuit Length		16.771***	16.721***	16.943***	20.148***	
		(1.835)	(1.771)	(1.546)	(1.953)	
Race Length		0.248**	0.212*	0.193*	0.459***	
		(0.121)	(0.118)	(0.103)	(0.161)	
Turns		−2.209***	−2.412***	−2.506***	−2.674***	
		(0.245)	(0.248)	(0.217)	(0.198)	
Round			0.368***	0.416***		
			(0.136)	(0.119)		
Rain				−10.111***	−9.667***	−11.948***
				(1.921)	(1.908)	(1.708)
Constant	119.739*	88.366**	94.582**	86.317**	−0.051	130.485***
	(60.913)	(41.131)	(39.768)	(34.724)	(42.337)	(21.876)
FE: Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Round	No	No	No	No	Yes	Yes
FE: Circuits	No	No	No	No	No	Yes
Observations	95	95	95	95	95	95
R^2	0.004	0.717	0.739	0.804	0.907	0.953
Adjusted R^2	−0.052	0.691	0.712	0.781	0.867	0.914

Note: Significance: *p<0.1; **p<0.05; ***p<0.01 :: Two tailed SE in parenthesis

Table 2.7: Effect of Uncertainty on SD of Performance in Races

	Dependent variable:					
	SD of Performance of Drivers in Race (SD Speed)					
	(1)	(2)	(3)	(4)	(5)	(6)
Drivers in Race	0.160	0.150	0.151	0.178	0.078	0.069
	(0.150)	(0.142)	(0.143)	(0.141)	(0.136)	(0.130)
Circuit Length		0.454^{**}	0.453^{**}	0.463^{**}	0.355	
		(0.187)	(0.187)	(0.184)	(0.253)	
Race Length		0.014	0.013	0.012	0.002	
		(0.012)	(0.012)	(0.012)	(0.021)	
Turns		−0.031	−0.036	−0.040	-0.069^{***}	
		(0.025)	(0.026)	(0.026)	(0.026)	
Round			0.009	0.012		
			(0.014)	(0.014)		
Rain				-0.451^{*}	-0.723^{***}	-0.798^{***}
				(0.229)	(0.247)	(0.235)
Constant	0.231	−3.110	−2.952	−3.321	1.480	2.279
	(3.591)	(4.186)	(4.207)	(4.141)	(5.477)	(3.004)
FE: Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Round	No	No	No	No	Yes	Yes
FE: Circuits	No	No	No	No	No	Yes
Observations	95	95	95	95	95	95
R^2	0.138	0.270	0.274	0.306	0.612	0.780
Adjusted R^2	0.089	0.202	0.197	0.223	0.447	0.595

Note: Significance: *p<0.1; **p<0.05; ***p<0.01 :: Two tailed SE in parenthesis

Table 2.8: Effect of Uncertainty on Risk Taking At Race Level

	Dependent variable:						
	Risk Taking(Number of Crashes)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Drivers in Race	0.314	0.338	0.332	0.337	0.347*	0.312	0.305
	(0.212)	(0.209)	(0.218)	(0.210)	(0.210)	(0.208)	(0.206)
Circuit Length		−0.025	−0.021	−0.131	−0.143		
		(0.246)	(0.249)	(0.240)	(0.241)		
Race Length		−0.026***	−0.026***	−0.024***	−0.024***		
		(0.008)	(0.008)	(0.008)	(0.008)		
Turns		0.039	0.039	0.033	0.032		
		(0.041)	(0.042)	(0.040)	(0.040)		
Round			−0.002	−0.002	0.002	0.011	
			(0.023)	(0.023)	(0.025)	(0.042)	
Rain				1.616***	1.668***	1.805***	1.807***
				(0.304)	(0.310)	(0.313)	(0.313)
Champion Decided					−0.079	−0.072	−0.022
					(0.512)	(0.546)	(0.511)
Rain x Champion Decided					−1.640	−2.749*	−2.746*
					(1.603)	(1.665)	(1.663)
Constant	−3.181	0.623	0.764	0.146	−0.124	−2.545	−2.372
	(5.239)	(5.406)	(5.603)	(5.394)	(5.406)	(5.220)	(5.172)
FE: Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Round	No	No	No	No	No	Yes	Yes
FE: Circuits	No	No	No	No	No	No	Yes
Observations	371	371	371	371	371	371	371
R^2	0.173	0.205	0.205	0.266	0.268	0.382	0.382
Adjusted R^2	0.124	0.150	0.147	0.210	0.208	0.265	0.267

Note: Significance: *p<0.1; **p<0.05; ***p<0.01 :: Two tailed SE in parenthesis

Table 2.9: Effect of Uncertainty on Risk Taking At Driver Level

	Dependent variable:					
	Crash					
	(1)	(2)	(3)	(4)	(5)	(6)
Grid Position	0.027***	0.019*	0.019*	0.019*	0.025**	0.024**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
Prior Crashes	−0.234***	−0.237***	−0.237***	−0.238***	−0.217***	−0.180***
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.045)
Driver Exp	0.002	0.002	0.002	0.002	0.001	0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Team Rank		0.065**	0.066**	0.066**	0.151***	0.150***
		(0.027)	(0.027)	(0.027)	(0.033)	(0.032)
Num Drivers		0.088	0.089	0.092	0.094	0.054
		(0.094)	(0.097)	(0.097)	(0.097)	(0.093)
Rain			0.794***	0.810***	0.798***	0.881***
			(0.105)	(0.106)	(0.106)	(0.104)
Champion Decided				−0.028		0.019
				(0.257)		(0.226)
Season Standing					−0.076***	−0.074***
					(0.015)	(0.015)
Champion Decided x Rain				−1.035		−1.159*
				(0.721)		(0.701)
Season Standing x Rain					0.033**	0.032**
					(0.015)	(0.015)
Constant	−0.297	−2.486	−2.994	−3.071	−4.370*	−2.640
	(1.065)	(2.543)	(2.619)	(2.621)	(2.639)	(2.517)
FE: Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Circuits	Yes	Yes	Yes	Yes	Yes	Yes
FE: Round	Yes	Yes	Yes	Yes	Yes	Yes
FE: Team	Yes	Yes	Yes	Yes	Yes	Yes
FE: Driver	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,471	7,471	7,471	7,471	7,471	7,471
Log Likelihood	−2,258.446	−2,255.125	−2,227.118	−2,225.716	−2,213.982	−2,206.834
Note:	Significance: *p<0.1; **p<0.05; ***p<0.01 Standard Error Clustered at the Race Level					

Table 2.10: Using driver standing in terms of Quarters – DRY RACES (1-4) vs WET RACES (5-8)

	Dependent variable:							
	Crash							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Quarter	0.020	0.021	0.020	0.017	−0.133	−0.121	−0.099	−0.116
	(0.177)	(0.176)	(0.176)	(0.175)	(0.374)	(0.366)	(0.365)	(0.353)
Third Quarter	−0.550**	−0.554**	−0.551**	−0.549**	−0.353	−0.338	−0.340	−0.299
	(0.232)	(0.232)	(0.231)	(0.231)	(0.456)	(0.445)	(0.442)	(0.429)
Last Quarter	−0.647**	−0.644**	−0.634**	−0.645**	−0.336	−0.373	−0.275	−0.348
	(0.281)	(0.281)	(0.278)	(0.278)	(0.554)	(0.540)	(0.535)	(0.518)
Prior Crashes	−0.193***	−0.200***	−0.216***	−0.223***	−0.165	−0.171	−0.175	−0.225**
	(0.056)	(0.056)	(0.055)	(0.055)	(0.110)	(0.108)	(0.108)	(0.104)
Grid Position	0.033***	0.033***	0.034***	0.034***	−0.010	−0.011	−0.012	−0.008
	(0.012)	(0.012)	(0.012)	(0.012)	(0.025)	(0.025)	(0.024)	(0.024)
Driver Exp	0.002	0.002	0.002	0.002	0.008	0.008	0.008	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.012)	(0.012)	(0.012)	(0.011)
Team Rank	0.084**	0.084**	0.086**	0.084**	0.207***	0.206***	0.200***	0.194***
	(0.038)	(0.038)	(0.037)	(0.037)	(0.068)	(0.067)	(0.067)	(0.065)
Champion Decided	−0.352	−0.386	−0.170	−0.186	−2.927	1.047	0.606	−0.191
	(0.270)	(0.258)	(0.237)	(0.228)	(2.367)	(1.007)	(0.888)	(0.787)
Round		0.104		0.106**		−0.943*		0.155
		(0.124)		(0.050)		(0.508)		(0.123)
Num Drivers	0.034	0.027	0.149	0.114	29.151	−0.649	−0.165	−0.154
	(0.109)	(0.105)	(0.102)	(0.100)	(1,562.346)	(0.764)	(0.433)	(0.305)
Race Distance			−0.008**	−0.011***			−0.007	−0.002
			(0.003)	(0.003)			(0.008)	(0.006)
Constant	−1.303	−1.442	−4.300	−2.825	−699.061	17.241	8.093	3.214
	(2.986)	(2.886)	(2.819)	(2.739)	(37,496.310)	(18.417)	(11.566)	(8.169)
FE: Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Circuits	Yes	Yes	No	No	Yes	Yes	No	No
FE: Round	Yes	No	Yes	No	Yes	No	Yes	No
FE: Constructor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Driver	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,169	6,169	6,169	6,169	1,306	1,306	1,306	1,306
Log Likelihood	−1,691.384	−1,702.122	−1,727.783	−1,754.886	−438.593	−449.598	−457.555	−477.581

Note: p<0.1; **p<0.05; ***p<0.01 S.E. Clustered at Race Level. Some non-significant covariates were dropped.

