

ABSTRACT

Title of Document: EFFECTS OF PERFORMANCE SCHEDULES ON
EVENT TICKET SALES

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Event scheduling is one of many important decisions facing event marketers in the entertainment industry (i.e., how should multiple performances be scheduled across markets, across venues, and over time?). While there is ample research examining the issues of costs and constraints associated with such a decision, virtually no research exists to examine the impact of these decisions on consumer demand. Hence, the objective of this dissertation is to examine how consumers respond to event marketers' scheduling decisions.

First, a scheduling effect may arise from performances within a market. When performances are scheduled closely in distance or time, their similarity in venue locations or performance dates may result in a stronger relationship and influence ticket sales. This relationship may have a positive effect on ticket sales because the similarity could signal the quality of an event and suggest the desirability of these performances. Thus, these performances attract more consumers and sell more tickets. However, the relationship could be negative. When performances are

close in distance or time, they become direct substitutes and compete for consumer patronage.

Another effect arises from an event distribution across markets. When an event travels from one market to another and each market has a different performance schedule, the word of mouth of this event may accumulate and carry over to later markets. If so, market sales may be a good proxy of word of mouth. How well (or poorly) an event sells in preceding markets may affect ticket sales in following markets.

This dissertation consists of three essays to examine the abovementioned scheduling effects. We contact a national ticket seller to acquire a dataset containing ticket sales of a family event traveling across 42 markets. The first essay analyzes a performance schedule in one metropolitan market and investigates the scheduling effect on ticket sales. The second essay employs all performance schedules in 42 markets to study heterogeneous market responses and propose explanatory factors. Finally, the third essay incorporates the distribution sequence of this event and examines whether ticket sales in preceding markets have a carryover effect to influence ticket sales in later markets.

EFFECTS OF PERFORMANCE SCHEDULES ON
EVENT TICKET SALES

By

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2009

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2009

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1 Introduction

Scheduling is one of many important decisions facing event marketers in the entertainment industry. To maximize revenues in a national market, event marketers have to not only make marketing mix decisions but also schedule performances across markets, across venues, and over time. Hence, these scheduling decisions result in a performance schedule within a market or across a national market for an event to perform in different venues and on various days. In this dissertation, we define a performance schedule as a summary of performances taking places in various venue locations and on different dates to examine potential effects of this performance schedule on ticket sales at a performance level and across markets.

Similar to airline and movie scheduling decisions, event marketers rely on costs and constraints in their scheduling process. They need to comply with venue availability and seating capacity to decide when to provide performances and how many performances to provide. They can minimize the travel distance across markets if it is expensive to move from one market to another. They can also shorten a performing period in a venue if the cost to rent a facility outweighs the benefits of having performances for a long period.

While there is ample research examining the issues of costs and constraints associated with such scheduling decisions, virtually no research exists to examine the impact of these decisions on consumer demand. In other words, it is unclear to event marketers how consumers in a market evaluate individual performances and how consumer inferences influence their purchase decisions such as which performance to buy and when to buy. Hence, at the

performance level, consumers' evaluations about performances in a schedule may affect the number of ticket sales of these performances and the pattern of these ticket sales over time.

It is important for event marketers to understand potential drivers for the number of ticket sales sold and the pattern of these ticket sales over time. Once they know the effects of these drivers, they will be able to estimate expected market demand and schedule performances accordingly. In this way, they can avoid revenue losses from undersupply and minimize costs resulting from potential oversupply. Additionally, event ticket sales are often available for purchases several months or weeks in advance, and these tickets are not sold at a constant rate throughout the advance-selling period. If event marketers understand the drivers for the sales rate, sales pattern can be easily established to monitor actual ticket sales over time and potentially adjust the marketing strategy as the event approaches.

As such, this dissertation aims to investigate the impact of performance schedules on ticket sales for a live performance event. Specifically, we propose two types of effects emerging from the scheduling decisions. One type of effect is likely to exist among performances within a market because of the way these performances are scheduled across venues and dates. For example, performances scheduled closely in distance or time might signal the quality of an event, the desirability of these venues or dates, or just the potential substitutes across venues or dates. If consumers make any of these inferences and perceive performances to be more or less favorable, the scheduling effect among performances within a market would influence how well each performance sells and when ticket sales occur.

The other type of effect might develop across markets where an event performs one after another. In other words, after an event performs in each market for a period, its word of mouth may arise and cumulate over time. If the word of mouth travels across markets and consumers

have positive feedbacks, how well this event does in previous markets could influence ticket sales in later markets. Because ticket sales in previous markets can capture the volume of word of mouth to some extent, it is plausible to observe ticket sales in previous markets to affect sales in later markets.

This dissertation consists of three essays to examine those possible scheduling effects mentioned above. For this purpose, we acquired a dataset containing ticket sales of a family event traveling across 42 markets. We start by characterizing a performance schedule in a single market and investigating its impact on the number of ticket sales at a performance level and the pattern of these ticket sales over time (i.e., essay one). From essay one, we conclude that performances scheduled close to each other in terms of distance can experience more ticket sales, and these tickets sell at a faster rate. On the other hand, performances scheduled close to each other in terms of time tend to sell fewer tickets, but do not exhibit any significant changes in their sale patterns. However, these results are established for one metropolitan market in our dataset. Hence, we expand the level of analysis to all 42 markets in essay two to ensure scheduling effects generalizable for this event and examine the heterogeneity across markets. Essay two confirms consistent scheduling effects across markets and identifies explanatory factors for the heterogeneity in effect sizes across markets. Finally, essay three proceeds to investigate scheduling effects at a market level and examines whether an event performing across markets affects ticket sales in these markets. Specifically, essay three reveals that markets to which an event travels sell more tickets when event marketers disperse performance dates or employ multiple venues in these markets. Additionally, these markets do not influence one another on their ticket sales, but their venues within the same market have such an effect. Although one may argue that the third essay does not have to be conducted after the first two

essays, we choose this sequence because we need to investigate the effect of a touring event across markets after we can understand and control for the effect of a performance schedule within a market.

The purpose of the first essay is to lay the foundation of this dissertation and to test whether scheduling decisions influence ticket sales of performances within a market. We begin by examining ticket sales at a performance level within a single market and differentiate between performances based on a set of scheduling characteristics. We derive a set of scheduling characteristics based on the venue locations and performance dates. According to these scheduling characteristics, we measure how closely performances are scheduled in terms of distance or time. A performance of a shorter geographic or temporal distance hence indicates its similarity in venue location or performance date to other performances.

After examining ticket sales of these performances as a function of their distance measures, we find that geographic and temporal distances between performances have different effects on ticket sales. More specifically, a shorter geographic distance between performances leads to more tickets sold and a faster sales rate for a performance. However, a shorter temporal distance between performances just causes decreases in the number of ticket sales but does not influence how fast tickets are sold.

Although it is not clear why consumers process geographic and temporal distances differently, it is clear that they refer to the way performances are scheduled as a means to make inferences about these performances. Their inferences about performances of a shorter geographic distance could be regarding the quality of an event, the desirability of their associated venues, or others. As a result, these performances sell more tickets and attract consumers to purchase tickets early. On the other hand, their inferences about performances of a shorter

temporal distance could be the high substitutability within a shorter period. Therefore, these performances compete for consumer patronage and suffer from sales cannibalization.

While the first essay demonstrates the significant effects of geographic and temporal distances on ticket sales, the results are for one market only. Yet, event marketers often need to make scheduling decisions for more than one market. It is not clear whether the results in this first essay are consistent across markets. For this reason, the objective of the second essay is to use all performance schedules of the same event to investigate heterogeneous market responses and identify explanatory factors.

To achieve this objective, we follow the same approach as in essay one and analyze all performance schedules. For performances within their associated market, we characterize them by their venue locations and performance dates and compute their geographic and temporal distances to other performances. Then, for each market, we model ticket sales of performances as a function of their distance measures to understand whether the heterogeneity exists in market responses. We then model these market specific parameters as a function of their market characteristics such as market population and additional scheduling characteristics such as travel sequence along the distribution to explain any differences across markets.

Our results show that market responses to performance schedules are heterogeneous and can be explained by market and additional scheduling characteristics. Specifically, when a market has a bigger population, the effects of days of week and baseline attractiveness are attenuated. Moreover, after an event travels to more markets that are geographically adjacent to a focal market, the focal market is less responsive to its baseline attractiveness and temporal schedule. Finally, a current market in a late distribution sequence tends to respond more favorably to a Sunday performance.

Results in essay two hence suggest a possibility that markets where an event travels one after another may be dependent. In other words, how following markets respond to their temporal schedule depends on how many geographically adjacent markets an event has visited. Another possibility is that there may be another means of integrating participating markets along a touring event such that ticket sales of preceding markets might directly influence ticket sales of following markets (rather than through the response parameters and geographically adjacent markets). If so, it is important to incorporate the temporal sequence in an event distribution and study the impact of preceding markets on following ones.

The primary objective of essay three, therefore, is to examine the impact of a sequentially distributed event across markets. Additionally, we consider the endogeneity between supply and demand for an event in case expected market demand influences event marketers' scheduling decisions and their schedule further affect ticket sales in a market.

To achieve this objective, we model the supply and demand for an event simultaneously. We model ticket sales of each market as a function of its performance schedule and the sequential distribution of this event. In addition to modeling the supply and demand simultaneously to account for the endogeneity, we use three variables to present the scheduling influences on market demand and employ the spatially weighted approach to incorporate different release timing and ticket sales of preceding markets in an event tour.

Our results show that a market experiences more ticket sales when event marketers disperse performance dates or book multiple venues in this market. Moreover, we show that the sequentially distributed event has an effect on ticket sales. However, this effect is significant across venues of the same market but not across markets. When an event performs in more than

one venue, its ticket sales in a preceding venue carry over to a later venue and influence its overall market sales.

The organization of this dissertation is as follows. Chapter 1 introduces the issues of scheduling facing event marketers and presents a general overview of each essay. Chapters 2, 3, and 4 discuss the three essays, respectively, in depth. Finally, Chapter 5 provides a brief summary of each essay, integrates essential results, and points out limitations and future directions to conclude this dissertation.

2 Essay 1: Scheduling to Sell: Examining the Impact of a Performance Schedule on Event Ticket Sales

2.1 Introduction

Scheduling is one of many important decisions facing event marketers in the entertainment industry. Besides decisions regarding marketing activities (e.g., pricing and promotions), event marketers have to schedule performances across markets, across venues, and over time. Typically, they rely on costs and constraints in their scheduling process (Etschmaier and Mathaisel 1985; Lohatepanont and Barnhart 2004; Eliashberg et al 2007) and use pricing, advertising, and days of week to describe how well an event can sell (Weinberg and Shachmut 1978; Putler and Lele 2003; Leslie 2004) or when ticket sales occur (Moe and Fader 2009).

While there is ample research examining the issues of costs and constraints associated with such scheduling decisions, virtually no research exists to examine the impact of these decisions on consumer demand. In other words, it is unclear to event marketers how consumers in a market may evaluate a performance schedule of an event and how consumer inferences influence their purchase decisions such as which performance to buy and when to buy. Hence, at the performance level, consumers' evaluations about performances in a schedule may affect the number of ticket sales of these performances and the pattern of these ticket sales over time.

From event marketers' perspective, they need to understand potential drivers for ticket sales in terms of the number of ticket sales and the pattern of these ticket sales over time. Once they know how these drivers influence market demand, they can estimate expected market demand accordingly and schedule performances to meet this market demand. In this way, they

can avoid revenue losses from undersupply and prevent decreases in profitability due to oversupply.

On the other hand, event ticket sales are often available for purchases several months or weeks in advance, and these ticket sales do not occur at a constant rate throughout an entire advance-selling period. If event marketers understand drivers for tickets selling at a different rate, they can portray the sales pattern as a benchmark and monitor actual ticket sales over time. Consequently, once event marketers find an actual pattern deviating from the benchmark, they can take actions in time.

In general, scheduling decisions affect the maximum number of tickets that an event can sell. When event marketers schedule a live performance event, they often allocate multiple performances across markets, across venues, and over time. Although the number of performances and the capacities of chosen venues constrain the maximum number of tickets an event can sell, empirical evidence shows that it is rare for the demand to exceed supply in this industry. Therefore, one possible impact of scheduling decisions is to constrain the maximum possible of ticket sales for an event although the supply is usually well beyond the actual demand.

Scheduling decisions might also influence consumer responses in a market. In other words, when consumers realize performances are scheduled in various venue locations and on different dates, they may try to rationalize why event marketers schedule performances in this way and then make inferences about these performances. If so, consumers could formulate different preferences for these performances to choose one performance to attend and purchase tickets at their desired time. At a performance level, consumer responses influence how well individual performances sell and when ticket sales of these performances occur.

Therefore, the objective of this essay examines the effects of scheduling characteristics of performances on ticket sales. Specifically, we use venue locations and performance dates as the scheduling characteristics of each performance, and we investigate whether performances scheduled closely in distance or time experience a different number and timing of ticket sales.

We define the timing of ticket sales as tickets sold at different times in an advance-selling period, and earlier or later timing of ticket sales suggests ticket sales occurred in the earlier or later advance-selling period. In other words, if scheduling characteristics have an effect, performances scheduled close in distance or time would experience more (or fewer) ticket sales. Their ticket sales would occur earlier (or later) than those scheduled farther apart in an advance-selling period, *ceteris paribus*.

One possible effect is to see performances scheduled close in distance or time experiencing more ticket sales and earlier timing of sales than those scheduled farther apart. For example, if event marketers want to signal the desirability of some venue locations or performance dates, they could allocate more performances to those specific venues or dates. In this way, consumers would perceive performances scheduled close in distance or time to be more attractive (due to the similar scheduling characteristics) and assign higher utilities to these performances. As a result, these performances could sell more tickets and experience earlier timing of sales than other performances.

Another possible effect is to observe performances scheduled farther apart in distance or time experiencing more ticket sales and earlier timing of sales than those scheduled nearby. In other words, when consumers have higher uncertainty about whether they can attend an event in a particular venue at a specific time, event marketers could sparsely allocate performances across venues and dates. In this way, consumers have more alternatives and higher flexibility regarding

when and where to attend. Hence, the chance for them to attend this event increases, and performances scheduled farther apart will be able to sell more tickets and experience earlier timing of sales. In contrast, performances scheduled nearby merely substitute one another within certain venues or dates. Consumers do not have to decide which performance they want to buy and can delay their purchase timing. Hence, these closely scheduled performances compete against consumer patronage and cannibalize ticket sales. To sum up, scheduling characteristics might have two possible but contradictory effects on ticket sales. We allow both possibilities and examine the effects of scheduling characteristics empirically.