Figure 2.1: Organizational Fit and Environment

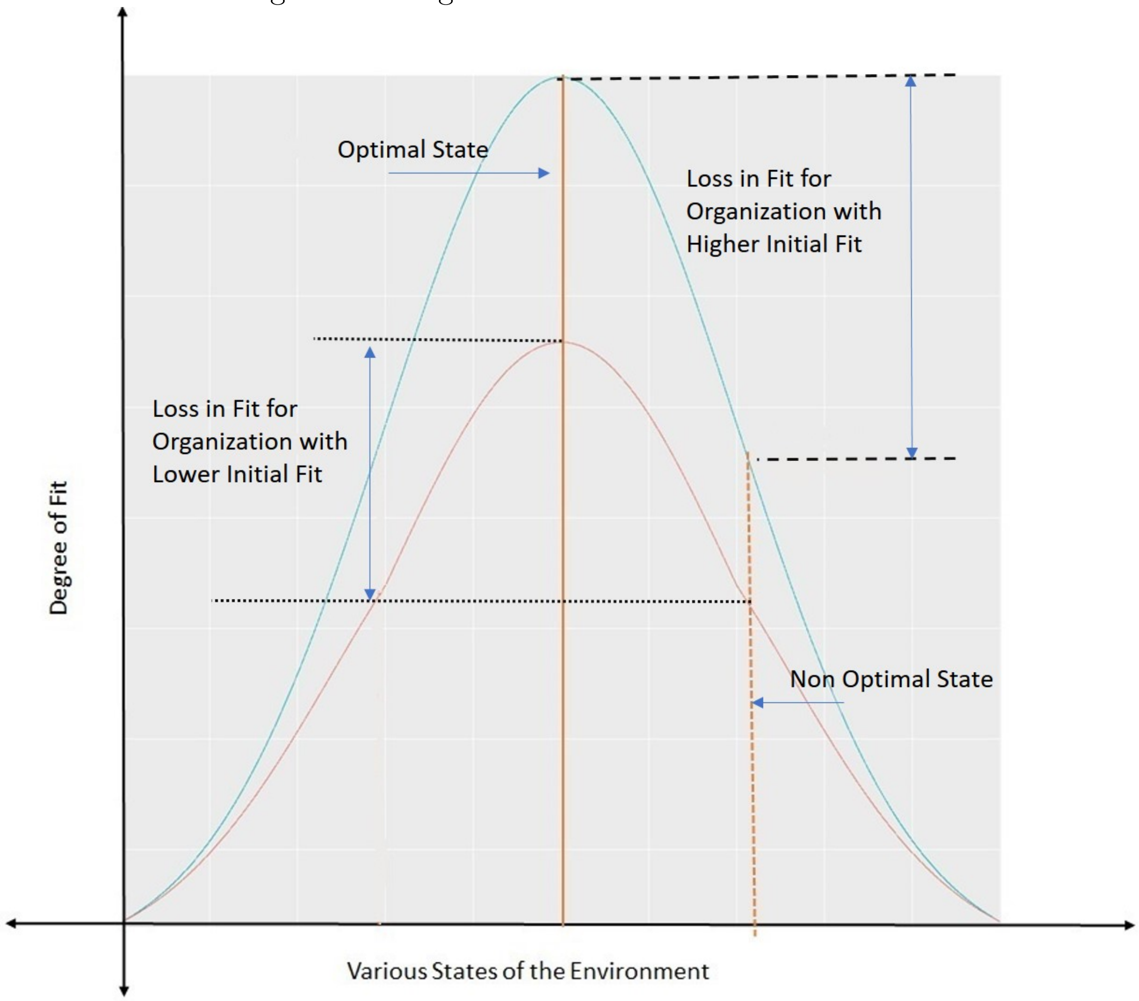


Figure 2.2: Number of Wet Vs Dry Race Across Years

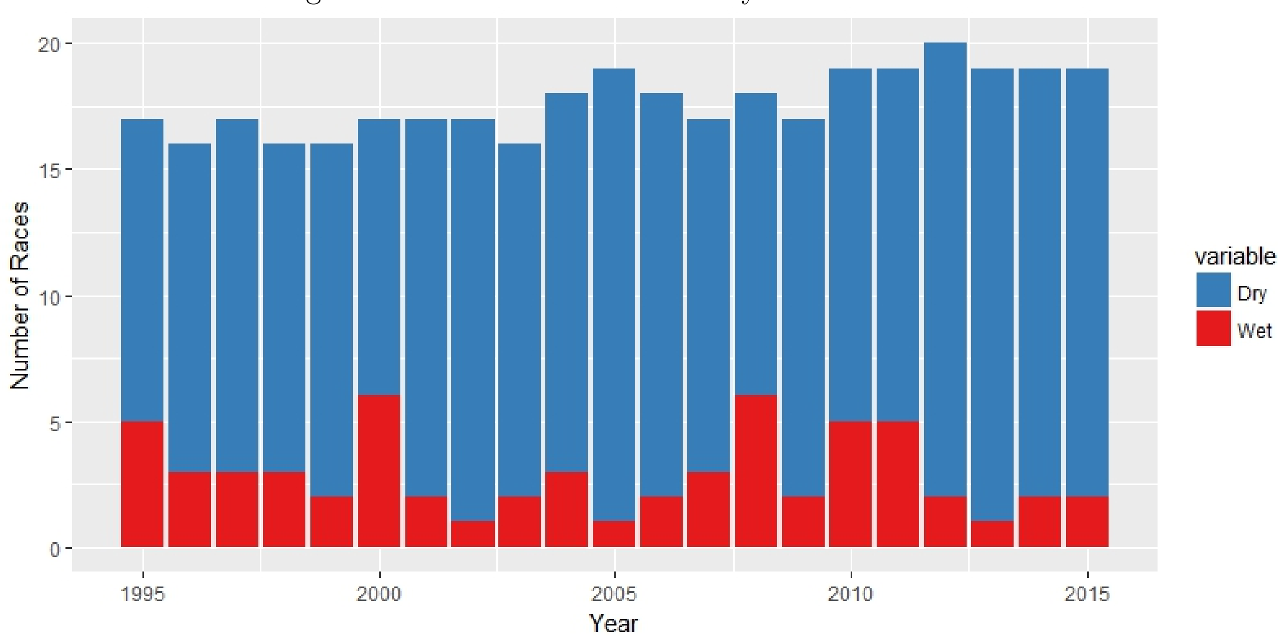
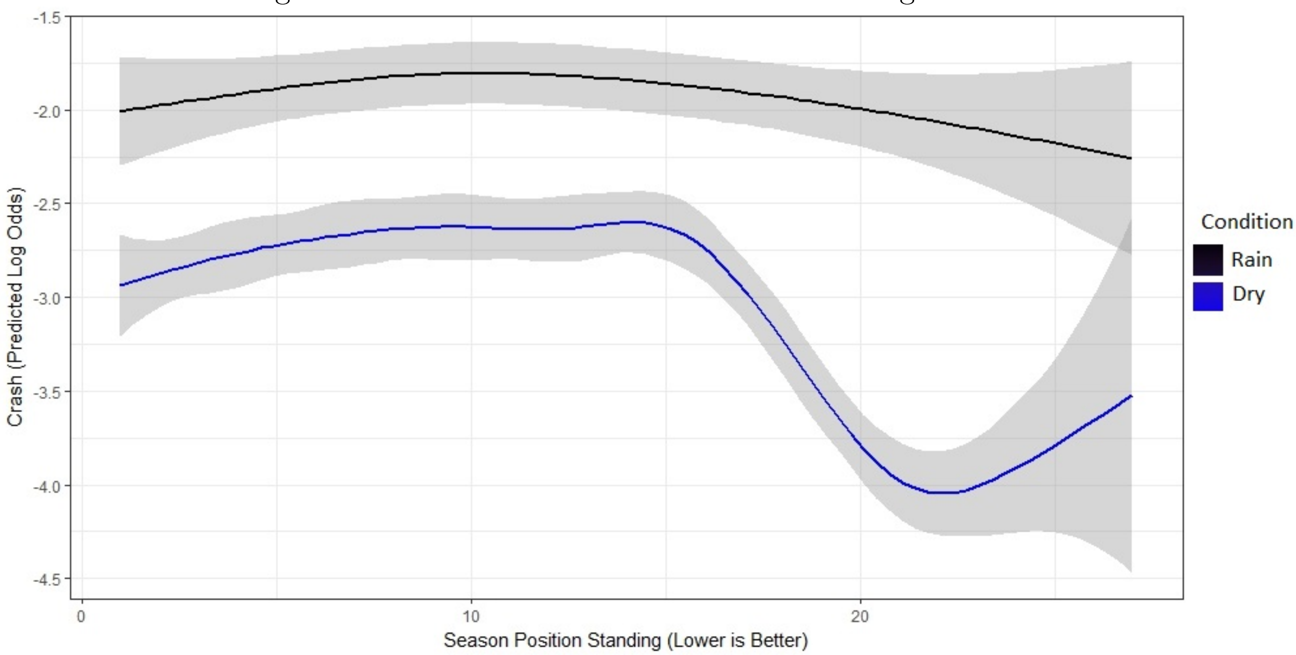


Figure 2.3: Interaction Effect of Season Standing and Rain



Chapter 3: Innovation and Competitive Positioning: Location Choice at the Consumer Electronics Show

3.1 Introduction

An important way in which firms compete is the positions that they stake out relative to one another. Firms position their products relative to each other, such as with Airbus's product line up versus Boeing's. Firms position themselves geographically versus one another, like restaurants at freeway exits. Firms can position themselves with the strategies they follow, such as differentiation versus low cost. Firms seek positions with high profitability, and then both defend current positions and seek better positions through actions such as marketing campaigns or new product introductions (Smith et al., 1992). In turn, firms respond to competitors' positioning. For example, Wang and Shaver (2014) show that firms reposition in response to changing competitive landscape.

While firms seek high profitability positions, they more naturally compete with firms similar to themselves along important dimensions. This behavior is the central premise of the localized competition literature. Baum and Mezias (1992) argue that firms with more similar resource requirements compete more intensely; consistent with localized competition, they show that hotels located in the more densely populated regions of distributions for size, experience higher failure rates. More recently Kalnins (2016) replicates and extends these findings, showing hotels located in densely populated regions of distributions of price and location, in addition to size, experience higher failure rate. While competition is localized, firms might seek better positions and move beyond their original localized competition group.

In seeking better positions, Schumpeter (1934) argues that firm competition is a series of innovation moves taken by firms to try and lead the market. Firms introduce new features to differentiate their products from competitors and to occupy niches (Benner and Tripsas, 2012). In turn, firms introduce new products in response to product introductions by rivals to protect their market share (MacMillan et al., 1985). Innovations are not only important for firms to gain and keep their customers, innovations by firms influence other stakeholders as well, such as stock markets (Bettis and Weeks, 1987). As such, I expect innovation to be an important stepping stone for firms to seek better positions and potentially move beyond their original localized competition group.

In this paper, I focus on how firms' innovations affect their competitive positioning. As a baseline, in the absence of firms having innovations, I expect localized competition: similar firms compete with each other. Deviations from localized competition occur when firms have innovations; an innovation wielding firm might choose to place itself in direct competition with a new set of firms by moving close to them in the competition space. Firms' innovations facilitate this repositioning.

From among important localized competition dimensions location, size, and price; I focus on size localized competition. Size is the only dimension that shows consistent results at a market (city) and sub-market (neighborhood) level in Baum and Mezias (1992) and Kalnins (2016). I examine where firms of different size locate in geographic space, relative to each other. With size localized competition, a smaller innovation wielding firm might choose to compete with larger firms by locating close to them geographically. The smaller firm's objective would be to gain some of the larger firms' customers. Of course, some larger firms might also have innovations themselves; whom the smaller, innovation wielding firm would want to avoid else the smaller firm while gaining some of the larger firm's customers, might end up losing more of its customers.

Besides competition, firms locating close to each other may create positive demand externalities, where proximate firms' aggregate activity heightens demand for all. A related consideration is that some locations in the competition space will feature more demand than others. Assuming such demand heterogeneity, firms would initially vie for the higher demand locations and if taken, then proceed to the worse ones. But note that an initially worse location might supersede initially better ones if multiple firms locate at the initially worse location and heighten demand via demand externalities.

Therefore, in studying firms' location decisions, I consider four mechanisms: (i) gains from taking neighboring firms' customers when a firm has an innovation, (ii) possible losses when neighboring firms have their innovations, (iii) gains from positive demand externalities, and (iv) heterogeneity in locations' demand across the competition space. With these four mechanisms, a focal firm's outcome is dependent not only on its choice but is clearly dependent upon many other firms' choices. A focal firm's potential gain can become a realized loss if neighbors have innovations that take some of the focal firm's customers. A focal firm can gain from positive demand externalities if other firms locate with it. To understand how interactions among these four mechanisms affect firms' choices and performance, I set up a simulation model.

Besides modeling these interdependencies, a simulation helps a couple of other ways. First, given these four mechanisms, a firm's optimal choice can change depending upon which of mechanisms has a greater effect relative to the others. While varying the mechanisms' relative effects, the simulation model allows me to predict whether and how firms' best location choices change. Second, the simulation model allows me to link key unobserved outcomes to observable ones that can be empirically tested. Measures of a firm's performance, such as the number of customers it captures from its location choice, are difficult to observe. But since customer demand is explicitly linked in the simulation to a focal firm's and its competitors' location choice, I can hypothesize and test where firms locate and their resulting neighbors' traits. And firms' location choices and their neighbors' traits are readily observable.

I test the simulation model's predictions on data from firms' booth locations at the annual Consumer Electronics Show (CES) from 2014 to 2016. The CES is a useful setting as (1) most firms in the consumer electronics industry attend, (2) the CES is an important venue for firms to showcase new and upcoming innovations, and (3) firms' booth locations are readily observable. A key feature is that the CES is a punctuated event lasting a couple of days during which all firms have the same objective: maximize their exposure. Booth location is a key determinant of maximizing exposure as some locations are closer to entrances and main aisles leading from entrances.

As the simulation's predictions are dependent upon the key parameters' values, such as the relative magnitude of the four mechanisms versus another; I vary all key parameter values across a large range and therefore the simulation's predictions are generalizable across these large ranges of values. The simulation predicts two traits of firms' location choices contingent on the firm's size and innovation: proximity to demand highpoints (entrances) and neighbor firm size. The simulation predicts that firms with an innovation typically position themselves next to larger neighbors, as firms leverage their innovation to take customers from larger neighbors and to benefit from demand externalities. The simulation predicts that this strategic behavior is strongest for the smaller and medium-sized firms with the largest firms behaving differently. The simulation predicts the largest firms position themselves closest to demand highpoints in the landscape since the largest firms prioritize the demand highpoints versus strategic concerns around whether they or their neighbors have innovations. These predictions from the model form the basis of my hypothesis which I test in my empirical context of CES.

In my empirical context, I find results consistent with the simulation's predictions. Amongst firms with innovation, I observe an inverted-U shape relationship between firm size and neighbor size suggesting differences in preferences and ability to benefit from innovation across firms of different sizes. Medium sized firms appear to alter their positioning the most upon having an innovation. While the largest firms prioritize positioning themselves close to entrances, which are the demand highpoints.

By examining firms' positioning, these results are consistent with the idea of firms using innovations as a stepping stone to compete with a different set of firms. In my context, firms that are larger in size. This provides insight into the evolution of competition.

3.2 Theory and Hypotheses

3.2.1 Spatial Competition, Innovation and Competitive Positioning

The literature on spatial competition in strategy research studies how firms position themselves with respect to their competitors across different contexts such as geographic, product, or temporal space. Much of this literature has its origins with Hotelling (1929), where firms compete for customers by choosing their position on a line segment and seek to capture local monopolies by locating apart from competitors. Underlying assumptions for this outcome is that firms are selling a commodity and demand is uniformly distributed. But in most settings, firms' goods are differentiated, and some positions will feature greater demand than others, which gives rise to strategic choices in positioning beyond locating apart. Firms target a position based upon their capabilities to capture a position's demand. If multiple firms have similar capabilities, they may target the same position and compete for the same set of customers. This logic of localized competition leads to more similar firms competing more directly with each other versus with dissimilar firms. For example, Baum and Mezias (1992) show a greater number of proximate similar-sized hotels decrease a focal hotel's survival. Similarly, Kalnins (2016) demonstrates that a higher number of similarly located and similarly priced hotels reducing a focal hotel's survival. Thus, depending upon the nature of demand and firms' capabilities, firms may be positioned either apart or together.

Positioning is dynamic. Firms may need to reposition themselves from time to time, as firms' environment, capabilities, or both change. A variety of reasons, either exogenous or endogenous in nature, could result in changes in the demand experienced in a particular position. Exogenous changes, such as in consumer preferences or underlying technology, can alter the different positions' relative attractiveness: consumer preferences might shift from compact cars to SUVs or vice versa; touchscreen technology saw netbooks killed off by tablets. Such changes could lead to firms shifting from positions with declining demand to those with higher and/or increasing demand.

Besides exogenous changes, changes endogenous to the firm also can lead to repositioning. A key endogenous change could be the innovations that the firm generates. Innovation is one of the primary means for value creation (Moran and Ghoshal, 1999). Through innovation, firms renew the value of their asset endowments and discover novel uses and combinations for their existing resources (Dougherty, 1992; McGrath et al., 1996). Renewing the value of their assets means that firms may be able to better defend their current position by offering customers an improved value proposition. Discovering novel uses means firms may be able to shift to other positions with greater demand. These two outcomes can be correlated: an innovation offers a better value proposition for a firm's existing customers at its current position but also can provide additional capabilities for a firm to serve other positions. For example, sport utility vehicles were originally based on truck frame platforms, but through product innovations, were redesigned to have a uni-body construction like passenger cars; this made SUVs more car like in ride and handling, and now SUVs compete with minivans as people movers.

Another source of repositioning is other firms' repositioning. Just as a focal firm might have innovation, its competitors may also. Since positioning is relative to competitors, competitors' repositioning may prompt a focal firm to reposition. Encroachment by competitors can reduce a position's viability, leading to repositioning. Similarly, retreat by competitors can enhance a position's viability, thus reducing the likelihood of repositioning. For example, Wang and Shaver (2014) show that firms alter their positions in response to the dominant firm's repositioning.

In a spatial competition context, innovation can help firms attract more demand. Innovation might allow a firm to update its offering to provide an improved value proposition that would draw customers. Or innovation, as an indicator of novelty, might draw consumers: Hirschman (1980) builds a framework that explains consumer behavior being driven by consumer's novelty seeking and other traits. Similarly Sheth (1992) develops a theory of consumer choice based upon five dimensions one of which is an alternative's capacity to arouse curiosity or provide novelty.

A firm might leverage an innovation's ability to attract more demand in its current position. Or a firm might find that repositioning is a better option, to the extent that the innovation gives the firm capabilities to exploit other positions. Thus, when having an innovation, firms face the choice of either staying at their current position in the landscape or shifting to another position that might be superior. Either staying or repositioning may not be a straightforward decision, due to multiple mechanisms affecting positions' demand.

3.2.2 Mechanisms affecting Competitive Positioning

I contend that multiple mechanisms determine the attractiveness of positions in the spatial landscape, and making the best choice entails evaluating all the mechanisms. There are a couple of mechanism types: heterogeneity of demand in the landscape, the level of positive demand externalities, and the effect of innovation on the focal firm and its competitors. I develop expectations for each of these mechanisms' effect on firm positioning separately, and then later combine them to evaluate them together.

Versus uniform demand everywhere, spatial landscapes tend to have heterogeneous demand: at different positions on the landscape, demand will differ. In geographic space, key locations like the intersection of busy streets or subway stations tend to experience higher demand. In product space, more people need passenger cars versus minivans. In temporal space, evening and weekends are higher demand periods for television and movie theaters. Firms would prefer positions that feature higher demand. But positions featuring higher demand will be attractive to more firms. Thus, those firms whose capabilities are best suited will populate the high demand positions, and firms with less suited capabilities will populate the lower demand positions. Take for example timing of movie openings: big budget action movies tend to open on summer holiday weekends that have high demand, which pushes other genres to open on lower demand weekends. And even among positions with lower demand, firms will be more or less suited for different positions depending upon their capabilities. Some genres of movies may be better than others at capturing second-tier weekends' demand. Firms will sort based upon their capabilities, to find a position offering the greatest demand. *Therefore, given firms with differentiated capabilities, I expect firms to choose positions with high demand that are commensurate with their capabilities.*

With firms choosing their best possible positions, some positions may draw multiple competitors. Firms that have similar capabilities are likely to choose similar positions. This collocation of competitors leads to the second mechanism: positive demand externalities from agglomeration. Marshall (1920) suggested both production/supply and demand benefits from geographic agglomeration. In my setting, I am interested in the demand externalities: with firms offering differentiated products, firms can reduce consumers search costs by collocating. Collocated firms offer customers a more efficient evaluation of competing choices, which leads to collocated firms attracting more customers than if they had located separately.

Positive demand externalities suggest that a focal firm would want to collocate with others. Among positions with multiple firms, those populated with firms that draw more customers will create greater demand externalities, which would make such positions most attractive. *Therefore, given positive demand externalities from firms collocating, I expect firms to choose positions proximate to more competitors, and competitors that draw more customers.*

In addition to these two mechanisms, there are mechanisms related to firms having innovations: both the focal firm and its competitors. There are a couple of assumptions about innovations that will inform firms' positioning and repositioning.

I assume that firms invest in innovations to improve their capabilities to capture demand, at their current position and/or relocate to other positions that feature greater demand. Of course, some innovations may yield minimal improvements for, be orthogonal to, or be otherwise ineffectual for capturing demand. My focus is on the subset of innovations that can improve firms' capabilities to capture demand.

I also assume that any innovation has some fixed cost to its development. These may be research, development, commercialization, and/or other costs. The particular category is unimportant for my purposes. What matters is that innovations have associated fixed costs. This has two important implications. First, innovations are discrete events. Innovations appear intermittently, rather than continuously. And depending on the magnitude of fixed costs, they may not only be discrete events, but also infrequent events. Thus, as a determinant of repositioning, innovation-driven repositioning will also be discrete and possibly infrequent events.

Second, given a fixed cost, a firm will gain greater return by using the innovation in a position that offers greater demand. This spreads the fixed cost across greater demand, thus improving the return on the innovation's fixed cost. This strongly suggests that firms with innovations will prefer to shift to positions that offer higher demand than their current one, rather than stay in their current position. This is contingent on the extent to which an innovation improves a firm's capabilities to serve other positions' demand; though as stated above, I assume firms invest in innovations to improve their capabilities to capture demand, at their current position and/or relocate to other positions that feature greater demand. And if firms realize that spreading of fixed costs is more advantageous in positions that offer greater demand, they then are likely to target innovations that improve their capabilities to relocate to other positions that offer greater demand.

Tempering this tendency to reposition is the uncertainty around an innovations' value in improving a firm's capabilities. Until an innovation is applied in the marketplace, it's true value is unknown. The firm will have some expectations as to how valuable an innovation is for improving the firm's capabilities, but these expectations are unlikely to match an innovation's true value. This suggests that a firm will not pursue innovation driven reposition with all innovations, but only those that it believes are substantial enough for it to be successful in a new position. *Therefore, I expect firms to pursue innovation driven repositioning when they have innovations that they believe to be of high value.*

Also, tempering a firm's tendency for innovation driven repositions is its competitors having their innovations. Positions that have higher demand are likely to feature multiple competitors. And any of these multiple competitors may have innovations themselves. While I just argued that firms will target innovations that improve their capabilities to relocate to positions featuring higher demand, if a firm is already at a demand highpoint, its innovative efforts will be focused on better defending its position. And this is the situation firms looking to move up will encounter: moving up firms will target innovation to help them shift to demand highpoints, while firms at high points will target innovations to help them defend their highpoint positions.

Competitors' innovations can have both positive and negative effects. On the positive side is the demand externality effect: a competitor's innovation increases the demand it can capture and thus potentially further magnifies the demand externality for proximate others. On the negative side, the better value proposition and/or novelty that the competitor's innovation provides means that some of the increased demand it experiences comes from proximate others. Thus, the magnification of demand externality is limited as some of the demand is just transferred among proximate competitors that contribute to the creation of the demand externality. If the focal firm is positioned with competitors that have innovations, it likely losses some of its customers to the innovation wielding competitor. And this direct loss is unlikely to be offset by any magnification of demand externality. *Therefore, I expect when firms pursue innovation driven repositioning, they avoid positions with competitors that have their own innovations.*

While I delineate these four mechanisms, a challenge in testing my expectations for firm behavior is that each expectation is based only on that one mechanism's effect in isolation from the other mechanisms. But mechanisms acting in isolation is unlikely. Once a focal firm can have innovations, its competitors must also be able to have innovations. Innovations result in innovation-driven reposition that in turn affects the extent of demand externalities. The extent of demand externalities changes positions' relative value versus just the original heterogeneous demand across the spatial landscape.

And some of the expected firm behaviors are in opposing directions or highly conditional. For example, an innovation wielding focal firm would want to reposition to a position of higher demand, but maybe not if some competitors in that position have innovations of their own. Typically, such offsetting effects would suggest an exercise in assessing which mechanisms' effect is larger than the other. But in this case, there are four mechanisms' effects to assess relative to each other. As such, any exercise in assessing which mechanism's effect is or mechanisms' effects are larger than others are problematic. Instead, I use a simulation, in which I can model all mechanisms simultaneously and vary all the mechanisms' relative effects versus each other, to develop expectations for firm behavior that reflect the system of effects that stem from firms having innovations.