Our modeling objective is to measure the scheduling characteristics of each performance and study the impact of these scheduling characteristics on the number and timing of ticket sales. We consider the possibility that consumers evaluate venue locations and performance dates differently. Thus, we differentiate the effect of scheduling across venues from the effect of scheduling across dates and then investigate these separately effects. Specifically, we refer to the previous effect as the effect of geographic scheduling or the effect of a geographic schedule and the later effect as the effect of temporal scheduling or the effect of a temporal schedule.

First, to measure the scheduling characteristics of performances, we characterize each performance in a schedule of an event by its venue location and performance date. Then, we compute the geographic and temporal distances between performances to understand how closely (or distantly) performances are scheduled across venues and dates. For example, performances of a shorter geographic or temporal distance to others are relatively closer to other performances than performances of a longer geographic or temporal distance.

Second, to examine the number of ticket sales across performances, we consider the possibility that some consumers might evaluate the venue locations and performance dates in a

schedule but eventually do not attend. To account for consumers who make purchases and those who miss out the opportunity to attend, we specify the number of ticket sales in the form of sales share within a potential target market. Then, we examine the share of each performance and the non-buyer segment within this potential market. We extend the competing destination model proposed by Fotheringham (1988) and model the share of each performance and the non-buyer segment as a function of the geographic and temporal distances between performances. By doing so, we can understand whether scheduling characteristics influence ticket sales at a performance level. In addition, using sales shares of individual performances and the population size in a target market as the number of potential buyers, we can obtain the number of ticket sales at a performance level. We can also obtain a market penetration rate by taking the sum of sales shares across performances.

Third, to examine the timing of ticket sales across performances, we first consider a general pattern of ticket sales for a performance. That is, a performance sells fewer tickets in the beginning of its advance-selling period and obtains more sales over time with the most arriving in the later period or the week of the performance. Although this is a general pattern over time, each performance still has a different sales rate. Some performances experience ticket sales occurred early (i.e., earlier timing of ticket sales) but others experience ticket sales arrived later (i.e., later timing of ticket sales). To account for variations in sales rate across performances, we employ a Weibull hazard model to capture the timing of sales over time for individual performances. We further model the sales rate of each performance as a function of its geographic and temporal distances to other performances to understand whether these scheduling characteristics explain the heterogeneity in sales rate.

Finally, we consider a possible endogeneity in scheduling decisions. Since the live performance industry has been established and event marketers have scheduled for a variety of events, event marketers may have incorporated their experiences into a scheduling process. If so, a performance schedule is endogenously determined. For example, event marketers might have scheduled more performances on weekends across all venues because they know these performances have higher performance attractiveness. It is also likely that they have scheduled performances based on the responses they expect in this market. Specifically, they may have scheduled performances closely in distance or time or farther apart, because they know consumers prefer performances of such scheduling characteristics. In case such an endogeneity exists in the scheduling process, we control for this possibility in our model development.

We contact a national ticket seller to obtain a dataset of a live performance event and use its ticket sales to examine the impact of its scheduling characteristics on ticket sales. Although this event performed across several markets, we use the performances in the New York metropolitan market as a subset. The reason is that performances scheduled in this market have richer variations in venue locations and performance dates. In short, this event had 70 performances across four venues in the New York metropolitan market and performed between March and June 2004.

Our results indicate that the effect of geographic scheduling differs from the effect of temporal scheduling on the number and timing of ticket sales. Performances scheduled closely across venues not only sell more tickets but also sell tickets at a faster rate. In contrast, performances sparsely scheduled across dates sell more tickets but do not have an impact on the timing of sales.

Our explanation for the observed effect of geographic scheduling is that event marketers may attempt to signal the desirability of some venues by scheduling more performances in those venues. Although the desirability of these venues may also be owing to population around these venues and consumers' shorter travel distance to these venues, we control for this possibility in our benchmark models and still find a significant effect of geographic scheduling. Therefore, in contrast with performances scheduled in distant venues, performances scheduled in nearby venues signal higher desirability or popularity to consumers. As a result, more consumers are interested in these performances and are more willing to purchase tickets earlier.

On the other hand, our explanation for the observed effect of temporal scheduling is that event marketers try to accommodate consumers' uncertain preferences to performance dates by scheduling performances sparsely across dates. In this way, performances on dispersed dates (or of a longer temporal distance) provide consumers higher flexibility and further sell more tickets. In contrast, performances within a short time span (or of a shorter temporal distance) substitute one another and cannibalize ticket sales.

In addition to the impact of scheduling characteristics on ticket sales, our results also indicate that there exists some endogeneity in the scheduling process. Event marketers consider how attractive performances are when they schedule performances across dates. However, our results show that event marketers have not yet incorporated the effects of geographic and temporal scheduling when they allocate performances across venues and dates.

The organization of this essay is as follows. We first review past works relevant to scheduling and event ticket sales. Then, we present our conceptual framework and model development. After a detailed data description, we provide our results and discuss possible rationale behind the scheduling effects. We also conduct two policy simulations to show how re-

allocating performances to a different venue or date would result different number and timing of ticket sales. Finally, we conclude this essay with limitations and next steps.

2.2 Literature Review and Conceptual Framework

2.2.1 Airline and Movie Scheduling

Because scheduling a live performance event is an important yet understudied research stream, we search literature in other contexts where scheduling is also critical to managers. We find airline and movie scheduling literature a good fit because managers have a common objective to schedule a series of flights, screens, or performances to meet the market demand. Therefore, we discuss studies in airline and movie scheduling in turn.

Airline Scheduling

Airline scheduling is a complex system. It involves demand estimation, pricing for different segments, flight scheduling for various routes, fleet assignments for individual flights, crew scheduling, aircraft rotation, flight gate assignments, and many other decisions (Etschmaier and Mathaisel 1985; Dobson and Lederer 1993; Jarrah et al 2000; Lohatepanont and Barnhart 2004; Dorndorf et al 2007). Therefore, any small changes require a series of adjustments in the entire system.

Traditionally, airline scheduling has been a constrained-optimization decision. Researchers use historical data to estimate demand and consider the expected demand to construct flight schedules (Dobson and Lederer 1993; Lohatepanont and Barnhart 2004). After schedule constructions, other departments evaluate proposed schedules to set airfares, assign aircrafts, and make other operational related decisions (Etschmaier and Mathaisel 1985; Dobson and Lederer 1993; Jarrah et al 2000; Dorndorf et al 2007). Finally, they examine associated

profits and revise flight schedules to ensure profit maximization. Therefore, in this iterative decision process, scheduling is primarily constraint-driven. An airline managers' objective is to maximize profitability while minimizing operational costs within feasible boundaries.

The similarity between airline scheduling and performance scheduling is the common scheduling nature. Airline managers and event marketers have to decide when and where flights or performances have to take place. Their conceptual objective is the same because they aim to launch a schedule to extract the most demand in a given market. However, the demand in the airline schedule is either treated as exogenous (McGill and van Ryzin 1999), based on historical data (Etschmaier and Mathaisel 1985), or dependent on price and departure and arrival times (Dobson and Lederer 1993). Researchers assume that dropping flights always leads to losses in revenues (Lohatepanont and Barnhart 2004) and have not yet investigated how scheduling density (e.g., frequencies of flights) influences ticket demand.

Movie Scheduling

In the movie industry, movie scheduling takes place after movie distributors release movies to exhibitors. The primary task that exhibitors perform is to allocate a number of screens within a theater to meet the local demand for this movie (Swami, Eliashberg, and Weinberg 1999; Eliashberg et al 2009). Compared with advertising effect on box office revenues, movie scheduling is a relatively new research direction in this industry (Eliashberg, Elberse, and Leenders 2006).

When it comes to the implementation of movie scheduling, exhibitors have to select movies that might contribute higher revenues because they have a limited number of screens in a theater. They usually start with estimating demand for a variety of movies and then select a smaller set of movies to play (Swami et al 1999; Eliashberg et al 2007; Eliashberg et al 2009).

After they choose movies of interest, they allocate available screens to these movies (Elberse and Eliashberg 2003). Although the general principle is that the longer exhibitors play a movie, the more revenues they get, the decreasing demand over time and the contract with distributors also determine how long a movie shows in a theater (Swami et al 1999). Finally, exhibitors refer to box office revenues in a previous week, movie genres, days of week, and times of day to revise their scheduling decision on a weekly basis (Elberse and Eliashberg 2003; Eliashberg et al 2007).

Movie scheduling is similar to airline scheduling in the sense that both contexts heavily rely on the operational constraints, and profitability maximization is the top priority. It is also similar to performance scheduling because within these contexts the purpose is to serve local demand by offering movies or performances at various days of week or times of day. However, researchers in movie scheduling usually assumes demand to be exogenous (Swami et al 1999; Eliashberg et al 2007; Eliashberg et al 2009) or influenced by marketing activities (Elberse and Eliashberg 2003). They have not yet considered the competition between theaters (Eliashberg et al 2006) or the impact of scheduling density on box office revenues.

To sum up, the focus of airline and movie scheduling is constraint optimization and profit maximization. Demand is often assumed exogenous and influences scheduling decisions. Whether these scheduling decisions influence demand deserves further investigation. Therefore, the objective of this essay is to examine the impact of scheduling on ticket sales in the context of a live performance event. Next, we review current research in event tickets to understand existing drivers for ticket sales before we discuss how scheduling could affect ticket sales.

2.2.2 Event Tickets

Live performance events typically refer to concerts, musicals, or circus acts, etc. that perform live in front of an audience. Because an event often provides multiple performances

across venues and dates, understanding how well each performance can sell is an important issue for event marketers and researchers. Hence, we review relevant works and discuss factors that influence the number and timing of ticket sales.

Number of Ticket Sales

Identifying drivers of ticket sales has been a common topic studied in marketing, economics, and performing arts literature. Researchers have used *product related drivers*, *consumer characteristics*, and *seasonality* to explain consumer attendance (Weinberg and Shachmut 1978; Currim, Weinberg, and Wittink 1981; Venkatesh and Mahajan 1993; Reddy, Swaminathan, and Motley 1998; Putler and Lele 2003; Leslie 2004). According to the number of events involved in the drivers, we further classify product-related drivers into (1) assortment-related drivers, (2) event-related drivers, and (3) performance-related drivers. We discuss these drivers and their importance in turn.

Assortment-related drivers often refer to factors related with a bundle of events. In other words, this type of drivers exists when multiple events are grouped together in a product offering. Researchers have shown that different bundle size, event types in a bundle, and associated seating benefits can attract varying degrees of demand because consumers have heterogeneous preferences to genres (e.g., operas, musicals), language types (e.g., Italian, English), and willingness to pay (Currim, Weinberg, and Wittink 1981; Havlena and Holak 1988; Venkatesh and Mahajan 1993). On the other hand, *event-specific drivers* refer to information of a specific event (e.g., pricing or critics' reviews for a Broadway show). While genre, pricing, and advertising are important for all types of events (Weinberg and Shachmut 1978; Weinberg 1986; Reddy et al 1998; Corning and Levy 2002; Putler and Lele 2003; Leslie 2004), previews and critics' reviews are more common for Broadway shows or theatrical events (Reddy et al 1998;

Corning and Levy 2002). Because a venue manager's objective is to increase ticket sales within a venue, they usually achieve their objective by bundling various events in a subscription package or scheduling a variety of events to attract consumer attendance. Therefore, the first two types of drivers are important from a venue manager's perspective.

Performance-specific drivers, on the other hand, do not limit the number of events needed but focus on the lower level of characteristics such as days of week or times of day (Weinberg and Shachmut 1978; Corning and Levy 2002; Putler and Lele 2003; Leslie 2004). In contrast with the first two types of drivers, this type of drivers is important to event marketers, especially when they promote a single event that tours across venues and dates. In other words, when an event has multiple performances across venues and dates, the assortment-related drivers are not applicable to a single event. The event-related drivers are important yet pricing and advertising are often planned at a market level and result in a constant effect across all performances. Consequently, event marketers can only rely on days of week and times of day as descriptive drivers to differentiate ticket sales of multiple performances.

The fourth type of driver is *consumer characteristics*. They often refer to consumers' income levels, willingness to pay, driving distances to venues, and tastes for genres (Moore 1966; Currim et al 1981; Venkatesh and Mahajan 1993; Leslie 2004). Although this type of drivers allow event marketers and venue managers to understand consumer preferences better, it is relatively difficult for event marketers to identify their potential consumers, especially when an event travels to a new market and there is no previous consumer information available to event marketers. The last type of driver is seasonality. It generally refers to the season (i.e., spring, summer, fall, and winter) that events or performances takes place and is commonly used as a control variable (Weinberg and Shachmut 1978; Weinberg 1986; Corning and Levy 2002).

As such, although there are five types of descriptive drivers for event tickets, there are not plenty of drivers useful for event marketers to understand variations in ticket sales at a performance level. Therefore, it is important for researchers to investigate additional drivers to explain such a variation.

Timing of Ticket Sales

To attend an event, consumers have to purchase tickets no later than its performance date. Throughout an advance-selling period, their purchase timing may range from very early (i.e., advance purchase) to the last minute (i.e., spot purchase). Historically, there are few studies in event ticket purchases. However, there are many in other contexts such as airline ticket purchases. Thus, we refer to studies in other contexts to discuss firms' motivation to advance sell and consumers' motivation to advance purchase tickets for an event.

Generally, advance selling is common in the service-related industry or in a long lead-time manufacturing industry. Although it is not necessary to charge lower prices in an advance-selling period (Xie and Shugan 2001), firms still tend to use a two-stage pricing (i.e., charge discounted rate in the early market but a regular rate in the spot market) as the primary tool to attract consumers' early purchases and secure some demand well in advance (Desiraju and Xie 1999; Shugan and Xie 2000; Cachon 2004; McCardle, Rajaram, and Tang 2004; Tang et al 2004). Two good examples of advance selling are that, first, a venue manager offers a bundle of events at a lower rate to attract early arrivals of subscription ticket sales (Currim, Weinberg, and Wittink 1981; Havlena and Holak 1988; Venkatesh and Mahajan 1993) and, second, an airline company charges a cheaper airfare to attract leisure travelers' advance purchases (Weatherford et al 1993; Gallego and van Ryzin 1994; Talluri and van Ryzin 2004).