3.3 Simulation Model

In general, there are several reasons to use simulation modeling for theory development. First, simulation modeling gives me the ability to specify the underlying logic that lies at the core of verbal theory with additional precision (Carroll and Harrison, 1998). Second, simulation modeling can elucidate the outcomes of the interactions among multiple underlying organizational and strategic processes, especially as they unfold over time (Repenning, 2003). Finally, simulations can overcome challenges stemming from data limitations to provide richer insight into multi-facet theoretical relationships among constructs (Zott, 2003). For these reasons, simulation can be a powerful method for sharply specifying and extending theory. In my setting, I benefit from all three of these reasons, as well as another novel one. To illustrate this additional reason, I first detail some specifics of my context.

I use an agent-based simulation to model where firms strategically position themselves on a spatial landscape to maximize demand. To maximize demand, firms consider four mechanisms when choosing their position: (1) heterogeneity in positions' baseline demand, (2) positions' positive demand externalities, (3) conquest demand gains when a firm has an innovation, and (4) demand losses when neighboring firms have innovations. In the prior theory section, while I hypothesized about firms' behavior for each of these effects separately, hypothesizing about their aggregate effect is non-obvious as a focal firm's demand maximizing choice is a function of these four mechanisms' relative magnitudes and importantly other firms' choices that affect these effects' relative magnitudes.

I use the simulation model to explicate a firm's decision making: firms will evaluate the demand implications of the four mechanisms, across positions; and chose the position offering the greatest total demand. This decision making is subject to a couple of key assumptions. First, I conceptualize firm heterogeneity as a single dimension: firm size; firms are larger or smaller, with larger firms being more competitive firms having capabilities that allow them to better capture demand at demand highpoints on the spatial landscape. This assumption is consistent with empirical work that finds firm size is a determinant of R&D expenditures, innovation (Acs and Audretsch, 1988; Hitt et al., 1990) and localized competition across firms (Baum and Mezias, 1992). The second assumption is that the spatial landscape is initially empty and that firms, by choosing their positions, fill in the empty landscape. An alternative is to pre-populate the landscape with firms either randomly or with some rule and then to have firms reposition themselves when an opportunity presents from another firm's entry or exit. I chose the former as a more unconstrained setting in which to model and understand firms' competitive positioning and a setting that is more analogous to my empirical context. Third, firms fill in sequentially, with larger firms choosing positions first. This is consistent with aspects of a Stackelberg leader-follower model: firms make strategic choices sequentially, with the follower knowing the leader's choice. Instead of output, in my context, firms choose positions. I assume the larger the firms, the more the leader it is, and the earlier it chooses. Fourth, some firms have innovations; I assume that innovations' novelty draws customers away from neighboring firms. Thus, innovations allow a firm to capture some demand from the specific competitors that they locate near to.

With these four assumptions, the position offering a firm the greatest total demand is influenced by both whether the firm has an innovation or not and the choices of the firms that chose before it. Of note, this indicates two levels of endogeneity: at a firm-level and a system-level. At a firm level, a firm's choice is affected by whether it has an innovation or not. Beyond this firm-level endogeneity, there is also system-level endogeneity. A firm's best choice is governed by other firms' choices, and these other firms' choices are in turn governed by whether they have innovations. With these two levels of endogeneity, the standard empirical techniques are inadequate; for example, a Heckman correction can address the firm-level endogeneity, but not the system-level endogeneity.

Accounting for these layers of endogeneity is another reason to use simulation modeling. I can explicitly model the endogenous processes. And thus, the predictions from the simulation account for endogeneity because the predictions result from explicitly modeling these inter-related endogenous processes. This then removes the need to account for endogeneity via empirical methods, which then allows the use of simpler empirical methods. Simulation modeling allows me to account for endogeneity in the theoretic development rather than in the empirics. This is an advantage in settings where there are multiple endogenous processes, which empirical methods have difficulty addressing, such as my setting.

Another important feature is that the simulation model allows me to link between unobserved constructs and constructs that can be empirically tested. I model firms maximizing demand based upon the four mechanisms, but demand is difficult to empirically observe either for any of the individual four mechanisms or in total. Therefore, I generate hypotheses from the simulation model for an outcome that can be empirically observed: the size of a firm's neighbors. Firms maximizing demand is linked to neighbor size: larger firms are likely to camp on positions with higher baseline demand; larger firms enhance demand externalities, and larger firms are a source of conquest demand.

Neighbor size is a datum that can be calculated from the simulation model since it tracks where each firm locates, which then can be used to calculate attributes of any firm's and all firms' neighbors.

After introducing additional simulation details below, it becomes apparent that simulation outcomes are driven by the values of key parameters, which determine the relative importance of the four mechanisms. Thus, I run the simulation model and vary these key parameters across a wide range of representative values. This allows me to predicted firm behavior across a wide range of situations. I then generate summary plots for the focal outcomes: the demand that firms experience and the size of firms' neighbors, which I use to generate my expectations. I then take my expectations to my data to test.

3.3.1 Simulation Details

I use an agent-based simulation model, in which firms locate on a landscape to maximize demand. The model has three stages. In the first stage, firms' heterogeneous traits are determined. Firms are heterogeneous in two dimensions: size and whether they have an innovation, and if so, how valuable their innovation is. I use size as a generic indicator of correlated firm traits such as assets, sales, employees, resources, etc. Of note, at this stage, firms have incomplete information on the value of their innovation; they know their innovation's value with some noise. The value, without noise, is revealed only in the second stage. This assumption is based on a firm not knowing the value until an innovation hits the market. Before this, the firm might have expectations of the value; but this expectation is unlikely to be an innovation's true value in the market. This type of incomplete information assumption is common; for example, Jovanovic (1982) models firms learning their efficiency only after entering an industry.

In the second stage, firms choose their locations sequentially, in size rank-order, with larger firms choosing first. The landscape has heterogeneous baseline demand: some locations feature more demand than others. Only a single firm can locate in each location. Firms locating adjacent to each other create positive demand externalities: firms experience more than locations' baseline demand if more and larger firms are adjacently located. With just these two demand effects, firms' behavior is somewhat obvious firms will locate at highpoints of the baseline demand. These highpoints draw larger firms, near whom other firms will locate to benefit from the demand externalities.

A strategic dimension emerges from introducing whether firms have innovations. When a firm has an innovation, I assume that the innovation's novelty draws customers away from neighboring firms. Such conquest demand may be more important to innovation wielding firms than locations' baseline demand or demand externalities. The amount of conquest demand will vary with (1) the innovation's value and (2) the focal firm's size relative to its neighbors' size. An innovation of greater value will allow a firm to take more customers from neighbors. But the size of firms also matters. When an innovation wielding firm is smaller, it can take more demand (relative to its size) from neighbors versus when an innovation wielding firm is larger. The smaller firm can readily find larger firms to locate close to; in contrast, a larger firm will be less able to find even larger firms to make its neighbors.

While an innovation wielding firm seeks to take demand from competitors, it needs to be wary of competitors that themselves have innovations. While the innovation wielding firm takes some demand from others, the competitors' innovations will allow them, in turn, to take some demand from the innovation wielding firm. Thus, the innovation wielding firm's net conquest demand will be lower if it locates close to competitors with innovations versus those without.

To avoid competitors with innovations, a firm needs to know which competitors have innovations. Just as a firm doesn't know the value of its innovation (only the value with noise); a firm also doesn't know the value of other firms' innovations. But while not knowing their value, a firm does know which competitors have an innovation or not. A firm also knows the mean of the distribution from which innovations' values are drawn, which it assigns to any competitor's innovation. This is akin to industry participants knowing that competitors are coming out with innovations, but not knowing the specifics. They can use history of past innovations' average value to predict competitors' forthcoming innovation value.

To link firm size and innovation, I conceptualize an innovation's value as effectively increasing a firm's size. Innovation's value is a multiplier of a firm's size. For example, if a firm is size 10 and has an innovation with a value of 1.2, then the firm's modified size is 12[1]. One implication of having an innovation is that a firm's size effectively becomes larger and conceivably, like a larger firm, move earlier in the size rank-order than they would if they didn't have an innovation. However, in order to match the simulation to my empirical context, I restrict earlier movement by firms in size rank-order. Comparison of simulation results with and without alteration of size rank-order suggests no difference between the two.

When a firm's turn occurs, it calculates the four effects' demand in all available locations and chooses the location with the greatest total demand. Available locations decrease for firms later in the move order. For the first firm, all locations are available; for later firms, fewer locations are available. The four effects' magnitude also changes with move order. Demand highpoints may only be available early on. Demand externalities appear and build only once firms locate near one another. Conquest demand is possible only after other firms to take demand from are on the landscape.

Of note, a firm's demand maximizing location choice is made with two levels of incomplete information. At a firm-level, a firm knows what competi-

[1] I don't differentiate based on a firm's size its potential innovation value. Larger or smaller firms draw from the same distribution for the value of innovations, which are used as multipliers of firm size. I could easily modify innovation value to favor either smaller or larger firms with more significant innovations, but for simplicity do not do so.

tors are already located where on the landscape, and knows which competitors have innovations, but has incomplete information about these innovations' values; and if the firm has its innovation, has incomplete information of its value. This incomplete information could lead to firms miscalculating conquest demand gains from its innovation and demand losses from others' innovations, and thus to choose a location that doesn't provide the maximum total demand. At a system-level, a firm chooses the demand maximizing location only based upon the firms that have already located on the landscape; it can't take into account firms' location decisions who have not yet located on the landscape. And thus, may also choose a location that doesn't provide the maximum total demand.

The third and final stage is after all firms have chosen their respective locations. Each firms' total demand is calculated, which is based upon where all the firms have located and firms' innovation's values, without noise.

I now introduce the more detailed model assumptions for firms, landscape that firms operate on, and how each of the four effects: (i) heterogeneity in locations' baseline demand, (ii) locations' positive demand externalities, (iii) conquest demand gains when a firm has an innovation, and (iv) demand losses when neighboring firms have innovations; affect demand.

There are N firms. They operate on a discrete, 2-dimensional landscape of x by y locations. I set N initially to 100 and x and y both to 10. While this sets the number of firms equal to the number of discrete locations on the landscape, my results/expectations are not sensitive to whether this equality is maintained; the simulation's results generalize to when the number of locations exceeds the number of firms and vice versa[2].

Firms are heterogeneous on two dimensions: size and whether they have innovations. Each firm *'i'* is allocated a size s_i. Firm sizes s_i are draws from a normal distribution with mean S and standard deviation σ_s. A portion of the N firms, *freq_inv*, are randomly assigned an innovation: inv_i. inv_i, the value of firms' innovations, is one plus the absolute value of a draw from a normal distribution with mean 0 and standard deviation σ_I; this yields values for inv_i that are greater than 1. For firms without an innovation, $inv_i = 1$. Firms don't know inv_i, but know inv_i plus a noise term, e_i, which is a draw from a normal distribution with a mean 0 and standard deviation, σ_e.

The implication for firm s_i with size s_i that has an innovation with value inv_i, is that the firm is effectively larger. The firm acts like a firm of s_i x inv_i size. This is the firm's innovation weighted size. But firms perceive that its innovation's value is $(inv_i + e_i)$, the value plus some noise. So the firm behaves as a firm with size, s_i x $(inv_i + e_i)$, their perceived innovation weighted size. Firms without innovations have $inv_i = 1$ and thus an innovation weighted size equal to their size, s_i.

[2]When number of firms exceed the number of locations, I assume that the excess number of firms do not enter during the second stage, and thus are eliminated from the total demand calculations in the third stage.

Heterogeneous location baseline demand, loc_dmd_{xy}, allows different demand in each location versus uniform demand across locations. Adjacent locations' demand could be totally random and unrelated or have some structure. I choose to impose some structure using two features. First, there are several discrete highpoints that are randomly assigned. Second, demand drops away from the highpoints based upon a multiplier, *decay*, which is less than one. For example, if a highpoint's demand were 10, then the locations adjacent to the highpoint would have demand = 10 x *decay*. The locations adjacent to those locations would have demand = 10 x $decay^2$; and so forth. Thus, demand propagating further outwards from a highpoint follows a spatial AR1 relationship at the rate, decay. Each highpoint's AR1 footprint can overlap with other highpoints' footprints such that a particular location's baseline demand results from the footprint of several highpoints. This could be visualized as a tent with multiple supporting poles. Each tent-pole is a highpoint, from which values decrease. Regions between two tent-poles are higher than regions around the periphery. With these two features, demand is broadly heterogeneous; but locally follows a smooth decay process.