Regarding consumers' motivation to advance purchase, extant literature has suggested various reasons for consumers' early versus spot purchases. In addition to reservation prices, consumers' uncertainty toward the consumption state also determines their purchase timing decisions (Desiraju and Shugan 1999; Shugan and Xie 2000). Specifically, they tend to procrastinate when they have higher uncertainty about whether they can attend an event in the future. In contrast, they tend to purchase early when they are more certain to attend in the future. Other psychological drivers include consumption utility and personal characteristics. For example, consumers may want to savor their vacation experience better by paying earlier (Prelec and Loewenstein 1998). Their tendency of being an innovator in their group versus being a follower also affects their purchase timing decision. Innovators tend to purchase earlier and influence followers in the later period (Moe and Fader 2002).

Although pricing has been a major factor to affect consumers' purchase timing, a recent study by Moe and Fader (2009) illustrated a need to re-evaluate the impact of pricing on the timing of ticket sales. Specifically, they examined the timing of ticket sales across different price tiers in the context of event tickets and found that consumers who purchase in advance are not affected by the price discounts or face values of tickets. This result is very different from airline tickets. Perhaps it is because there are no so-called "business" or "leisure" buyers in the context of event tickets. Hence, the reason for consumers to advance purchase event tickets is not clear and deserves further investigation.

2.2.3 Impact of Scheduling on Ticket Sales

The objective of this essay is to examine the impact of scheduling on ticket sales of performances of the same event. Because performances are scheduled with different frequencies across venues and dates, the similarity in these scheduling characteristics varies across

performances. We refer to literature in context effect, signaling, retail location, and distribution services for possible effects of these scheduling characteristics.

Context Effect

Context effect has been extensively studied by behavioral literature (Huber, Payne, and Puto 1982; Huber and Puto 1983; Simonson 1989) where researchers investigate how alternatives of dominated or dominating attributes influence consumer choices. In general, this stream of literature proposes violation of proportionality (Luce 1959). Researchers examine situations when products of similar attributes are more attractive (i.e., attraction effect) and when they are substitutable (i.e., substitution effect) and where alternatives in the middle level of attributes are more favorable (i.e., compromise effect) (Huber et al 1982; Huber and Puto 1983; Simonson 1989). In other words, when consumers have uncertain preferences to product attributes, they would choose alternatives based on various reasons (Simonson 1989). A dominating alternative may have a higher choice share under the attraction effect although it may have a lower share under the substitution effect (Huber et al 1982; Huber and Puto 1983). However, it is also likely that consumers prefer the new added alternative that has compromised attributes under the compromise effect.

The relevance between the context effect and the scheduling effect is that similarity between alternatives (i.e., performances in this case) could influence consumer perception and choice decisions. As consumers pay more attention to alternatives that share a similar attribute level (Huber et al 1982), they might focus on evaluating performances in the same or near venues (or on the same or near dates) and find these performances more attractive or substitutive. At the aggregate level, the similarity in these scheduling characteristics could further determine how well these performances sell. On the other hand, performances of compromised attributes

(e.g., in a preferred venue but on a less preferred date or vice versa) might also sell differently from other dominating or dominated performances.

Signaling

Signaling has been studied in marketing to address the issue of product quality. The assumption for signaling to work is under the separating equilibrium (Chu and Chu 1994) that manufacturers are credible and have high transaction costs to signal (Moorthy and Srinivasan 1995). Therefore, credible manufacturers can use money-back guarantees (Moorthy and Srinivasan 1995) or an extended warranty (Padmanabhan and Rao 1993; Lutz and Padmanabhan 1995; Soberman 2003) to signal the quality of their product. They can also sell their products in reputable retailers for consumers to infer the reputation of manufacturers, especially when their reputation is not directly observable to consumers (Chu and Chu 1994; Purohit and Srivastava 2001).

We relate signaling with performance scheduling because it is likely that event marketers want to signal the performing quality of an event to a market. Because sending a false signal can be expensive (e.g., incremental costs for multiple performances and revenue losses from empty seats), we assume event marketers are credible. They could increase the number of performances in a market to signal event popularity. They could also allocate these performances densely in some venues or on particular dates to suggest popularity or desirability of these venues or dates. As a result, depending on which signal event marketers want to send, they will schedule performances differently. After consumers receive the signal and believe the credibility, they could adjust their preferences and make purchase decisions accordingly.

Retail Location

In the retail industry, store locations influence consumers' shopping destination and store choices (Fotheringham 1988). Therefore, collocating or keeping some distance away from primary competitors has been an important issue in retail location literature (Mazzeo 2002; Vitorino 2007; Zhu and Singh 2009). Although some studies show that shorter geographic distance between retailers leads to direct competition and decreases in store profitability (Watson 2005; Orhun 2005; Seim 2006; Thomadsen 2007; Zhu and Singh 2009; Zhu, Singh, and Manuszak 2009), other studies indicate benefits for retailers to locate closely (Mazzeo 2002; Vitorino 2007; Zhu, Singh, and Dukes 2007). For example, retailers collocating in a shopping center provide consumers a larger product assortment (across stores) such that these retailers can attract more consumers to the shopping center (Vitorino 2007; Zhu et al 2007). Motels, on the other hand, collocate in a highway exit to facilitate consumer search and attract more traffic (Mazzeo 2002).

The relevance between retail location and performance scheduling is that event marketers, like retailers, have to consider how far in distance or time they should keep performances apart to avoid substitution within the same event (i.e., cannibalization). On the other hand, event marketers might also consider scheduling performances closely enough to provide more alternatives or signal the popularity to attract more demand. Therefore, if the substitution between performances outweighs the collocating synergy, performances scheduled closely could suffer fewer ticket sales and slow sales arrival (because consumers can always wait until the last minute). Otherwise, densely scheduled performances would experience more ticket sales and faster sales arrival.

Distribution Services

In addition to abovementioned spatial differentiation in retail location, retailers also try to differentiate themselves from other competitors by improving their distribution services (Betancourt 2004). Distribution services generally refer to the extent of services that retailers are able to deliver to consumers. These services include product assortment, assurance of product delivery at consumers' desired time or in the desired form, spatial accessibility between stores and consumer residences, and so on (Betancourt 2004). For example, retailers can provide a larger assortment of products, extend business hours, or open more store locations to enhance their distribution services.

In the live performance industry, similarly, both venue managers and event marketers may aim to enhance their distribution services. To accommodate consumers who have different tastes, venue managers may improve their assortment by scheduling a variety of events in their venues. On the other hand, event marketers may consider consumers who have state uncertainty about to which venue they want to go and which date they can attend. In this case, they might schedule performances in multiple venues and disperse performance dates to allow consumers to attend at their own convenience. In other words, if event marketers schedule performances sparsely across venues and dates, these performances could accommodate more consumers at different times and in different venues. In this way, sparsely scheduled performances will sell more than densely scheduled performances.

2.2.4 Conceptual Framework

Although there may be several reasons to explain event marketers' scheduling decisions and consumers' decision process, this information is unfortunately unobservable to researchers. Hence, we can only use the abovementioned literature to speculate potential scheduling effects.

To sum up, if event marketers want to signal quality, they will increase the number of performances and schedule these performances closely in distance or time to attract more consumers. Then, consumers will perceive these performances to be more popular. Consequently, more consumers will attend these performances and these consumers will be more likely to purchase tickets in advance. On the other hand, if event marketers schedule performances to enhance their distribution services, they will schedule performances across multiple venues and disperse performance dates farther apart. In this way, performances scheduled farther apart are able to accommodate more consumers and sell more tickets. Yet, it is still possible for consumers to procrastinate given their uncertainty for the consumption state. As such, based on different streams of literature, we can anticipate different scheduling mechanisms and consumer responses.

However, if event marketers do not have a specific scheduling strategy but schedule performances to comply with operational constraints such as venue availability and seating capacity, their scheduling process is similar to airline and movie scheduling. Then, the impact of scheduling could be positive or negative. According to the retail location literature, event marketers may expect performances in close distance or time to have a substitutive relationship and cannibalize ticket sales. They may also expect a collocation synergy between performances to attract more demand. From consumers' perspective, they may make their own inferences about these performances based on different contexts. According to the attraction effect, they may perceive performances of similar scheduling characteristics to be more attractive. Hence, these performances will sell more tickets and these ticket sales will arrive earlier. In contrast, consumers may perceive these performances to be highly substitutable (i.e., substitution effect)

and delay their purchase timing. If so, these performances will sell less and sell more slowly than do those of dissimilar scheduling characteristics.

However, event marketers may not just simultaneously schedule performances densely (or sparsely) across venues and dates. They may sometimes schedule performances densely in certain venues to signal venue popularity yet disperse performance dates to accommodate consumers' uncertainty of attendance timing. Similarly, they may schedule performances densely on certain dates as popular leisure activities but allocate these performances in several distant venues to increase spatial accessibility. Consequently, if event marketers have separate objectives and schedule accordingly, consumers will find performances scheduled closely in distance (or time) but distantly in time (or distance). In this way, performances have different scheduling characteristics across venue locations and performance dates, and consumers will evaluate a geographic and temporal schedule separately. Hence, the effect of geographic scheduling may differ from the effect of temporal scheduling. We allow this possibility and empirically test these scheduling effects.

On the other hand, to study the impact of performance schedules on ticket sales, we also have to control for the attractiveness of performances on different days of week and the potential endogeneity between scheduling decisions and expected market response. In other words, if event marketers have some knowledge about how a market responds to a performance schedule and then use this knowledge to schedule performances, the performance schedule will be endogenously set and the scheduling impact will be biased. In case the endogeneity exists, we propose to examine the effect of performance schedule on ticket sales and control for the endogeneity simultaneously. Figure 2-1 below summarizes our conceptual framework.

Figure 2-1: Conceptual Framework

2.3 Model Development

2.3.1 Model Overview

To test the potential impact of scheduling, our modeling objective is to measure the scheduling characteristics of each performance and study the impact of these scheduling characteristics on the number and timing of ticket sales. Thus, our model development consists of four steps. First, we measure the scheduling characteristics to capture the similarity or dissimilarity in venue locations and performance dates across performances. Second, we examine the number of ticket sales across performances. Because it is possible that some consumers evaluate the venue locations and performance dates but do not attend (i.e., non-buyers), we incorporate the impact of scheduling characteristics on the size of non-buyer segment. In this way, event marketers can understand how much market potential they have captured and how much they have missed out. Third, we examine the timing of ticket sales across performances. Because each performance sells tickets at a different rate and experience different timing of ticket sales in an advance-selling period, it is important to capture heterogeneous sales patterns and explain the differences. Finally, we consider a possible endogeneity between performance scheduling and market response. If event marketers know the effects of scheduling on the number of ticket sales, they could allocate performances based on the positive or negative effect and expected performance attractiveness. Under this situation, performance scheduling is endogenous with market response (Manchanda, Rossi, and Chintagunta 2004). It is important to control for this endogeneity to ensure unbiased model results. Figure 2-2 below summarizes our model development and we discuss each modeling element in turn.

Figure 2-2: Model Overview

2.3.2 Scheduling Characteristics

To capture the similarity or dissimilarity in scheduling characteristics of performances, we refer to a performance schedule of an event and differentiate between performances based on their venue locations and performance dates. We create two measures to represent the scheduling similarity in this performance schedule to understand how performances are scheduled closely or distantly across venues and dates.

Specifically, we take the inverse geographic distance (in miles) between performances as the geographic density measure and the inverse temporal distance (in days) between performance dates as the temporal density measure (Fotheringham 1988). In this way, performances scheduled in the same or proximate venues will have a higher value in geographic density to represent similarity in the geographic schedule. Performances scheduled on the same or near dates will have a higher value in temporal density to show similarity in the temporal schedule. Therefore, our specifications for the density measures are as follows:

$$(1) \quad \text{GEO}_j = \frac{1}{J-1} \sum_{j'=1, j \neq j'}^J \frac{1}{\text{miles}_{jj'}}$$

$$(2) \quad \text{TMP}_j = \frac{1}{J-1} \sum_{j'=1, j \neq j'}^J \frac{1}{(1 + \text{days}_{jj'})}$$

where GEO_j is the geographic density for performance j ($j=1,2,\dots, J$), TMP_j is the temporal density for performance j , $\text{miles}_{jj'}$ represents the geographic distance between venues of performance j and j' ($j \neq j'$), and $\text{days}_{jj'}$ represents the temporal distance between performance dates of j and j' .

To compute the distance between venue locations and performance dates, we use driving distance (in miles) between the venues of j and j' as $\text{miles}_{jj'}$. We also specify $\text{miles}_{jj'}=1$ for

performances in the same location to avoid the denominator equal to zero. In addition, we use the absolute value of distance (in days) between performances j and j' as $\text{days}_{jj'}$. However, we specify the denominator as $(1+\text{days}_{jj'})$ in equation (2) to avoid performances on the same date having a zero temporal distance.

Therefore, with respect to a target performance j , after taking its average (inverse) geographic and temporal distance to other performances, GEO_j and TMP_j suggest its average geographic and temporal density. The higher GEO_j and TMP_j of this performance, the closer this performance is to other performances. As such, this performance is densely scheduled around other performances and has higher similarity in venue locations and performance dates.

2.3.3 Number of Ticket Sales

To examine the number of ticket sales across performances and understand how much market potential event marketers miss out, we apply a competing destination model by Fotheringham (1988) and specify the share of each performance and the non-buyer segment as a function of scheduling characteristics. By doing so, we can understand whether geographic and temporal scheduling influence ticket sales at a performance level. In addition, using sales shares of individual performances and the population size in a target market, we can obtain the number of ticket sales expected at a performance level. We can also obtain a market penetration rate by summing sales shares across performances.