I allow each location to house only one firm; thus the firm in location x,y captures loc_dmd_{xy}, on average. Around this average, I build in firm-specific variation based on firm size. I take size as a proxy for correlated firm traits including resources. Thus, I expect larger firms those with more resources to be able to extract more demand from any given location versus a smaller firm. For example, using a restaurant analogy, a McDonalds will extract more demand from a location than a generic burger joint. The firm-specific baseline demand at location x,y is the baseline demand, loc_dmd_{xy}, scaled by the firm's size, s_i, relative to the average firm size, S: $loc\_dmd_{xy,i} = loc\_dmd_{xy}$ x (1 + (s_i x inv_i)/S). inv_i enters the equation as a firm's innovation value effectively increases a firm's size.

Positive demand externalities from firms agglomerating, $agglom\_dmd_i$, is defined by the number of firms adjacent to the focal location and their sizes. With a discrete, two-dimensional landscape, a focal location has eight adjacent neighbors two horizontal, two vertical, and four diagonal. The underlying assumption is that greater activity draws customers more than what the firms would experience separately because collocated firms reduce customers' search costs (Shaver and Fredrick, 2000). The additional demand experienced is defined by the aggregate size of the neighbor firm(s) in the adjacent eight location(s) times *externality*, a multiplier that is greater than zero. These neighbor sizes are their innovation weighted sizes.

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costs (Shaver and Fredrick, 2000). The additional demand experienced is defined by the aggregate size of the neighbor firm(s) in the adjacent eight location(s) times *externality*, a multiplier that is greater than zero. These neighbor sizes are their innovation weighted sizes.

Conquest demand for an innovation wielding firm, $inno\_gain_i$, comes from locating adjacent to other firms and attracting some of these firms' customers away. This is based on the assumption that some customers have a preference for novelty. I define $inno\_gain_i$ as the neighbor's size, $S_{neighbor}$, times the ratio of the focal firm's innovation weighted size, (s_i x inv_i), over the sum of the focal firm's innovation weighted size and the neighbor firm's size: $inno\_gain_i = S_{neighbor}$ x $(s_i$ x $inv_i)$ / $[(s_i$ x $inv_i) + S_{neighbor}]$. This is a monotonically increasing function with respect to neighbor's size: taking a larger portion of a small neighbor's customers is worse than taking a smaller portion of a large neighbor's customers. While a gain for the focal firm, this is simultaneously a loss for the donor firm. For firms without an innovation, $inno\_gain_i$ is zero.

Of course, if neighboring firms have their innovation, the neighbors will attract some of the focal firm's customers away as well, based upon the same equation. Thus, firms need to be concerned about such demand losses: $inno\_loss_i$. All firms whether they have their innovations or not are subject to demand loss; for all firms, $inno\_loss_i$ can be non-zero.

Based on these four effects, firms will choose the location that features the greatest total demand. In assessing these four effects, firms will not know their exact effect since the firms have incomplete information on both the value of their innovation as well as other firms' innovations.

While having detailed the simulation structure above, in my implementation of the simulation I set a couple of key parameters so that the simulation more closely fits my empirical context. I also vary some key parameters so that the simulation predicts firms' behavior across a wide variety of conditions. These are detailed below.

s_i, a firm's size is N$\sim$(S, σ_s). I set this to be N$\sim$(20, 5). *freq_inv*, the portion of firms in the population with innovations, I vary between 0.0 and 0.4. inv_i, the value of a firm's innovation is 1 + N$\sim$(m$_I$, σ_I). I vary m$_I$ between 0.0 and 0.30 and σ_I is set to be as 0.25*m$_I$. The value of inv_i is set to be 1 + N$\sim$(m$_I$, σ_I). e$_i$, the noise added to a firm's innovation's value is N (0, σ_e). I set this to be N$\sim$(0, .02). $basedemand_{xy}$ is the heterogeneous baseline demand by location, which is determined by the number and location of highpoints and decay, the spatial AR1 reduction from the highpoints' demand for adjacent locations. I establish four highpoints at the periphery of the landscape (to better fit my empirical context). I vary these highpoint values from 10 to 20, allowing for comparable levels of demand from the four mechanisms. I set *decay* equal to 0.2. *externality*, the extra demand firms experience from having proximate neighbors; I vary between 0.0 and 0.2 times the aggregate of neighboring firms' sizes.

3.3.2 Inference from the Simulation

The simulation predicts two outcomes at a firm's demand maximizing location: firm's total demand (as well as each of the four mechanisms' individual demand effect) and firm's neighbors' average size (constructed by knowing where every firm locates). These outcomes will be governed by the values of key parameters in the simulation. A couple of parameters change the importance of the four mechanisms' demand effects relative to each other. Heterogeneous baseline demand becomes relatively more important when the number of demand highpoints increases and when decay is less aggressive. Demand externality becomes relatively more important by increasing the value of externality. Conquest demand and demand losses become more important by increasing *freq_inv*, the portion of firms in the population with innovations and inv_i, the value of firm's innovations. While I vary all of these parameters to assess their impact on firms' outcomes, as I note earlier, firm strategic behavior emerges from innovation's effect through conquest demand and demand losses. As such for the subsequent discussion, I fix the number of demand highpoints (four), and decay (0.2). I choose these values so that each of these four demand effects has a similar relative influence on total demand. The analysis that I present generalizes to other situations where these fixed parameters are set to a wide range of other values; doing so primarily changes each demand effect's size relative to the others. I focus on just two variables, inv_i and s_i; and how variation in their values affect total demand or neighbor size. These three dimensions, I then can plot as a 3D surface to describe their relationship.

When a firm's turn occurs, the simulation determines its best location choice - the location offering it the greatest total demand. The simulation also at the same time determines the firm's best location based upon a counterfactual for a firm with innovation, taking its innovation away; for a firm without innovation, giving it an innovation (which I set to the mean innovation value). With and without innovation, the firm is likely to choose different locations. And these different locations result in commensurately different total demands. The difference between total demands that the firm would experience at the two locations is an estimate of the gain from having an innovation and/or the loss from not having an innovation.

I plot this gain from innovation as a function of inv_i and s_i in Figure 3.1. Firm's innovation value, inv_i is on the x-axis. Firm size, s_i is on the y-axis. Change in total demand the gain from having an innovation is on the z-axis. A similar plot can be made for when firms with innovations have them taken away. The change in total demand will be universally negative, but otherwise is a mirror image of Figure 3.1. The lattice shown in Figure 3.1 is constructed by getting the mean value of change in total demand for Firm size, s_i, and Innovation, inv_i, across a wide range of values. Size, s_i, varies from 2 to 38 with increments of 1. Since Firm size is a continuous range of values (random draws from a normal distribution), I group firms of firm size (s_i,±0.5) into each of the 37 points. Innovation, inv_i varies from 0.02 to 0.48 at increments of 0.01. As innovation values are in discrete in nature, no similar grouping as with firm size is needed. The result is a total of 1739 points for constructing the surface shown in Figure 3.1.

Each point in the lattice corresponds to the average demand change for all firms that have an innovation inv_i in the simulation. Firms with size and innovation value outside the range shown on the axes were not included as the density at such regions was sparsely populated (overall ¡ 0.1%: since firm size are drawn from a normal distribution, draws from the tail are uncommon), and therefore were dropped.

Unsurprisingly, Figure 3.1 indicates that gaining an innovation positively affects firms' total demand: the range of total demand change is positive regardless of values for inv_i and s_i. While always positive, looking at the y-axis from the larger to smaller firms, the effect of s_i is nonlinear: change in total demand is minor for the largest firms, but rises quickly and then falls gradually for smaller firms. The largest of firms, who pick first, prioritize gains from heterogeneous baseline demand rather than conquest gains from innovation; they locate at the demand highpoints. Once the highpoints are taken, conquest gains from innovation matters, as shown by the quick rise. As I move further down the size rank order, the impact of having an innovation falls. This results because smaller firms move later, and their location choice set diminishes commensurately; as earlier movers take better locations, all that remains are locations that yield smaller conquest demand. Looking at the x-axis, increases in firms' average innovation value, inv_i, accentuates the non-linear relationship between firm size and total demand change. The strategic benefit of conquest demand increases with firms' average innovation value.

Figure 3.1 shows innovation's effect on total demand. But, as noted previously, total demand (or any of the four mechanisms' demand effect) are difficult to observe. To link the simulation's expectations to an empirical context, I have the simulation calculate not only total demand but also an empirically observable outcome: neighbor firm size. Neighbor firm size is an indirect indicator of total demand: larger firms are likely camped on baseline demand highpoints; larger firms enhance demand externalities, and larger firms offer greater conquest demand. On the 2D discrete landscape, interior locations have eight neighboring location (edges have five and corners have three). Each neighboring location may be occupied by a firm, a neighbor; or be unoccupied. When a firm's turn occurs, the simulation calculates the average size of its neighbors; while interior locations have eight neighboring locations, some of them may be unoccupied, so the number of neighbors for the calculation usually is less than eight.

Figure 3.2 plots average neighbor size as a function of firm size, s_i, and firm's innovation value, inv_i. Change in average neighbor size from having an innovation is on the z-axis. Figure 3.2's shape is similar to that in Figure 3.1 on the y-dimension, for firm size, s_i: change in average neighbor size is minor for the largest firms, but rises quickly and then falls gradually for smaller firms. But Figure 3.2's shape differs on the x-dimension, for firm's innovation value, inv_i: instead of being monotonically increasing as in Figure 3.1, it has an inverted U shape. This difference gives me insight into the firms' strategic behavior. Looking at Figure 3.1, the shape along the y-axis for firm's innovation value, inv_i: while monotonically increasing, its rate of increase flattens out when inv_i is around 0.35. This flattening corresponds to the maxima in Figure 3.2. The inverse U-shape is driven by firms switching priority between two sources of demand externalities versus gains from their innovation. For firms having an innovation of low or medium size, externality demand is typically the biggest contributor to overall demand; consequently, a firm prioritizes locating next to the largest possible neighbors. And large neighbors with innovations are even better, as they draw even more customers, increasing the extent of externalities. As the size of the innovation increases, the gains from innovation start to dominate the demand from externalities. The firm prioritizes locating next to neighbors that don't have their innovations allowing the firm to capture neighbors' customers without commensurate loss of its own. These neighbors might not be the largest of potential neighbors, thus explaining the decrease in the size of neighbors upon having large innovations.

With these three sets of effects, I differentiate between firms with and without innovation (solid line or dashed line) for a total of six lines. Across all three effects, the difference between the solid and dashed line is an indication of how having an innovation changes that demand effect. The lines' jaggedness at the extremes of firm size is the result of having fewer observations to calculate the average values because firm sizes are pulls from a normal distribution.

Looking at heterogeneous location demand's two (black) lines, the demand is high for larger firms and falls for smaller firms towards zero. Recall with my heterogeneous demand landscape resembled a tent supported by multiple tent-poles. The tent-poles are the highpoints with lower regions between the tent-poles, and the lowest regions around the periphery, where demand decreases to zero. Larger firms take the highpoints and higher locations, leaving lower demand locations for smaller firms. Looking at the difference between the solid and dashed lines, the value of having an innovation is fairly constant regardless of firm size. This is because there is no strategic element to heterogeneous location demand. A firm extracts firm-specific demand that is a function of its innovation weighted size. Innovation effectively makes the firm larger, which allows it to extract more demand from any given location, which accounts for the gap between the solid and dashed lines.