Competing Destination Model

Among various extensions of the logit model, we consider the competing destination model proposed by Fotheringham (1988) as a good alternative. The competing destination model extends the traditional logit model by releasing the property of independence from irrelevant alternatives (IIA) (Luce 1959; McFadden 1974). It examines consumers' spatial

choice set as a function of geographic distance between stores. Then, the composition of the spatial choice set further influences consumers' store choices. If stores of shorter geographic distance have higher chance to be in consumers' choice set, these stores will attract more consumers and have higher choice shares. However, if stores of shorter geographic distance have a lower chance to be in consumers' choice set, these stores will substitute one another and have lower choice shares. The specification of the competing destination model is as follows (Fotheringham 1988):

$$(3) \quad P_{ij} = \frac{\exp(V_{ij}) \cdot l_i(j \in M)}{\sum_{j'=1}^J \exp(V_{ij'}) \cdot l_i(j' \in M)}$$

where P_{ij} denotes the probability that consumer i shops in retail outlet j , V_{ij} represents the deterministic utility of retailer j to consumer i , and $l_i(j \in M)$ is the likelihood that retailer j is in consumer's spatial choice set. After aggregating P_{ij} across consumers, P_j represents the market share of a retailer j in a studied market of interest (González-Benito 2005).

Moreover, to measure the likelihood of spatial choice set, Fotheringham specified the likelihood as a function of average inverse geographic distance between retail stores (Fotheringham 1983; Fotheringham 1988) and empirically test the role of geographic distance:

$$(4) \quad l_i(j \in M) = \left(\frac{1}{J-1} \sum_{\substack{j'=1 \\ j \neq j'}}^J \frac{w_{j'}}{d_{jj'}} \right)^\theta$$

where $d_{jj'}$ is the geographic distance between a target store j and a competing store j' , $w_{j'}$ is the weight for the competing store j' , and θ is the parameter indicating the role of geographic distance. More specifically, if $\theta > 0$, stores of shorter geographic distance to other stores will have higher chance to be included in consumers' choice set. If $\theta < 0$, in contrast, stores will have

lower chance to be included. Finally, if $\theta = 0$, geographic distance does not affect the composition of consumers' spatial choice set.

Extension of Competing Destination Model

To examine the separate effects of geographic and temporal scheduling, we extend the competing destination model by incorporating the geographic and temporal density values and allowing separate parameter values for these scheduling characteristics. In addition, we include the non-buyer segment in a market as another alternative for potential buyers. In this way, we can understand how scheduling characteristics affect the sales share of performances and the size of non-buyer segment. Our adaption is as follows:

$$(5) \quad P(j) = \frac{\exp(V_j) \cdot GEO_j^{\theta_1} TMP_j^{\theta_2}}{1 + \sum_{j'=1}^J \exp(V_{j'}) \cdot GEO_{j'}^{\theta_1} TMP_{j'}^{\theta_2}}$$

where $P(j)$ denotes the sales share of performance j , V_j represents the attractiveness of this performance (which we will discuss later), GEO_j and TMP_j are the geographic and temporal density values of performance j , and parameters θ_1 and θ_2 represent the scheduling effects.

If θ_1 or $\theta_2 > 0$, geographic or temporal scheduling has a positive effect. Performances of similar venue locations or performance dates will enjoy higher sales share. In contrast, if θ_1 or $\theta_2 < 0$, geographic or temporal scheduling has a negative effect. Performances of similar venue locations or performance dates will substitute one another and suffer from sales cannibalization. However, if θ_1 or $\theta_2 = 0$, scheduling has no impact on sales share. Moreover, we can use the population size in a target market (which we will discuss in the data section), POP , to calculate the expected number of ticket sales for any performance: $Sales(j) = POP \times P(j)$. We can also obtain the market penetration rate by summing sales share across performances (i. e., $\sum_{j=1}^J P(j)$) and understand the size of non-buyer segment as $1 - \sum_{j=1}^J P(j)$.

To measure and control the effect of performance attractiveness (V_j), event ticket literature has suggested various drivers for ticket sales that can be a good proxy for attractiveness. However, because we focus on analyzing multiple performances of the same event, only performance-related drivers are applicable. Therefore, we specify V_j as a function of days of week indicators (Friday, Saturday, and Sunday). The reason for us to choose these three days of week indicators is that past studies indicate that performances on those days have higher attractiveness (Corning and Levy 2002; Putler and Lele 2003). Hence, we specify performance attractiveness as a control covariate for the number of ticket sales and incorporate a random error term for unobserved attractiveness:

$$(6) \quad V_j = \alpha_0 + \alpha_1 \text{FRIDAY}_j + \alpha_2 \text{SATURDAY}_j + \alpha_3 \text{SUNDAY}_j + \varepsilon_j \quad \text{where} \quad \varepsilon_j \sim N(0, \sigma^2)$$

where α_0 reflects the baseline attractiveness, α_1 , α_2 , and α_3 suggest the effects of days of week on incremental performance attractiveness for a Friday, Saturday, or Sunday performance, and $E[V_j]$ represents the expected performance attractiveness.

To sum up, we adapt the competing destination model to understand the effects of geographic and temporal scheduling on the sales share of performance and the size of non-buyer segment. We also control for the performance attractiveness due to the days of week effects. Although a linear regression or spatial model can also examine the number of ticket sales across performances, our model specification is more appropriate than a regression or spatial model. A linear regression is commonly used in event tickets literature (Moore 1966; Weinberg and Shachmut 1978; Weinberg 1986; Reddy et al 1998; Corning and Levy 2002). However, it cannot examine the sales share of each performance and the non-buyer segment at the same time. In other words, a linear regression does not allow us to understand how much of the market performances have captured and how much they have left untapped. In contrast, our proposed

model can accomplish all of these limitations of a linear regression model. In comparison to a spatial model, the model proposed in this dissertation specifically measures the effects of performance schedules as drivers of ticket sales and not just modeling the spatial correlation between performances (Bradlow et al 2005).

2.3.4 Timing of Ticket Sales

To examine the timing of ticket sales across performances, we first consider a typical sales pattern for a performance. In general, a performance starts selling tickets 12 weeks prior to its performing date. It usually sells fewer tickets in the beginning of its advance-selling period and obtains more sales over time with the most arriving in the later period or the week of the performance. Given this typical pattern, however, each performance still has a different sales rate. Some performances experience ticket sales arrived earlier (i.e., earlier timing of ticket sales) but others experience ticket sales arrived later (i.e., later timing of ticket sales).

Figure 2-3 below illustrates three patterns of ticket sales in an advance-selling period. First, the solid line in Figure 2-3 (Case 1) is one common pattern, where consumers have low probability to purchase well in advance. As time passes, the probability of a ticket transaction slowly increases and peaks at the week of performance. However, there are some situations where consumers expect performances to be of greater performance attractiveness or higher popularity. As a result, they are more willing to purchase earlier and result in more ticket sales arriving in the middle of an advance-selling period, as shown in the dotted line of Figure 2-3 (Case 2). Yet, there is another case when consumers think performances of lower performance attractiveness and/or of higher substitutability. In this instance, they do not want to commit early and wait until the week (or the day) of a performance. Therefore, ticket sales for such a

performance are very low in the entire advance-selling period and only peak in the spot market. The broken line in Figure 2-3 (Case 3) represents this pattern.

Figure 2-3: Pattern of Ticket Sales Over Time

Weibull Hazard Model

Although performances usually follow a similar pattern as seen in Figure 2-3 (Case 1), there still exists variability of sales pattern among performances (e.g., Case 2 and Case 3 in Figure 2-3). To account for variations in sales rate across performances, we need a model that is flexible enough to capture various sales patterns and examine the performance-specific sales rates. Hence, we specify a Weibull hazard model to fit the timing of ticket sales because of its flexibility in capturing various sales patterns, as shown in Figure 2-3. A Weibull hazard process has the following properties:

$$(7) \quad h_j(t) = \lambda_j c_j t^{c_j - 1}$$

$$S_j(t) = e^{-\lambda_j t^{c_j}}$$

$$F_j(t) = 1 - S_j(t) = 1 - e^{-\lambda_j t^{c_j}}$$

where, with respect to a performance j , $h_j(t)$ is the instantaneous hazard rate for a ticket purchase made at time t given this transaction has not yet been made, $S_j(t)$ is the survival rate for a ticket purchase that has not yet occurred up to time t , and $F_j(t)$ is the cumulative probability for sales to arrive over time. More specifically, λ_j is the slope parameter for performance j to represent how fast ticket sales arrive ($\lambda_j > 0$), and c_j is the shape parameter to capture an overall pattern of ticket sales ($c_j > 0$).

For any discrete time t (e.g., week) in an advance-selling period, the probability of a ticket purchase becomes:

$$(8) \quad P_j(t) = F_j(t) - F_j(t-1) = e^{-\lambda_j(t-1)^{c_j}} - e^{-\lambda_j t^{c_j}}$$

However, ticket sales in the context of a live performance event have to arrive no later than the performance date. We adjust the probability of a ticket purchase in the spot market (i.e., the week of the performance) as follows:

$$(9) \quad P_j(T_j) = 1 - e^{-\lambda_j(T_j-1)^{c_j}}$$

where T_j is the number of advance selling weeks for performance j .

In addition, because we often observe seasonality (e.g., Thanksgiving, Christmas, etc.) or marketing activities in an advance-selling period, we can include a time-varying covariate to control for resulting sales bumps. Therefore, we rewrite equations (7), (8), and (9) as follows:

$$(10) \quad h_j(t) = \lambda_j c_j t^{c_j-1} e^{\beta_j X_{jt}}$$

$$S_j(t) = \exp\left\{-\lambda_j \sum_{u=1}^t [u^{c_j} - (u-1)^{c_j}] e^{\beta_j X_{ju}}\right\}$$

$$F_j(t) = 1 - \exp\left\{-\lambda_j \sum_{u=1}^t [u^{c_j} - (u-1)^{c_j}] e^{\beta_j X_{ju}}\right\}$$

$$P_j(t) = \exp\left\{-\lambda_j \sum_{u=1}^{t-1} [u^{c_j} - (u-1)^{c_j}] e^{\beta_j X_{ju}}\right\} - \exp\left\{-\lambda_j \sum_{u=1}^t [u^{c_j} - (u-1)^{c_j}] e^{\beta_j X_{ju}}\right\} \quad \forall t = 1 \dots (T_j - 1)$$

$$P_j(T) = \exp\left\{-\lambda_j \sum_{u=1}^{T-1} [u^{c_j} - (u-1)^{c_j}] e^{\beta_j X_{ju}}\right\}$$

where X_{jt} is a time-varying covariate or seasonality indicator and β_j is its associated parameter. Consequently, the timing of ticket sales for each performance changes with its parameters λ_j , c_j , and β_j .

Heterogeneity in Sales Patterns

To capture and explain the heterogeneity in sales pattern, we further specify the sales rate of each performance as a function of its geographic and temporal density measures. We also include two control covariates to ensure unbiased effects of these scheduling characteristics. The first covariate is the length of advance-selling period because Moe and Fader (2002, 2009) found that sales tend to arrive more slowly under a longer advance-selling period. In addition, because consumers may purchase tickets much earlier when they expect performance to be more attractive, we incorporate the expected performance attractiveness as the second control covariate. Consequently, we specify the Weibull parameters (λ_j and c_j) and the covariate effect (β_j) to follow the multivariate normal distribution. We take the log transformation for the Weibull parameters to ensure positive values:

$$(11) \quad \begin{bmatrix} \log(\lambda_j) \\ \log(c_j) \\ \beta_j \end{bmatrix} \sim MVN(\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_1)$$

where

$$\boldsymbol{\mu}_j = \boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_1 GEO_j + \boldsymbol{\gamma}_2 TMP_j + \boldsymbol{\gamma}_3 T_j + \boldsymbol{\gamma}_4 E[V_j]$$

where $\boldsymbol{\mu}_j$ is the vector of expected Weibull parameters and covariate effect, GEO_j and TMP_j are the geographic and temporal density measures in equations (1) and (2), T_j is the number of advance selling weeks for performance j , $E[V_j]$ is the expected performance attractiveness in equation (6), and $\boldsymbol{\gamma}_0$, $\boldsymbol{\gamma}_1$, $\boldsymbol{\gamma}_2$, $\boldsymbol{\gamma}_3$, and $\boldsymbol{\gamma}_4$ are the vectors of parameters for these covariates.

Therefore, using the parameter results in equation (11), event marketers can understand why some performances experience earlier timing of ticket sales while other experience later timing of ticket sales.

2.3.5 Endogeneity in Performance Scheduling

Finally, we consider a possible endogeneity in scheduling decisions. Since the live performance industry has been established and event marketers have scheduled for a variety of events, event marketers might have incorporated their experiences into a scheduling process. In other words, how densely event marketers allocate performances across venues may be dependent on the effect of geographic scheduling, and how densely event marketers allocate performances across dates may be dependent on the effect of temporal scheduling. Moreover, it is also likely that event marketers increase the total number of performances and schedule those on weekend to increase the performance attractiveness. If so, the geographic and temporal density values vary with the scheduling impact and the expected performance attractiveness.

To control for this type of endogeneity, we refer to a modeling approach proposed by Manchanda et al (2004). In their research of pharmaceutical detailing, they mentioned that sales representatives visit various doctors with different frequencies, and sales representatives determine the frequencies based on how many prescriptions a doctor writes without any detailing and how strong the effect of detailing is if they visit this doctor. They pointed out the endogeneity between the decision of detailing and the effect of detailing, and further proposed a model to correct this endogeneity.

In other words, they specified the expected prescription volume from a doctor as a function of its baseline volume, the magnitude of detailing, and the detailing effect:

$$(12) \quad \ln(\mu_i^*) \cong \left[\frac{\beta_{0i}}{(1 - \beta_{2i})} \right] + \left[\frac{\beta_{1i}}{(1 - \beta_{2i})} \right] Det$$

where $\ln(\mu_i^*)$ is the expected volume of prescription, $\left[\frac{\beta_{0i}}{(1 - \beta_{2i})} \right]$ is the baseline prescription volume, Det is the frequency of office visits, and $\left[\frac{\beta_{1i}}{(1 - \beta_{2i})} \right]$ is the effect of detailing.

To model the endogenous detailing behavior, they specify the expected value of detailing ($\ln(\eta_i)$) as a function of the baseline prescription volume and the effect of detailing:

$$(13) \quad \ln(\eta_i) = \gamma_0 + \gamma_1 \left[\frac{\beta_{0i}}{(1 - \beta_{2i})} \right] + \gamma_2 \left[\frac{\beta_{1i}}{(1 - \beta_{2i})} \right]$$

In this way, if detailing is indeed endogenous, the parameter γ_1 or γ_2 will be significantly different from zero, and the endogeneity between detailing and its effect is under control.

To control for the possible endogenous scheduling behaviors, we take the same modeling approach as Manchanda et al (2004). We specify geographic and temporal density measures (GEO_j and TMP_j) as a function of expected performance attractiveness ($E[V_j]$ in equation 6), and the effects of scheduling characteristics (θ_1 and θ_2 in equation 5). Because GEO_j and TMP_j in equation (1) and (2) are between 0 and 1, we take the logit transformation for these density measures and specify them following the multivariate normal distribution:

$$(14) \quad \begin{bmatrix} \text{logit}(GEO_j) \\ \text{logit}(TMP_j) \end{bmatrix} \sim MVN(\mathbf{m}_j, \Sigma_2)$$

where

$$\begin{bmatrix} m_{1j} \\ m_{2j} \end{bmatrix} = \boldsymbol{\phi}_0 + \boldsymbol{\phi}_1 E[V_j] + \boldsymbol{\phi}_2 \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}$$

As such, if scheduling decisions are indeed endogenous and reflect on the density measures, the parameters $\boldsymbol{\phi}_1$ or $\boldsymbol{\phi}_2$ will be significantly different from zero and this endogeneity will be taken into account.

2.4 Data Description

We contact a national ticket seller to obtain a dataset of live performance events. Because of the confidentiality agreement with our data provider, we cannot disclose our data

provider or the names of events. However, we will describe the nature of the events and the behaviors observed in the dataset.

In this dataset, there were two events touring across several cities in the U.S. Each event had a different number of performances in a city and lasted for a different period. For each performance, we observe its venue location and performance date. In addition, we also have detailed information regarding when tickets were purchased, for how much money, at which price levels, and through which channels. Moreover, we are also able to observe the pattern of ticket sales because transactions were recorded at a daily level. Table 2-1 provides a detailed description of each field in our data set, which contains abundant information about the live performance event and has many research opportunities for marketing researchers.

Table 2-1: Description of Variables in the Dataset

2.4.1 Description of Events

The events we have in the dataset are two popular family events. They are live entertainments that targets on families with young children. In general, there are several types of family events such as children's music and theater (e.g., *The Wiggles* and *Dora the Explorer Live!*), circus (e.g., *Ringling Brothers and Barnum & Bailey* and *UniverSoul Circus*), ice shows (e.g., *Disney on Ice* series), magic shows (e.g., *Xtreme Magic* and *Steve Wyrick*), and so on. They usually travel across the U.S. or stay in a local market such as Las Vegas. The family events we have are within the abovementioned categories.

For the two events we have, one sold 2.2 millions of tickets between January and June 2004 and travelled across 50 cities on 245 dates for 449 performances. The other sold 0.8 millions of tickets between January and May 2004 and travelled across 17 cities on 85 dates for 157 performances. The reason for the sales discrepancy is that one event had multiple

performing groups touring across cities simultaneously while the other had only one group performing in our observed time span. Although these two events travelled to numerous cities during their tours and had three cities in common (i.e., Jacksonville, FL; Miami, FL; Phoenix, AZ), these events did not perform in those cities at the same time but at least 2.5 months apart. Therefore, we assume there was no direct competition between these events to affect ticket sales.

Although both events are representative in terms of their ticket sales and the number of performances, we take only one event in this dissertation to keep the event attractiveness constant and examine merely the scheduling effect on ticket sales. In this way, once we confirm a significant scheduling effect, we can further incorporate the renown of different events as an extension. As such, we choose the event that had more performances. Among 50 cities that this event toured, we also find some cities were within the same metropolitan markets (e.g., New York and other metropolitan markets). This observation suggests that the event had multiple stops in some markets and had higher variations in both geographic and temporal schedules. Hence, we further select performances in the New York metropolitan market¹ and examine the impact of geographic and temporal schedules on ticket sales in essay one. In summary, this event had performances in Continental Arena in East Rutherford, NJ, Nassau Coliseum in Uniondale, NY, Madison Square Garden in New York, NY, and Sovereign Bank Arena in Trenton, NJ, respectively between March and June 2004 for 70 performances.

2.4.2 Description of Ticket Sales

Because a dataset of event tickets is not commonly available in marketing, we first examine ticket sales by price levels and channel types to describe how much money people usually pay and through which channel. Then, we examine the distribution of ticket sales across

¹ We follow the Census Bureau data to define the boundary of a metropolitan market.

performances to understand how many tickets each performance sells and when ticket sales arrive.

Ticket Sales by Price Levels

We first aggregate ticket sales by price levels and performances to examine any different sales distributions across price levels. On average, the admission fees to a performance (including face value, facility fees, and service charges) are \$30.44 and there are about six price tiers for consumers to choose. Although seating quality in a venue determines the price levels, 83% of ticket sales are contributed by mid-priced levels (i.e., price levels 2, 3 and 4) with average price ranges from \$20 to \$50.

Specifically, price level 3 (mean price=\$25.31, std= 3.66) represents 50% of ticket sales, and price level 4 (mean price= \$20.02; std= 3.17) and price level 2 (mean price= \$50.16; std= 6.89) contribute 21% and 12% of ticket sales, respectively. In addition, we find the average admission fees are relatively equal across venues and days of week. In other words, price variations are within a performance (via price levels) but not across venues or days of week.

Ticket Sales by Channel Types

Next, we aggregate ticket sales by channel types and performances to examine ticket sales across channels. Although consumers can purchase tickets through any of the six available channels (i.e., primary box office, secondary box office, Hermes (automatic phone), Internet, outlet, and phone), we find majority of ticket sales are made through the primary box office (62% of ticket sales), following by the Internet (22% of ticket sales) and a ticket outlet (11% of ticket sales). A possible reason for a primary box office to be a dominating channel choice is that consumers do not have to pay for the convenience charges when they buy tickets in a box office.

Ticket Sales by Performances

We also aggregate ticket sales across performances. As Figure 2-4 shows, a performance on average sells 8,316 tickets but has its standard deviation being 3,525. Upon a closer look of the sales distribution by days of week (based on performance dates), we find that weekend performances tend to have more ticket sales than weekdays. Yet, the variation of ticket sales on the same day of week is still prominent. The boxplot in Figure 2-5 summarizes the sales distributions by days of week and indicate a clear variation even on the same day of week. For example, a Friday performance sells 8,112 tickets on average but has a big standard deviation of 2,509, and a Saturday performance has average ticket sales of 9,552 but has the standard deviation being 3,808. According to Figure 2-5 and the observation that each performance has similar price levels, it is convincing that there must be additional factors to explain the variations in ticket sales. Although one can argue that ticket sales are due to venue capacities, we find the sizes of capacity in the four venues are similar and there are no sold out for any performance. Hence, we do not consider the impact of venue capacity on ticket sales in this essay.

Figure 2-4: Sales Distribution by Performances

Figure 2-5: Sales Distribution by Days of Week

Finally, we aggregate daily ticket sales into weekly sales to examine the sales pattern for each performance. On average, ticket sales arrive up to 15 weeks prior with the range between 11 and 19 weeks. Table 2-2 presents the ticket sales across performances and the breakdown of weekly sales throughout an advance-selling period in Table 2-2. On average, a performance sells 8,316 tickets with 24% of sales arrived one month prior, 33% of sales arrived 2 to 4 weeks prior, and 42% of sales arrived in the week of performances. Figure 2-6 shows a sales pattern for a randomly chosen performance and it is a common pattern in our dataset. However, given this

similar pattern across performances, some performances experience ticket sales much earlier than other performances (e.g., 59% vs. 3% of total sales arrived in the early stage) yet other performances do not have as many ticket sales arrived in the last week (e.g., 75% vs. 11% of total sales arrived in the spot stage). The boxplot in Figure 2-7 demonstrates the heterogeneity in the timing of ticket sales across performances throughout an advance-selling period.

Table 2-2: Summary of Ticket Sales

Figure 2-6: Weekly Sales Pattern of a Performance

Figure 2-7: Heterogeneity in Timing of Ticket Sales across Performances

2.4.3 Covariate Specifications

Before we estimate the proposed model, there are several covariates not directly provided in the dataset that require our attention. They are the geographic and temporal density measures (GEO_j and TMP_j), the days of week indicators ($FRIDAY_j$, $SATURDAY_j$, $SUNDAY_j$), the estimated population size in the target market (POP), the length of advance-selling period (T_j), and the time-varying covariate (X_{jt}). We discuss and specify these covariates in turn.

To compute the density measures, we first refer to venue locations and use the GoogleTM maps to find the driving distance (in miles) between venues. The numbers in Figure 2-8 indicate the venue locations in the New York metropolitan market and represent the travel sequence across venues. In addition, the numeric values between venues represent the mileage between venues (i.e., $mile_{ij}$). We summarize the geographic distance between venues and the number of performances in each venue in Figure 2-9 and follow equation (1) to calculate the geographic density for each performance. Next, we refer to performance dates to calculate the temporal distance (in absolute values) between performances (day_{jt}). According to the performance dates

and their temporal distance to others in Figure 2-10, we apply equation (2) to compute the temporal density for every performance.

Figure 2-8: Venue Locations and Driving Distances

Figure 2-9: Summary of Geographic Distance

Figure 2-10: Summary of Temporal Distance

To compute the days of week indicators, we refer to performance dates to identify on which days of week performances take place (i.e., FRIDAY, SATURDAY and SUNDAY). Although some performances are scheduled on the same date, unfortunately our data does not indicate time of day for the performances.

Next, we compute the population size in the target market (POP). Given that the event targets families with young children, we define the target market as the population of families with children under 10 years old. To compute the market size, we refer to the U.S. Census Bureau for the 2000 data to find the total number of families with children under 18 years old and the percentage of all children who are under 10 years old. We multiply these two numbers to get the family population with children under 10 years old and then multiply the average family size to get the population size in the target market. According to these calculations, there are 4,082,615 potential consumers in the New York metropolitan market. We use this market size and ticket sales across all performances to find the market penetration rate to be 14%, which means the non-buyer segment represents 86% of the target market.

To measure the number of advance selling weeks (T_j in equation 11) as a control covariate, we compute the difference between the first sale date and the performance date for each performance. Then, we divide this number by seven to convert the advance-selling period

to weeks. Although tickets may be available for sales prior to the first sale date, we think our approach a good proxy given very few sales arrived in the early selling period.

Finally, because we observe Christmas within the advance-selling period for some performances, we incorporate a time-varying indicator (X_{jt}) in equation (10) to control for a possible pre-Christmas shopping and resulting sales bumps. For each performance j , we code $X_{jt}=1$ if the advance selling week t is consistent with the pre-Christmas shopping week (i.e., 7 days prior to Christmas). Otherwise, $X_{jt}=0$. Table 2-3 summarizes the descriptive statistics of covariates.

Table 2-3: Descriptive Statistics of Covariates

2.5 Model Estimation and Benchmark Comparison

2.5.1 Estimation

We choose the Bayesian statistics approach to estimate the number of ticket sales, the timing of ticket sales, and the endogeneity in a performance schedule simultaneously. We specify appropriate and diffuse priors for our parameters in the WinBUGS program and estimate the model over 40,000 iterations. After checking the convergence criteria, we check the autocorrelation plots for all covariates, discarded 30,000 iterations for burn-in, and use the remaining iterations as the posterior distribution. We specified the prior distribution of parameters below:

Priors for modeling the number of ticket sales:

$\alpha_0 \sim N(-6,10)$	For the baseline performance attractiveness
$\alpha_i \sim N(0,100)$	For the effects of days of week (where $i=1, 2,3$)
$\theta_i \sim N(0,100)$	For the effect of scheduling characteristics (where $i=1, 2$)
$\sigma^2 \sim IG(0.1,0.1)$	For the variance of the performance attractiveness

Priors for modeling the timing of ticket sales:

$\gamma_{ik} \sim N(0, 100)$ For the Weibull parameters and the covariate effect
(where $i=0, 1, 2, 3, 4$ and $k= 0, 1, 2, 3$)

$\Sigma_1^{-1} \sim \text{Weibull}(I_3, 3)$ For the variance-covariance of the Weibull parameters and the covariate effect

Priors for modeling the endogeneity in performance schedule:

$\phi_{ik} \sim N(0, 100)$ For the expected geographic and temporal density values
(where $i=0, 1, 2$ and $k= 1, 2$)

$\Sigma_2^{-1} \sim \text{Weibull}(I_2, 2)$

2.5.2 Benchmark Comparison

Before presenting our model results, we specify benchmark models to compare with our proposed model to rule out alternative explanations for our proposed scheduling effects. First, because the central focus of our modeling efforts is to examine the impact of scheduling characteristics, one ideal benchmark model is to exclude any scheduling effect but only incorporate performance attractiveness (i.e., *Benchmark 1*). Second, some venue locations are more popular than others. For example, a venue in the New York city might be more attractive than another venue in Uniondale. Therefore, we consider the second benchmark that incorporates the venue-specific indicator variables. Finally, Population density around the venue locations could also explain ticket sales. In other words, event marketers may schedule more performances in a specific venue because the population density in this venue is high and the scheduling decision is simply to meet potential market demand in this venue. To rule out this alternative explanation, we extend our proposed model by including the population density around each venue location of performances as another explanatory variable (i.e., *Benchmark 3*).

We estimate our proposed and benchmark models to compare the model fit using the deviance information criteria (i.e., DIC, Spiegelhalter et al 2002):

$$(15) \quad DIC = D(\bar{\xi}) + 2pD$$

where $D(\bar{\xi})$ is the deviance evaluated at the posterior means $\bar{\xi}$ and pD is the effective number of parameters in a model, calculated as the difference between the posterior deviance and the deviance of the posterior mean.