Looking at demand externalities two (blue) lines, these increase rapidly from zero for larger firms; demand externalities by definition do not exist until some firms locate on the landscape and other firms locate adjacent to them. Externalities then plateau and diminish slowly. The reduction results from demand externalities being a function of neighboring firm size and larger firms moving before smaller one. As all firms want to locate next to larger ones to experience greater demand externalities, there is a smaller firm feeding up on larger firm dynamic. This feeding up keeps differences in neighbor firm size to a minimum. This smooth reduction in neighbor firm size results in the gradual reduction of demand externalities. Looking at the difference between the solid and dashed lines, medium-sized firms benefit more from having an innovation. This results from the strategic behavior for conquest demand described below, where firms seek larger neighbors. Given that firms with innovations seek larger neighbors, this is differential for demand externalities is a secondary effect.

Looking the two (red) lines for the net of conquest demand and demand loss from neighbors' innovation, there is a substantial difference between the solid and dashed lines. This difference is much greater than the differences for heterogeneous location demand or demand externalities, which is consistent with my position that firms behave strategically for this demand effect. Note also that for firms without innovation the effect is negative across the entire size range. When firms lack innovation, they become targets for other firms with innovation who are looking to take some of their customers. Turning to the solid line, it's initial flat for larger firms, then climbs rapidly to a maximum, then declines at a somewhat constant rate, but goes negative for smaller firms. Large firms prioritize heterogeneous landscape demand over conquest demand, but once highpoints and the best locations near highpoints are taken, then firms start to prioritize conquest demand. Because conquest demand is a function of the donor firm's size and firms moving in size rank order, conquest demand decreased gradually. Larger innovation wielding firms find slightly larger donor firms to locate next to. This feeding up prevents big differentials in neighbor firm size from forming. This smooth reduction in neighbor firm size results in the gradual reduction of conquest demand. Eventually, the landscape is so filled in that the smaller firms face only bad choices. All available spots have some neighbors that are both larger and have an innovation. This results in not conquest demand, but demand losses for smaller firms, even those that have innovations themselves.

3.3.3 Testable Predictions

I can interpret the above figures to state predictions from the simulation model, some of which are testable in my empirical context.

Figure 3.1 offers two predictions. First, when a firm has an innovation, the greater a firm's innovation, the greater the increase in demand that it experiences. Second, when a firm has an innovation, the relationship between firm size and demand is an inverted U, with medium size firms deriving the greatest benefit from having an innovation. As I am unable to measure demand in my context, I am unable to test these two predictions.

Figure 3.2 offers two predictions. First, when a firm has an innovation, the relationship between the innovation's size and neighbor size is an inverted U shape. Second, when a firm has an innovation, the relationship between firm size and neighbor size is an inverted U, with medium size firms having the largest neighbors.

In my empirical context, I am not able to measure an innovation's value, inv_i, only whether a firm has an innovation or not. This collapses Figure 3.2's 3-dimensional surface, eliminating the innovation's value dimension, to 2-dimensions. This alters Figure 3.2's first prediction, and becomes: when a firm has an innovation, its neighbor size is larger. Figure 3.2's second prediction remains the same. Therefore:

> **Hypothesis 1:** Firms with an innovation have larger neighbors.

> **Hypothesis 2:** For firms with an innovation, the relationship between the firm's size and their neighbors' size is an inverted U shape.

Figure 3.3 offers an additional prediction beyond those from Figures 1 and 3.2. Since demand externalities and conquest demand are (close to) zero for the largest firms, the largest firms will prioritize heterogeneous landscape demand. And in maximizing demand from this mechanism, the largest firms will locate at the landscape's highpoints. In my empirical context of the Consumer Electronics Show, the venue's entrances are the highpoints. Therefore:

Hypothesis 3: Largest firms locate on and nearest to heterogeneous landscape demand highpoints (entrances).

I test H1, H2, and H3 in my empirical context.

3.4 Data & Methods

I test the simulation model's predictions with the data from firms' booth locations at a trade show, the Consumer Electronics Show (CES) that is held annually in Las Vegas. Every year the CES attracts a full range of firms in the consumer electronics industry. A central feature is that some firms use the opportunity to announce upcoming new products, which run the full range from major product announcements to minor product updates.

This setting matches the simulation model in that firms are looking to maximize their exposure at the CES; they want to experience the most traffic (demand) possible. To do so, firms choose their booth location. Traffic at their booth location will be affected by how close the booth is to the entrances (heterogeneous location demand), who their neighbors are (externality effect), and whether a firm has and its neighbors have new products to publicize (conquest and loss demand). Reflecting the incomplete information for the value of a firm's innovation, firms may suspect the appeal of their new product, but won't know how customers respond until it is revealed at the CES. Among competitors, firms have some knowledge of whether competitors have innovations since firms often issue press releases in advance of the CES publicizing future new product announcements, but information about the new products typically is incomplete.

My data is for 2014, 2015, and 2016 editions of the CES and comes from scraping the Consumer Electronics Association website each year. For each year, I know the exhibitors in the Central Hall at CES and their booth location choice. The Central Hall houses the leading consumer electronics firms and experiences the most demand of all the halls at the CES; the other halls focus on automotive accessories, mobility options, etc. I capture each firms' both location, from which I can observe (i) every firms' neighbors and (ii) distance to the entrances.

For this study, I take innovation as new or incrementally new products that firms bring to exhibit at CES. To determine whether a firm announced a new product at the CES, I make use of two data sources: media articles and CES Innovation awards. First, I search all available newspapers, magazines, and blogs articles from the Lexis-Nexis database starting three months before a year's CES and ending one month after the year's CES. To determine whether the firm has an innovation that year, I do a combination of automated and manual text analysis. I find articles that contain keywords such "new product", "unveil", "latest" and other variants near "CES" and its variants. I then manually examine each of these filtered articles to determine whether indeed the article discusses the firm is having an innovation during that year. Second, the CES has an annual innovation award for multiple product categories. I considered firms under consideration for an award to also have an innovation that year. The text search flagged 19.8% of firms in my sample as having an innovation, and 17.7% of firms in my sample were under consideration for an award over the years. The intersection of these two sources led to 26.4% of firms being flagged as having an innovation in the overall sample.

For the given period, I have 409 firm-year observations with a total of 185 unique firms. A snapshot of Central Hall, 2015 is provided as Figure 3.5.

3.4.1 Booth Allocation at CES

Understanding the booth allocation process is critical. For the context to be suitable to test the simulation's predictions, firms must have a choice over their booth locations. To assess this, I (1) examined information on the Consumer Technology Association (CTA who runs the CES) website and then (2) spoke to the top executive at the CEA who is in charge of the CES. The CTA website provides information on how exhibitors can request booths and booth locations. This information provides substantial insight into the booth allocation process. For example, it specifically asks for an applicant's five booth location preferences. However, to gain a full understanding of the process, I conducted a semi-structured interview with the Vice-President of Operations at CTA who is specifically responsible for all elements of organizing the CES.

Booth allocation at the CES is primarily a function of money spent. Spending is captured by priority points. A firm earns priority points proportional to its spending for its booth and related services in a given year. The price of a booth depends on its size. These priority points accumulate year after year so that a firm exhibiting at the CES longer than others has more priority points, all other things equal. Firms with more priority points choose earlier. Firms that are current exhibitors in a year often choose their next year's location soon after, based upon their priority points. Unallocated locations are available to new or intermittent exhibitors after the conclusion of a year's CES. Such firms submit location requests, which are processed in the order that they are received. For requests that are received around the same time, priority is given to the firm with more priority points. At the conclusion of a year's CES, roughly 30% of next year's booth locations is allocated within the first week; these typically being the booths closest to the entrances.

When choosing locations, firms are knowledgeable about where other firms that have chosen earlier are located. Firms that typically choose next year's location by the conclusion of the current year's CES are larger firms that want the same or similar locations year after year. After the CES concludes, the CEA website lists and updates were taken and vacant locations. And an exhibitor can contact the CEA for more detailed information, such as the identity and location of important reference firms as firms typically have strong preferences to be located close to or far away from certain other firms. Firms also can and do alter their location choices throughout the year, subject to the stock of remaining vacant locations.

The snapshot of CES's Central Hall in Figure 6 shows that booths closer to the entrances are larger and therefore more expensive and systematically decrease in size farther away from the entrances. So regardless of its priority points, a firm may have the option of paying more for a larger booth to move closer to an entrance. But as the number of booths close to entrances is limited, moving very close to an entrance purely in one year's spending without accumulated spending is unlikely. Consistent with this, the venue maps across years reveal that typically the bigger firms stay in the same spot year after year, while the medium-sized and smaller firms move around.

Firms choose their spots in the order decided by the priority points and have knowledge of spots, both taken and vacant, at the time of their choosing. This enables the firms to strategically choose the location of their booth, taking into consideration their innovation and other firms' choices. The structure of the process allows the firms relative flexibility in choosing their location taking into consideration their expectation of innovation which is similar to the structure in my simulation model.

3.4.2 Measures

My focal dependent variable is “Neighbor Size”, which I operationalize as the average firm size of the focal firms’ immediately adjacent neighbors. As the CES has several booth sizes, a particular booth may vary from having 1 to 12 neighbors. For each year of three years I examine, I code a matrix capturing who neighbored whom. I consider firms across aisles as neighbors; firms adjacent to each other, but not those blocked by a physical barrier.

Another outcome I consider is “Distance to an Entrance”. Hypothesis 3 states that the largest firms will be at or near entrances. While this is an outcome for the largest firms, it is also then an important determinant of neighbor size for other firms. So, distance to the entrance is both a dependent and independent variable. Thus, having an innovation might drive a firm to locate close to an entrance to maximize demand, while being able to compete with larger neighbors due to the innovation. Additionally, I use whether a firm locates next to an entrance as a control variable in some of the specifications where neighbor size is the dependent variable. To calculate the mean distance to an entrance, I use a year’s venue map and calculate the walking distance between a location and each of the CES Central Hall’s five entrances and then take the average of the five values.

My focal independent variable, “Innovation”, is whether a firm has innovation in a particular year. This time varying measure is constructed from text searches of archival data and lists of innovation award nominees, as described previously.

Firm size, "Firm size" is log number of employees. I also try log of revenues, with similar results to those presented later. I choose this measure since some of my firms are small and privately owned, for which data beyond employees or sales is limited. I get the majority of employee and revenue data using a variety of sources such as Hoover's, Business Source Complete, Factiva and company websites. In a couple of instances when a firm wasn't listed on Hoovers, I searched broadly on Google for the firm's information. Firm size varies by year for the large and medium-sized firms. For some of the smaller firms, however, firm size for different years was not available, and the same size was used for the missing values.

While the CES setting has several features that map well onto my simulation, there are other aspects of the CES that may also drive firm location behavior that I need to account for. A key one is the type of products categories that a firm participates in. The type and number of products a firm exhibits at CES would affect its location behavior.

Firms might want to locate next to firms that have similar products to benefit not from general demand externalities, but product category specific demand externalities. Alternately, firms might want to locate next to firms with products that are complementary to its own. For example, firms bringing phone/tablet/TV accessories may want to locate near firms exhibiting phones/tablets/TVs.

I take several approaches to accounting for the type and composition of product categories that a firm participates in. At the most basic, I use dummy variables for 43 consumer electronics categories that are defined by the CES. Some categories may lead firms to locate near or farther from entrances, thus also affecting neighbor size.

In addition to including category dummy variables, I try two different approaches to representing categories' effects. Analogous to the firms participating in the same versus complementary categories, I develop measures for product category competition and complementarity.

I create a product competition measure, "Product Competition", to reflect that some product categories have more exhibitors. This is a count of firms in the same category, with a larger count being greater competition. As firms participate in multiple categories, I take the average of the individual categories' counts. This measure has various possible outcomes. A firm with a high competition score might want to locate next to a firm with a low score to escape from high competition. Categories with high counts may lead to firms locating apart for differentiation. Categories with low counts might lead to firms collocating to generate demand externalities.