Table 2-4 summarizes the model fit across the benchmark and proposed models. According to the DIC reported for every model, we find that incorporating the scheduling effect is definitely superior. Although adding city effects improves the DIC from 157,134 (Benchmark 1) to 156,459 (Benchmark 2), city effects cannot explain the ticket sales as well as does the proposed model (DIC= 156,221). Moreover, we find our proposed model has a similar fit to Benchmark 3 (DIC=156,220). Although Benchmark 3 has a smaller DIC value by one unit, Ntzoufras (2009, p.220) suggests that a model performs better than another does if the DIC difference is greater than 2. Therefore, we conclude that our proposed model is as good as Benchmark 3.

Finally, we compare the parameter results between these two models and find significant and consistent effects of scheduling characteristics on ticket sales. Although the third benchmark model also shows that the population density and travel distance from consumers' residences to venues is relevant, results in this benchmark model still indicate a significant geographic effect. In other words, although consumers may prefer a venue nearest to them, it is still very likely that consumers are willing to travel to a farther venue that has a stronger association with a leisure activity (Okada 2005).

Therefore, we are confident that there are scheduling effects to influence consumer decisions and ticket sales across performances. We discuss the parameter results and their implications in the next section.

Table 2-4: Benchmark Models and Model Fit

2.6 Results

2.6.1 Number of Ticket Sales

Table 2-5 summarizes our parameter results for the number of ticket sales. First, we find that performances on Saturday and Sunday have higher attractiveness to increase ticket sales than those on other days of week ($\alpha_2 = 0.35$; $\alpha_3 = 0.34$). This result is consistent with prior literature (Corning and Levy 2002; Putler and Lele 2003) and shows the importance of controlling for performance attractiveness when examining the impact of scheduling characteristics.

Second, we find that scheduling indeed influences how many tickets each performance can sell. When performances are scheduled closely in venues and have a shorter geographic distance to other performances, they attract more consumers and sell more tickets ($\theta_1 = 0.32$). Additionally, when performances are scheduled sparsely along a time span and have a longer temporal distance to others, they attract more consumers and sell more tickets ($\theta_2 = -0.14$). Because the geographic and temporal density measures have different effects on ticket sales, these results suggest that consumers evaluate geographic and temporal schedules separately and have different responses.

Table 2-5: Results for the Number of Ticket Sales

As we mentioned earlier, event marketers' scheduling and consumers' decision making are both unobserved processes to researchers. Hence, we can only speculate possible underlying mechanisms based on prior literature and our results. One way to interpret different consumer responses to geographic and temporal schedules is that event marketers have several objectives when they schedule performances. These objectives influence their scheduling decisions and

consumers' reactions. For example, their objectives may be to signal venue popularity and enhance assurance of product delivery at the desired time. If so, they will schedule performances closely in venues of interest yet sparsely across performance dates. From consumers' perspective, after they see such geographic and temporal schedules, they receive the signal of venue popularity and find the flexibility in attendance timing. Then, they shape their preferences to favor performances of such scheduling characteristics and further influence their purchase decisions. As a result, these performances sell more tickets than other performances.

Alternatively, event marketers may not have a predetermined scheduling strategy in mind. The geographic and temporal schedules are the consequences of constrained optimization. If so, consumers will make their own inferences about these performances. For consumers who do not have specific preferences to venue locations and performance dates, they might evaluate performances differently based on different contexts. For instance, they may find an event highly associated with some venues because these venues are close to each other and offer more performances. Due to the similar venue locations and shorter geographic distance between venues, these venues may catch consumers' attention better and become consumers' preferred venues when consumers attend an event. Performances in these venues hence share this common advantage to attract more consumers and sell more tickets.

On the other hand, consumers may perceive an event highly associated with some days of week because many performances are scheduled around those days. Therefore, these days of week would catch more attention and become more salient when consumers consider when to attend. However, consumers usually have uncertainty for the future and prefer a wider range of dates for selections. Closely scheduled performances at any time could merely substitute one another and suffer from sales cannibalization.

According to these two interpretations, one implication for event marketers is that they should keep their scheduling strategy (if they indeed have such a strategy) to schedule performances densely in venue locations but sparsely across performance dates. Even if they do not have such a strategy but only practice constrained optimization, our results provide them another useful scheduling implication. That is, they should incorporate the scheduling effects (i.e., a positive geographic effect but a negative temporal effect) into their decision process as new constraints to find the most optimal solution.

2.6.2 Timing of Ticket Sales

Table 2-6 describes the parameter estimates and indicates that geographic density and the number of advance selling weeks have significant effects on the Weibull parameters ($\gamma_{11} = -7.56$; $\gamma_{12} = 0.93$). Because the objective of this paper is to examine the scheduling effect while controlling for the number of advance selling weeks, we discuss the geographic effect on the timing of ticket sales more in details.

Table 2-6: Results for Timing of Ticket Sales

However, it is less straightforward to observe the *net* effect of geographic density on the timing of ticket sales based on the parameter results. We proceed to simulate performances of different levels of geographic density to visually show their effects on the timing of ticket sales. Therefore, Figure 2-11 presents three hypothetical performances of different levels of geographic density but of the same performance attractiveness. The solid line illustrates the expected timing of ticket sales resulting from geographic density being the mean value observed in our dataset (GEO). The two dashed lines show the expected timing of ticket sales for two performances where their geographic density values are one standard deviation higher or lower than the mean, respectively. We can observe from Figure 2-11 that once the geographic density increases by

one standard deviation from the mean (GEO +1SD), the cumulative ticket sales after 12 weeks of advance selling increase from 11% to 25% of its expected total amount. In contrast, when the geographic density decreases by one standard deviation from the mean (GEO -1SD), only 7% arrived after 12 weeks. Therefore, we conclude that performances in densely scheduled venues have shorter geographic distance to other performances such that they sell tickets at a faster rate than those of longer geographic distance.

Figure 2-11: Impact of Geographic Density on Timing of Ticket Sales

Our intuition for this result is that venues where these performances are closely scheduled share the similarity in venue locations and geographic density. These venues can catch consumers' attention and lead to an attraction effect. In other words, even after controlling for performance attractiveness, consumers still think performances in these venues more attractive. As a result, they are willing to purchase tickets much earlier.

The implication of this result is that event marketers can monitor when and how fast ticket sales arrive based on the geographic density information across performances. They can use the expected timing of ticket sales as benchmark measures to compare with realized sales. In this way, they can be aware of possible sales deviation in an advance-selling period rather than in the week of performance. Additionally, it is also important for operational and financial planning because event marketers can adjust their concession and security throughout an advance-selling period to make sure a performance is not over or under staffed. Moreover, they can have a better knowledge with the cash flows based on the expected timing of ticket sales.

Regarding the sales bump as a result of pre-Christmas shopping effect (β_j), we find that geographic density, number of advance selling weeks, and expected performance attractiveness all contribute positive effects ($\gamma_{13}= 4.84$; $\gamma_{33}= 0.97$; $\gamma_{43}= 2.45$). Yet, temporal density does not

have such an effect. In other words, performances of higher attractiveness tend to experience earlier timing of ticket sales. The attractiveness comes from the expected individual performance attractiveness (due to the days of week effect) and the geographic density. Because performances of shorter geographic distance are perceived more attractive even after controlling for individual performance attractiveness, these performances are more salient to consumers as Christmas gifts².

2.6.3 Endogeneity in Performance Scheduling

As we have mentioned, the scheduling decision is likely endogenous and dependent on expected performance attractiveness or effects of geographic and temporal scheduling. As such, the results discussed above are only managerially meaningful if we accommodate the potential endogenous scheduling decisions. Table 2-7 indicates some evidence about the endogeneity in performance scheduling. Specifically, event marketers consider the expected performance attractiveness when designing a temporal schedule ($\phi_{12}= 0.26$). When they expect a performance to be more attractive, they schedule more performances similar to this one. Consequently, there are more performances scheduled temporally close to each other, resulting in higher temporal density. However, event marketers neither incorporate performance attractiveness when designing a geographic schedule, nor do they incorporate the geographic and temporal effects. This result implies that event marketers may primarily rely on performance attractiveness in their scheduling decision whether they are aware of the scheduling effects.

Table 2-7: Results for Endogenous Performance Scheduling

² We considered other covariates, such as the cumulative sales of earlier performances, but found that it had no significant impact on the timing of ticket sales.

2.7 Policy Simulation

To demonstrate the scheduling effects on ticket sales, we conduct a policy simulation by varying the geographic schedule (Scenario 1) or temporal schedule (Scenario 2) to compare with the current setting. To make a fair comparison and restrict a new schedule within the same geographic and temporal range, we only re-allocate one performance, keep the rest unchanged, and evaluate the differences in ticket sales for the target performance as well as the entire market.

2.7.1 Scenario 1: Geographic Change

According to results of the number of ticket sales, performances generate more sales volume when they are scheduled in the same or proximate venues and have a higher geographic density. Hence, in Scenario 1 we reschedule a performance from Venue 2 (Nassau Coliseum) to Venue 3 (Madison Square Garden) in Figure 2-9, the most densely scheduled venue in our dataset. As a result, geographic density of this performance increases. We also keep the same performance date to ensure unchanged performance attractiveness and temporal density.

Figure 2-12 presents the impact of schedule changes on ticket sales. After relocating a performance from Nassau Coliseum to Madison Square Garden, its ticket sales increase from 5,102 to 7,132, resulting in a difference of 2,031 tickets (which is 24% of average ticket sales per performance). On the other hand, the overall market sales increase from 532,285 under the existing schedule to 535,424 tickets in Scenario 1. Note that the 3,140 increases in market sales are greater than 2,031 increases in a target performance. This increase in market sales provides the evidence of market expansion. Hence, a geographic schedule after minor changes can attract more consumers to the rescheduled performance and increase the market penetration.

Figure 2-12: Effect of Schedule Changes on Ticket Sales

Relocating the target performance to a different venue also changes the timing of ticket sales. Under the modified schedule, the cumulative ticket sales of the target performance reach 60% of total sales after 12 weeks, yet the same performance only sells 28% under the original schedule. Figure 2-13 shows that weekly sales of this performance arrive at a different rate and results in different patterns. This implies that any monitoring or benchmarking of early ticket sales needs to incorporate the geographic density in a schedule.

Figure 2-13: Effect of Schedule Changes on Timing of Ticket Sales

2.7.2 Scenario 2: Temporal Changes

According to our results from studying the number of ticket sales, the second learning is to disperse performance dates to accommodate more consumers and increase ticket sales. Therefore, in Scenario 2, we reschedule the same target performance in Scenario 1 to two weeks earlier. Yet, we keep its venue location and day of week constant. In this way, this target performance has the same level of performance attractiveness and geographic density, yet with a lower level of temporal density.

In contrast with Scenario 1 where we see substantial changes in the number and timing of ticket sales, we observe much smaller changes in Scenario 2. This is consistent with the smaller parameter values for temporal density compared to those for geographic density (see Table 2-5 and Table 2-6). Specifically, ticket sales for the rescheduled performance increase very slightly by 385 tickets under the modified temporal schedule and the difference in total sales in the market is also quite small (772 tickets). Figure 2-12 also shows minimal differences in the percentage of tickets sold in the first 12 weeks. Hence, these results imply that geographic scheduling is more important than temporal scheduling. A geographic schedule has a greater influence on the number and timing of ticket sales than does a temporal schedule.

2.8 Conclusions

2.8.1 Summary

In the live entertainment industry, scheduling performances and estimating ticket demand are two primary tasks facing event marketers. Because these tasks have been treated as two independent problems by event marketers and marketing researchers, this essay aims to bridge performance scheduling and demand estimation by examining the potential impact of scheduling on ticket sales.

According to different streams of literatures, we find that it is possible to see closely scheduled performances selling more than distantly scheduled performances, yet it is also possible to see the opposite effect. Therefore, we allow these two possibilities and empirically test the effect of scheduling characteristics on the number and timing of ticket sales. Specifically, we characterize performances of the same event by their venue locations and performance dates. Using their scheduling characteristics, we construct two density measures (i.e., geographic and temporal density) to capture how close in distance or time performances are scheduled to each other. Then, we model the number and timing of ticket sales as a function of these density measures. In addition, we also control for a possible endogeneity in case event marketers incorporate market responses in their scheduling process.

We contact a national ticket seller to obtain a dataset of a live performance event and use its ticket sales to examine the impact of its scheduling characteristics on ticket sales. This event had 70 performances across four venues in the New York metropolitan market and performed between March and June 2004.

Our results indicate that performances of different scheduling characteristics sell differently in terms of their number and timing of ticket sales. Specifically, we find that the

effect of geographic scheduling differs from the effect of temporal scheduling. Performances scheduled closely in distance not only sell more tickets but also sell tickets at a faster rate. In contrast, performances scheduled sparsely in time sell more tickets but do not have an impact on the timing of sales.

Our explanation for the observed effects is that event marketers may schedule performances to signal the desirability of venues and accommodate consumers' uncertain attendance timing. In this way, performances in the desired venues and along a wider temporal stretch are more attractive to consumers (even after we have controlled the individual performance attractiveness).

2.8.2 Limitations and Next Steps

Although this essay shows significant effects of geographic and temporal scheduling on ticket sales, the results are for one market only. However, event marketers often need to make scheduling decisions for more than one market. Thus, it is not clear whether the results in essay one hold in other markets. Hence, the objective of essay two is to use all performance schedules of the same event to investigate heterogeneous market responses and identify explanatory factors. We discuss essay two in the next chapter.

Table and Figures

Table 2-1: Description of Data Fields

Category in the Data Fields	Description
Event	Name of event
Identification number	Used to differentiate repeat performances of the same event
Performance date	Month-Date-Year
Venue location	Name of a venue and its location (City and State)
Transaction types	Indicate individual purchases, group purchases, school purchases and so on
Sales date	Month-Date-Year
Channel types	Six channel types: <i>Primary Box Office, Secondary Box Office, Hermes (Automatic phone), Internet, Outlet, and Phone.</i>
Price levels	Label of price levels
Price paid	Indicates the <i>face value, facility charges, service charges,</i> and the total price paid
Daily tickets	Number of tickets sold

Table 2-2: Summary of Ticket Sales

	Mean	Std Dev	Min	Max
<i>Total Ticket Sales</i>	8,316	3,525	1,827	15,810
<i>Ticket Sales by Stage</i>				
Early Sales <i>(one month prior)</i>	24%	14%	3%	59%
Late Sales <i>(2-4 weeks prior)</i>	33%	9%	15%	53%
Spot Sales <i>(performance week)</i>	42%	14%	11%	75%

Table 2-3: Descriptive Statistics of Covariates

	Description	Mean	Std Dev	Min	Max
GEO	Geographic Density	0.368	0.185	0.128	0.540
TMP	Temporal Density	0.118	0.022	0.063	0.144
FRIDAY	Friday performance	0.157	0.367	0	1
SATURDAY	Saturday performance	0.300	0.462	0	1
SUNDAY	Sunday performance	0.286	0.455	0	1
T	Number of advance-selling weeks	15	2.044	11	19

Table 2-4: Benchmark Models and Model Fit

	<u>Benchmark Model</u>			<u>Proposed Model</u>
	1	2	3	
Performance attractiveness	✓	✓	✓	✓
City effects		✓		
Population around venues			✓	
<i>Model Fit</i>				
DIC	157,134	156,459	156,220	156,221

Table 2-5: Results for the Number of Ticket Sales

Parameter	Description	Median	(STD)
<i>Scheduling Effect</i>			
θ_1	Effect of geographic density	0.32	(0.05)**
θ_2	Effect of temporal density	-0.14	(0.05)**
<i>Expected performance attractiveness: E[V_i]</i>			
α_0	Baseline value of event	-6.32	(0.12)**
α_1	Friday effect	0.15	(0.13)
α_2	Saturday effect	0.35	(0.12)**
α_3	Sunday effect	0.34	(0.13)**
σ^2	Variance of performance attractiveness	5.45	(1.02)

** significant at the 95% highest posterior density

Table 2-6: Results for the Timing of Ticket Sales

Parameter	Description	Median	(STD)
Weibull slope parameter: $\log(\lambda_j)$			
γ_{01}	Intercept	3.11	(3.62)
γ_{11}	Effect of geographic density	-7.56	(2.20)**
γ_{21}	Effect of temporal density	0.67	(2.99)
γ_{31}	Number of advance-selling weeks	-1.08	(0.21)**
γ_{41}	Expected performance attractiveness	-0.63	(0.77)
Weibull shape parameter: $\log(c_j)$			
γ_{02}	Intercept	-0.64	(1.03)
γ_{12}	Effect of geographic density	0.93	(0.24)**
γ_{22}	Effect of temporal density	0.23	(0.98)
γ_{32}	Number of advance-selling weeks	0.05	(0.02)**
γ_{42}	Expected performance attractiveness	-0.16	(0.17)
Time-varying pre-Christmas shopping effect: β_j			
γ_{03}	Intercept	2.09	(3.24)
γ_{13}	Effect of geographic density	4.84	(2.51)*
γ_{23}	Effect of temporal density	1.63	(3.04)
γ_{33}	Number of advance-selling weeks	0.97	(0.28)**
γ_{43}	Expected performance attractiveness	2.45	(0.81)**
Variance-covariance matrix: Σ_I			
	$\log(\lambda_j)$	$\log(c_j)$	β_j
$\log(\lambda_j)$	17.38	-1.3	-11.49
$\log(c_j)$		0.13	0.77
β			12.58

** significant at the 95% highest posterior density

* significant at the 90% highest posterior density

Table 2-7: Results for Endogenous Performance Scheduling

Parameter	Description	Median	(STD)
<i>Expected geographic density: m_1</i>			
ϕ_{01}	Intercept	0.18	(0.91)
ϕ_{11}	Expected performance attractiveness	0.22	(0.15)
ϕ_{21}	Effect of geographic density	0.04	(0.97)
<i>Expected temporal density: m_2</i>			
ϕ_{02}	Intercept	-0.61	(0.75)
ϕ_{12}	Expected value of performance	0.26	(0.12)**
ϕ_{22}	Effect of temporal density	-0.03	(1.01)
<i>Variance-covariance matrix: Σ_2</i>			
	m_1	m_2	
m_1	0.36	0.07	
m_2		0.06	