For product category complementarity, “Product Complement”, I create a 2-dimensional matrix representing the 43x43 possible combinations of product categories. For each firm in my sample, I increment the appropriate cells by one based upon the product categories that it participates in. For example, if a firm participates in TVs, mobile phones, and DVRs then the TV-phone, TV-DVR, and phone-DVR cells get incremented by one. I do the same for all firms. I divided each cell's score by the total across all cells, in a given year at the CES. In the final matrix, the value in each cell now represents the % of firms carrying products in a given pair of product categories. A higher % indicates that the pair of product categories is more likely than other combinations, which I take as indicating that category pair is more complementary more firms have chosen to participate in that category pair. To construct a firm specific measure of product complementarity, I sum the % scores for the product categories that a specific firm participates in. For example, for the firm that participates in TVs, mobile phones, and DVRs; I take the average from the TVs row (this is the average complementarity of TVs with all other product categories), mobile phone row, and DVR row. I sum these three averages, which gives me that firm's complementarity given the product categories that it participates in. A firm with high complementarity may be more interested in locations near firms offering products in complementary categories. Both the measures of product complementarity and competition were created for each firm-year.

I also measure the number of product categories a firm participates in, "Total Categories". Most firms at CES exhibit products in several product categories in a given year. Firms exhibiting in a large number of product categories might want to stay away from similar firms to avoid competing over multiple product lines.

I also include year dummies; firms' spending at CES and thus their location choices might be affected by macroeconomic differences. One limitation is that I only have three years of data. With panel data, I'd prefer to have firm fixed effects, but key variables, Firm size, and 43 Product category dummy variables have little within-firm variation. While I present results from pooling the three years of data, I run models for each year individually, and the results are similar in nature in direction and significance to those from the pooled data.

3.4.3 Empirical Analysis

The simulation predicts Neighbor Size and Distance to Entrance, which are continuous measures, as a function of Firm size and whether firms have an Innovation. In my empirical analysis, I employ an Ordinary Least Squares model to test my hypothesis from my simulation model. Of note, while I typically would be concerned with endogeneity with my empirical methods, in this case, I have accounted for endogeneity theoretically in generating my expectations. The predictions of the simulation model result from the explicit articulation of the underlying mechanisms, which is what I will test empirically. My model specification is:

Neighbor $\text{Size}_{i,t} = \beta_0 + \beta_1\text{Firm Size}_{i,t} + \beta_2(\text{Firm Size}_{i,t})^2 + \beta_3\text{Inno}_{i,t} + \text{Interaction Terms} + \text{Controls}_{i,t} + \epsilon_{i,t}$ — (1)

Distance to $\text{Entrance}_{i,t} = \beta_0 + \beta_1\text{Firm Size}_{i,t} + \beta_2(\text{Firm Size}_{i,t})^2 + \beta_3\text{Inno}_{i,t} + \text{Interaction Terms} + \text{Controls}_{i,t} + \epsilon_{i,t}$ — (2)

The subscript 'i' is the firm indicator while the subscript 't' is the time indicator for the panel dataset, $\epsilon_{i,t}$ is the error term of the model. I begin by estimating the effects of the various control variables on a firm's location behavior. I then add my independent variable to the model.

3.5 Results

Table 3.1 shows descriptive statistics, and Table 3.2 shows correlations between the variables in my models. From the descriptive statistics, I can observe that on firm size, the distribution is left-skewed with a long tail. About 26.4% of the firms in my sample have innovations. A typical firm displays products in about 5.7 categories at the show across the years with the maximum being 21 for Sony in 2014.

The negative correlation between firm size and distance to entrance suggest that larger firms typically locate near the entrances. Understandably, larger firms have products in a larger number of categories. Additionally, the positive correlation between firm size and innovation suggest that larger firms typically bring innovations more frequently to CES when compared to smaller firms.

Looking at Table 3.3, models 1-6 have Neighbor Size as the dependent variable. Models 1-2 contain controls variables only. The control variables *Total Categories, Product Competition* and *Product Complement* show little statistical significance across the models. This is likely due to my inclusion of 42 category dummy variables for 43 CES defined product categories, which are statistically significant as a group. *Total categories* does become statistically significant when *Firm size* is introduced, as the two are correlated (0.25 from Table 2). While this collinearity might artificially result in significant t-tests for the correlated variables, the change in R-squared between column 2 and 3, from 0.273 to 0.369, indicates that inclusion of *Firm size* is an important variable in explaining *Neighbor Size*.

Models 3-6 introduce the focal variables incrementally. Hypothesis 1 predicts that firms with an innovation have larger neighbors. This is tested in model 5. The coefficient for *Innovation* is positive and significant indicating support for Hypotheses 1 which relates innovation and neighbor size. Hypothesis 2 predicts that for firms with innovation, the relationship between the firm's size and their neighbors' size is an inverted U-shape. This is tested in model 6, which adds *Firm size* and *Firm size*^{2} interacted with *Innovation*. The positive and significant coefficient for *Firm Size x Innovation* along with a negative and significant coefficient for *Firm Size*^{2} *x Innovation* suggests an inverted-U shape relationship between Firm Size and Neighbor Size for firms with innovation, which supports Hypothesis 2. For smaller firms, upon having an innovation, they locate themselves near larger neighbors to capture the value of their innovation similar to what I observe in my simulation. But, as the firm size grows larger, the mean size of neighbors continues to fall, consistent with the fact that the largest firms prioritize demand from entrance rather than from neighboring firms giving an inverted-U shape to the curve.

Models 7-11 in Table 3.3 have Distance from Entrance as the dependent variable. Similar to with *Neighbor Size* as the dependent variable in Models 1-6, here also *Product Competition* and *Product Complement* show little statistical significance across the models 7-11. The 42 category dummy variables for 43 CES defined product categories are also statistically significant as a group. But here *Total categories* does have a consistently negative and significant effect: firms with products in more categories are closer to the entrances, all else equal. Hypothesis 3 predicts that the largest firms will locate close to demand highpoints, which are the entrances. The negative and significant coefficient of *Firm Size* across models 811 provides support for Hypothesis 3. Though the positive and significant coefficient on *Firm Size*^{2} tempers this support. The function monotonically decreases for about 85% of the firms with increasing firm size and then begins to increase. The reason behind this form is the way the measure *Distance to Entrance* is constructed, which is the mean distance to all entrances. For the largest firms, this can be high since they are close to only one entrance and distant from other entrances.

Comparing coefficients of *Size of Firm x Innovation* and *Size of Firm^2 x Innovation* between models 6 and 11 in Table 3.3 provides me with an interesting observation. These coefficients are significant in model 6, for the *Neighbor size* dependent variable, but not model 11, for the *Distance to Entrance* dependent variable. In model 6, the two coefficients capture the strategic behavior of firms when they have innovations; the positive and negative coefficients for the linear and squared term, respectively, define an inverted U-shape: this strategic behavior of locating next to larger neighbors is greatest for medium-size firms. But these same variables don't have an effect for *Distance to Entrance*. In combination, these results suggest that medium-sized firms, with innovations, are looking for larger neighbors to benefit from, but not the larger neighbors that are near entrances. This suggests that the strategic behavior of innovation wielding medium-sized firms seeking larger firms is occurring not near entrances where most of the largest firms are positioned, but away from the entrances, in the interior. And in the interior there are likely clusters of larger firms: the coefficients for *Firm Size* and *Firm Size^2* in models 3-6 suggest that the larger a firm, the larger it's neighbors; which is driven by the externality mechanism. Such clusters of larger firms in the interior become attractions for innovation wielding medium-size firms. This behavior is quite different from simple priors which might suggest that all firms want to be close to demand highpoints such as entrances. This finding suggests that some firms can maximize their demand by locating in the interior and pulling customers away from neighbors. On a competitive landscape, good choices are exogenously determined demand highpoints, but also alternate highpoints that are endogenously determined by the presence of competitors that act as donors.

3.6 Discussion

I investigate the effect of a firm having an innovation on its competitive positioning. I expect that a firm armed with innovation to position itself more aggressively relative to the type of firm it competes with; that a smaller firm with innovation will position itself near larger firms than it would otherwise. I refine my expectations using a simulation to model several underlying mechanisms and then test the simulation's predictions using empirical data from the Consumer Electronics Show (CES).

The simulation helps in several ways. First, it allows me to model underlying mechanisms that drive firms' location choice explicitly: (1) gains from taking neighboring firms' customers when a firm has an innovation, (2) possible losses when neighboring firms have their innovations, (3) gains from positive demand externalities, and (4) heterogeneity in locations' demand across the competition space. Second, by explicitly modeling the underlying mechanisms and their interactions, the simulation allows me to address the endogeneity of firms' choices. A focal firm's choice is a function of the prevailing landscape which is determined by many other firms' choices; this system of endogeneity is hard to account for using empirical methods. Third, the flexibility of the simulation allows me to model firm choices over a wide range of values for the key parameters so that the simulation's predictions are generalizable across a wide range of scenarios. Additionally, it helps me overcome the handicap of limited data I have from my empirical context; I can't observe customer demand/traffic, but I can observe firms' location choices and attributes of their choices that link to customer demand/traffic and therefore test predictions focus on these outcomes. Finally, the simulation helps me generate hypotheses that I test using empirical data. The versatility of the simulation model helps me mimic the context of CES while still being abstract and flexible to be used for other competitive landscapes.

The Consumer Electronics Show is an empirical context with some desirable features: (1) most firms in the consumer electronics industry attend, (2) the CES is an important venue for firms to showcase new and upcoming innovations, (3) firms choose their booth locations with an eye to maximizing customer demand/traffic, (4) firms' booth locations are readily observable. My empirical analysis supports for my hypothesis which was generated using the simulation model. My empirical results indicate that firms with innovation position themselves closer to larger firms to benefit from demand externalities and to attract some of the larger firms customers away based upon their innovation. This result is, however not varies with firm size. Larger firms focus on choosing a position near demand highpoints, and whether they have an innovation has limited impact on their positioning decision. However, having an innovation greatly influences the choices of the medium and smaller sized firms. As a consequence, I observe an inverted-U shape relationship between the size of the firm and those of the neighbors for firms with innovation.

An interesting finding is that all firms don't prioritize exogenously determined demand highpoints. While the largest firms do, medium-sized firms act strategically when armed with innovation to seek out larger firms in the interior, apart from exogenously determined highpoints. Larger firms in the interior, that group together, become pseudo, endogenously determined highpoints for medium-sized firms.

The results in my paper have implications for managerial choices especially for managers of small and medium-sized firms. The demand highpoints are inherently attractive. But such prized positions might not be readily available to the small and medium-sized firm, whose positioning choices might be constrained by larger competitors. The results of my paper suggest that in addition to demand highpoints, other attractive positions in the competitive landscape can be created by other firms' positioning choices. Firms can position themselves close to these endogenously created demand highpoints, especially when they possess an innovation. Having an innovation can allow managers to alter the positioning of their firms and aid their ability to directly compete with the larger firms by locating at these quasi-demand high points which are near positions of larger firms.

Table 3.1: Summary Statistics Table

Statistic	N	Mean	St. Dev.	Min	Max
Neighbor Size	409	4.726	2.268	1.099	11.688
Firm Size	409	4.391	3.310	0.693	12.590
Innovation	409	0.264	0.441	0	1
Distance to Entranace	409	135.449	68.974	10.300	250.100
Product Competition	409	30.705	13.253	1.000	74.500
Product Complement	409	8.810	6.015	0.008	27.781
Product Categories	409	5.746	3.687	1	21

Table 3.2: Correlation Matrix

	Variables	1	2	3	4	5	6	7
1	Neighbor Size	1						
2	Firm Size	0.43	1					
3	Innovation	0.45	0.19	1				
4	Distance to Entrance	-0.24	-0.16	-0.17	1			
5	Product Competition	-0.17	-0.35	-0.02	0.09	1		
6	Product Complement	0.04	0.05	0.11	0.02	0.38	1	
7	Total Categories	0.11	0.25	0.13	-0.02	0.06	0.92	1

Table 3.3: Effect of Innovation on Neighbor Size

	Dependent variable:										
	Neighbor Size						Distance to Entrance				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Total Categories	0.168	−0.161	−0.942**	−0.971**	−0.762*	−0.718*	−40.772***	−30.484**	−31.150**	−33.453**	−33.623**
	(0.462)	(0.452)	(0.435)	(0.433)	(0.403)	(0.397)	(14.448)	(14.845)	(14.774)	(14.596)	(14.600)
Product Competition	−0.007	−0.007	−0.001	−0.003	0.004	0.003	−0.089	−0.170	−0.260	−0.357	−0.316
	(0.019)	(0.019)	(0.017)	(0.017)	(0.016)	(0.016)	(0.603)	(0.599)	(0.598)	(0.591)	(0.591)
Product Complement	0.163	0.158	0.122	0.130	0.134	0.114	−0.551	−0.102	0.203	0.139	0.609
	(0.198)	(0.192)	(0.179)	(0.178)	(0.165)	(0.163)	(6.189)	(6.140)	(6.112)	(6.031)	(6.041)
Distance to Entrance		−0.008***	−0.006***	−0.007***	−0.005***	−0.005***					
		(0.002)	(0.002)	(0.002)	(0.001)	(0.001)					
Size of Firm			0.301***	0.037	0.102	−0.150		−3.660***	−13.117***	−13.730***	−15.914***
			(0.041)	(0.136)	(0.127)	(0.149)		(1.381)	(4.619)	(4.562)	(5.469)
Size of Firm^2				0.023**	0.014	0.040***			0.835**	0.951**	1.069**
				(0.011)	(0.011)	(0.013)			(0.389)	(0.386)	(0.477)
Innovation					1.748***	0.927				−26.787***	−56.922**
					(0.228)	(0.647)				(8.193)	(23.763)
Size of Firm x Innovation						0.618**					11.133
						(0.270)					(9.997)
Size of Firm^2 x Innovation						−0.062***					−0.666
						(0.021)					(0.794)
FE: Prod Categories	Yes***	Yes***	Yes***	Yes**	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***
FE: Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	409	409	409	409	409	409	409	409	409	409	409
R^2	0.224	0.273	0.369	0.376	0.465	0.484	0.179	0.194	0.204	0.228	0.232

Note: Significance: *p<0.1; **p<0.05; ***p<0.01 :: Two tailed SE in parenthesis

Figure 3.1: Demand Difference for Firms

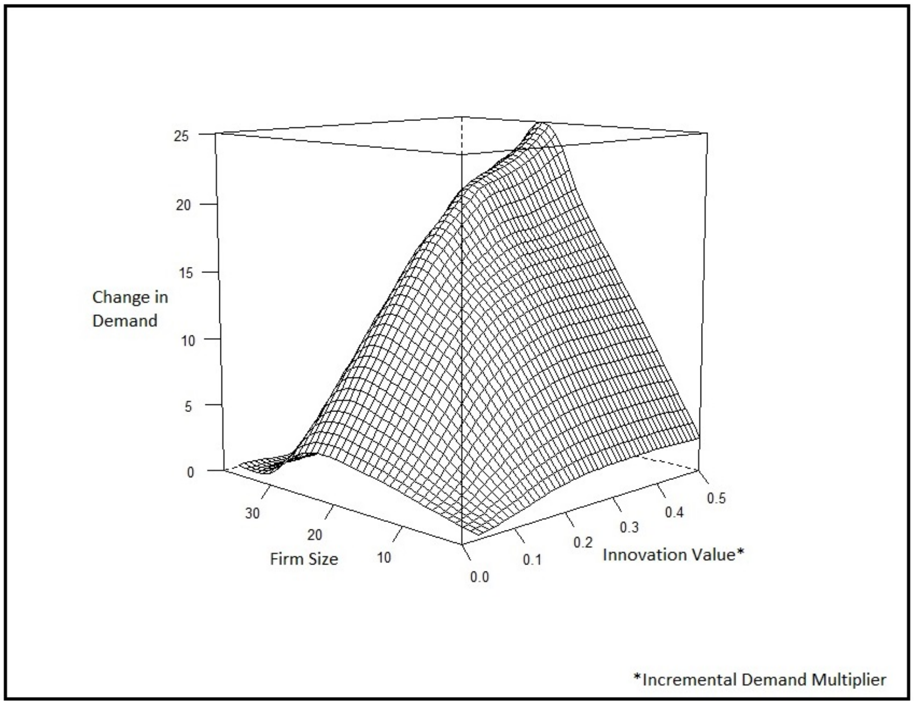

Figure 3.2: Difference in Neighbor Size

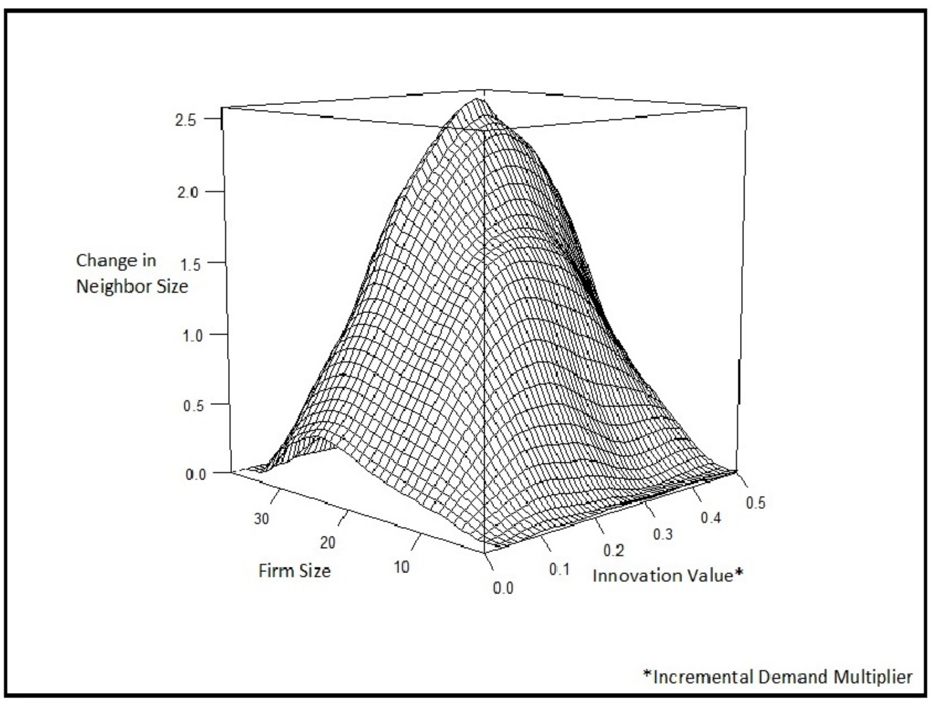

Figure 3.3: Difference in Demand from various sources for firms with and without Innovation at time of choice

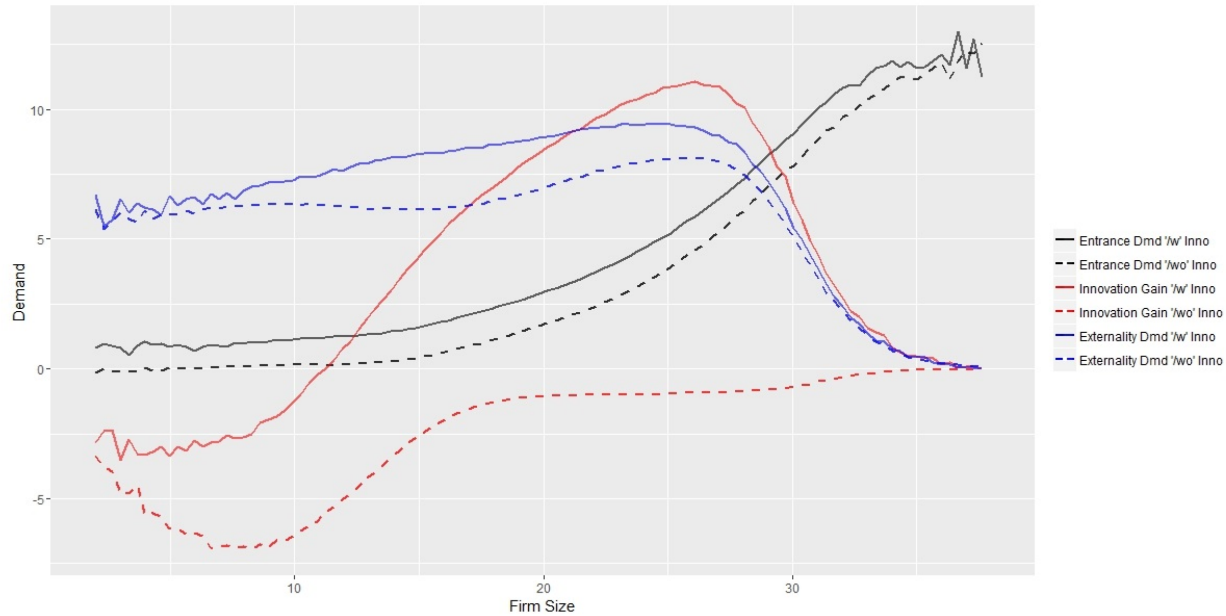

Figure 3.4: Number of Product Categories by Firm

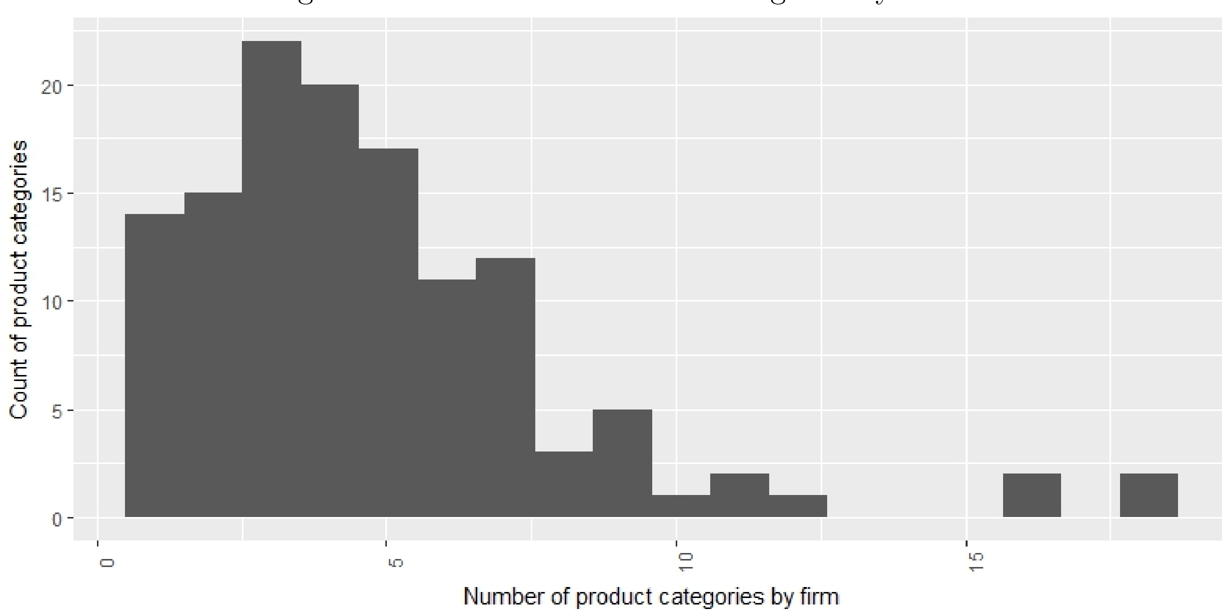

Figure 3.5: Layout from CES 2015 Central Hall

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