** significant at the 95% highest posterior density

Figure 2-1: Conceptual Framework of Spatial Decomposition

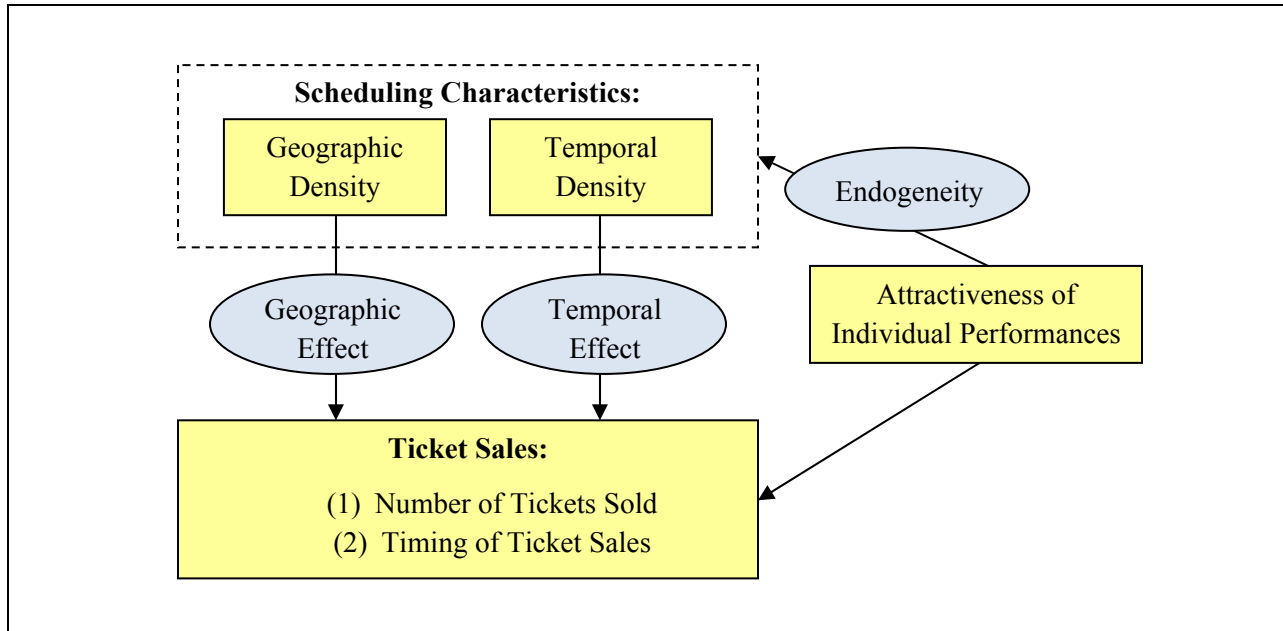


Figure 2-2: Model Overview

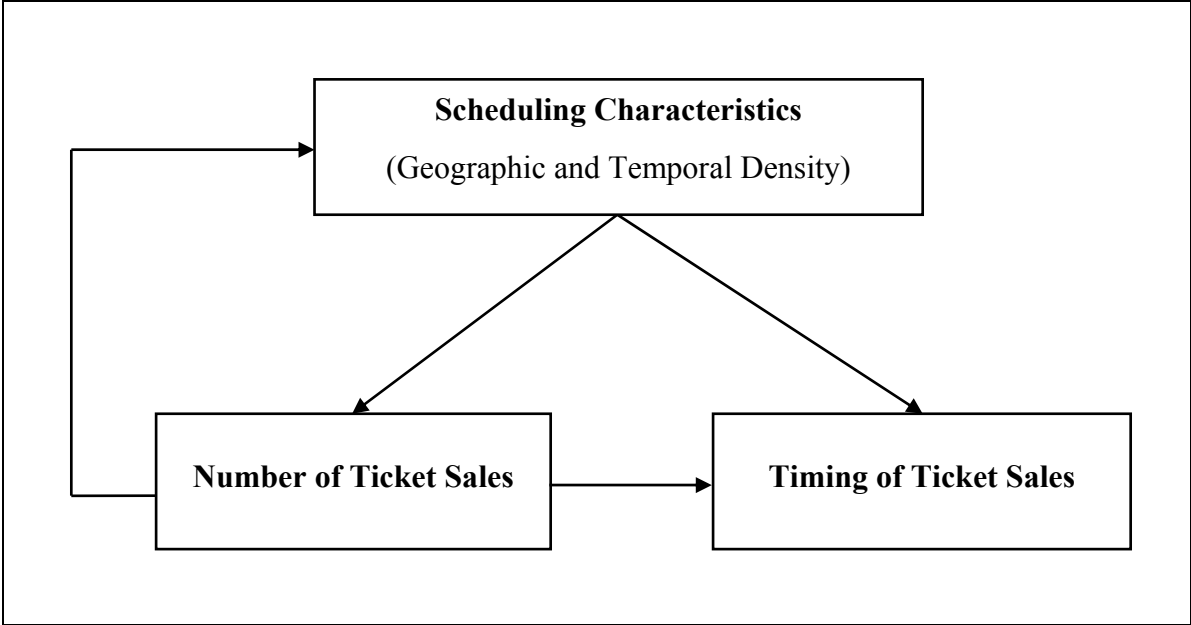


Figure 2-3: Probability of Ticket Sales over Time

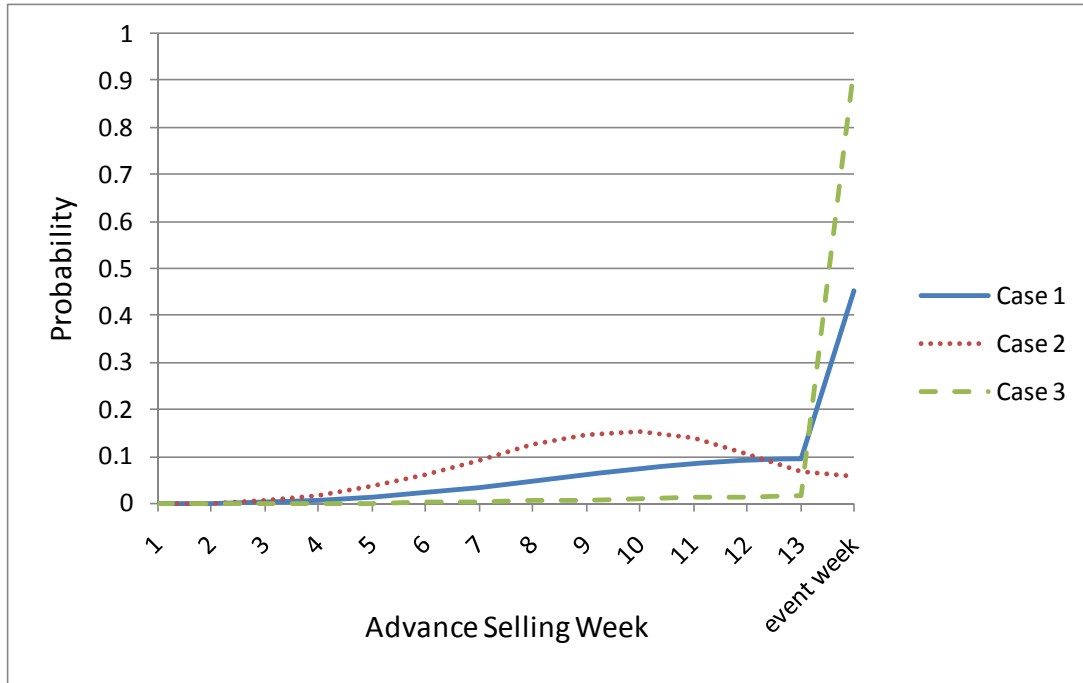


Figure 2-4: Sales Distribution by Performances

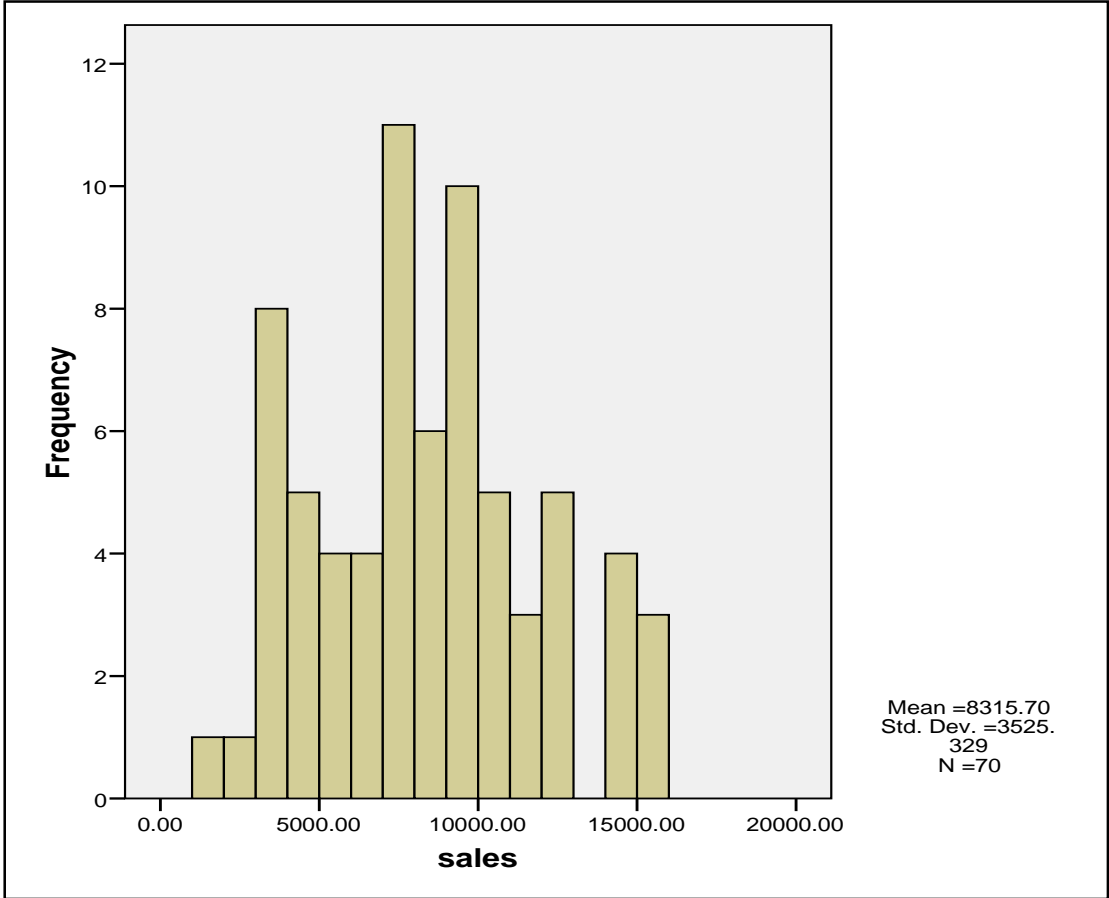


Figure 2-5: Sales Distribution by Days of Week

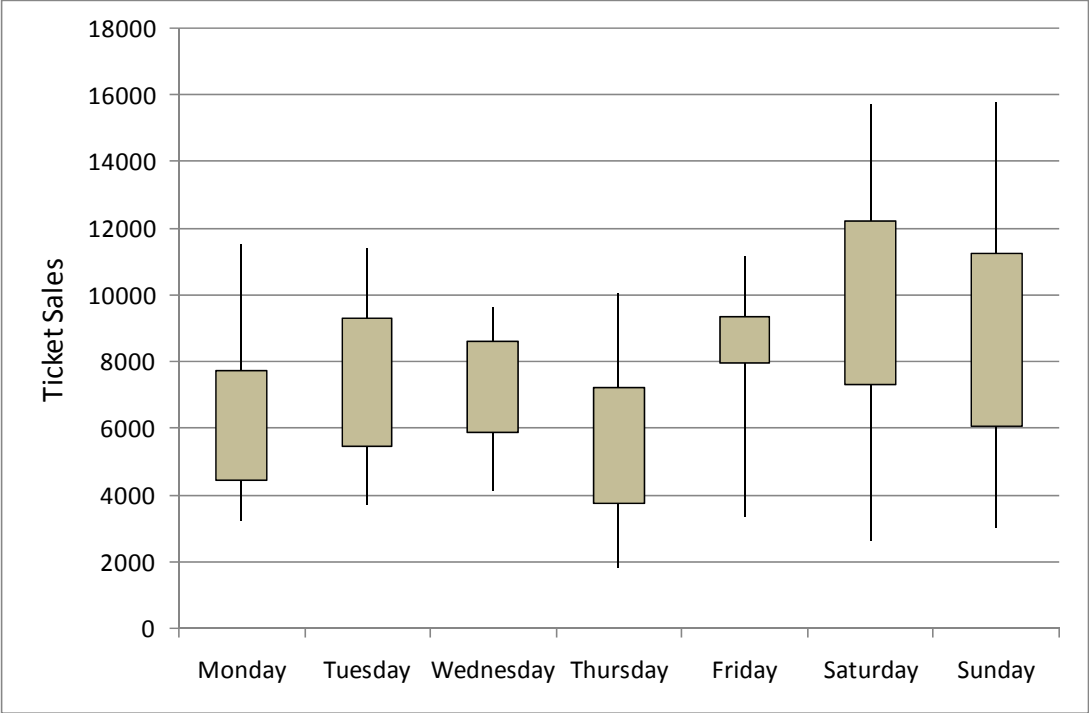


Figure 2-6: Weekly Sales Pattern of a Performance

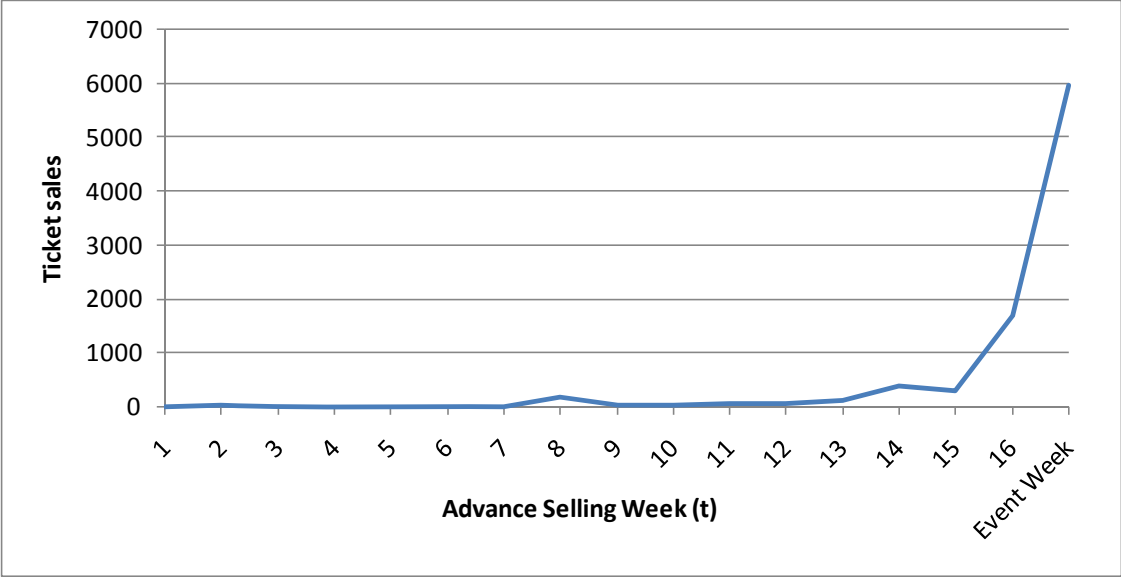


Figure 2-7: Heterogeneity in Sales Pattern Across Performances

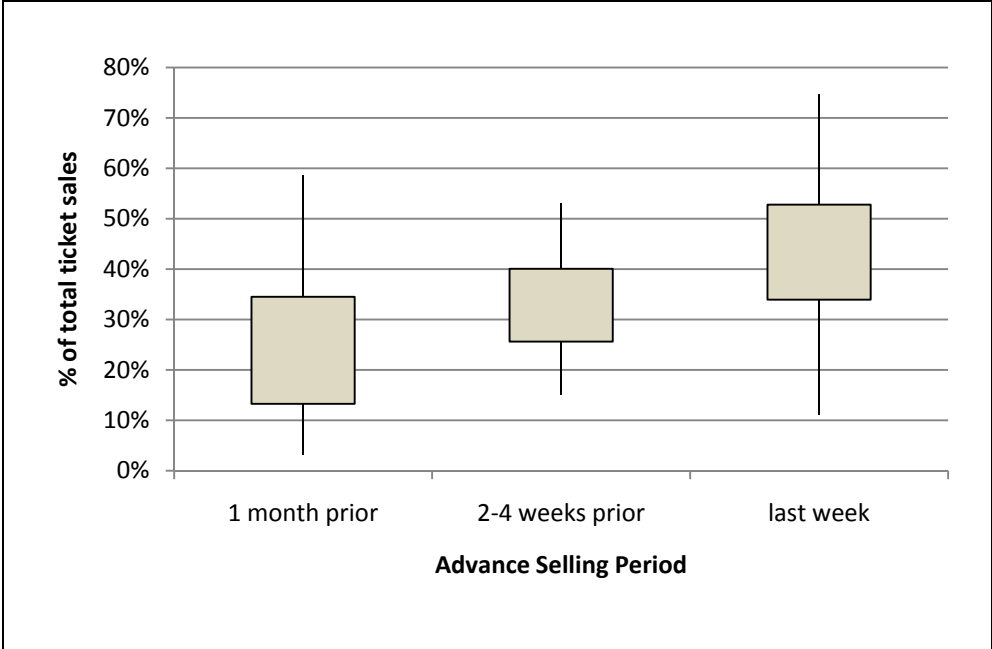
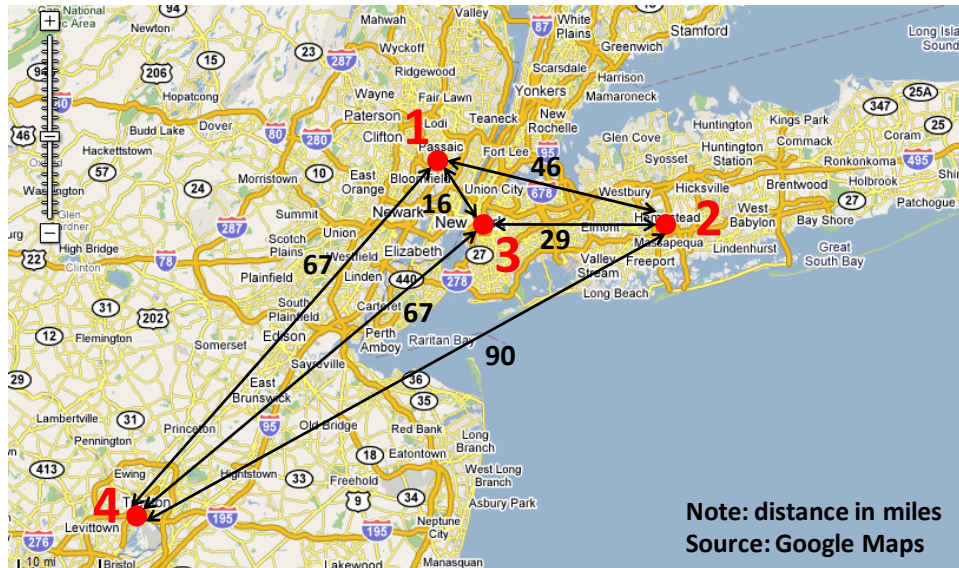


Figure 2-8: Venue Locations and Driving Distances



Note: the number in Figure 2-8 indicates the sequence that the event travelled. That is, the event went to Venue 1, 2, 3, and 4, respectively.

Figure 2-9: Summary of Geographic Distance

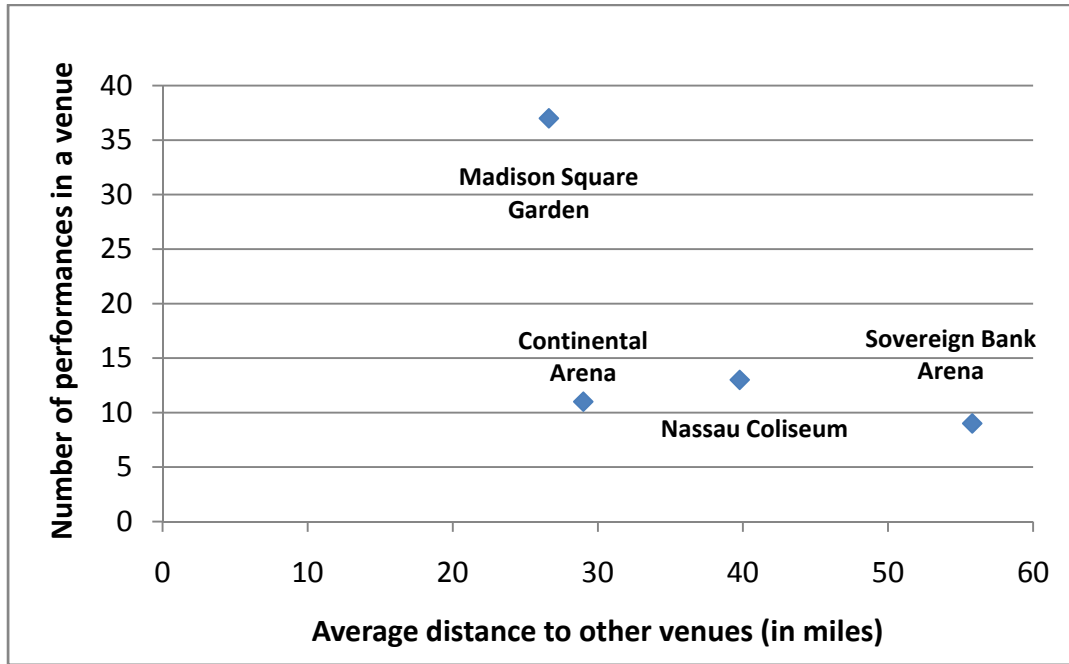


Figure 2-10: Summary of Temporal Distance

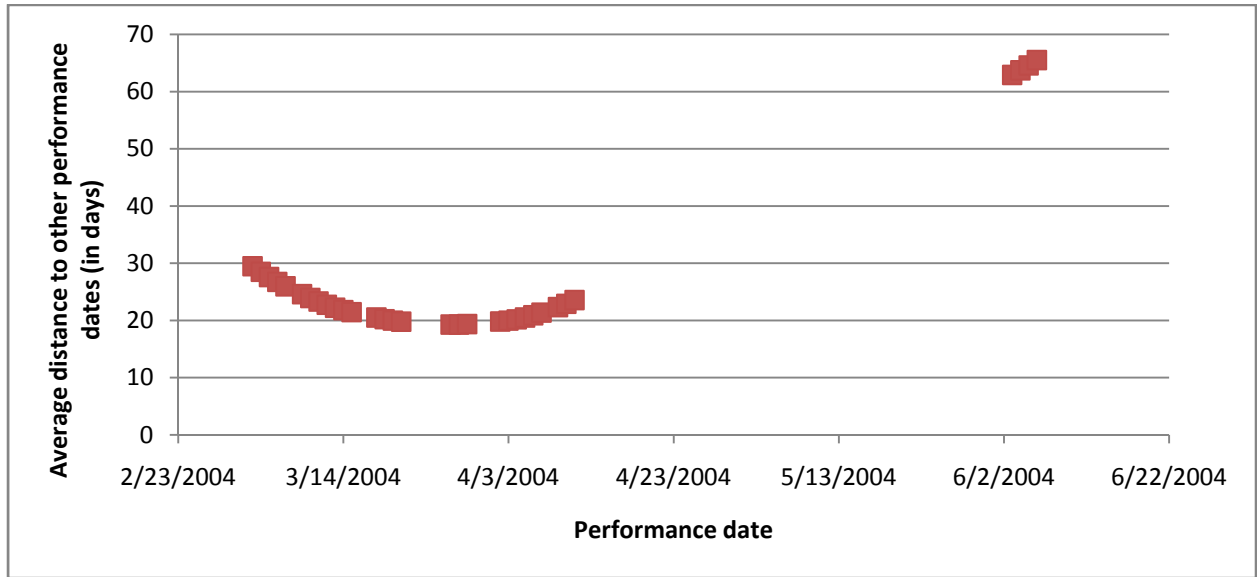


Figure 2-11: Impact of Geographic Density on Timing of Ticket Sales

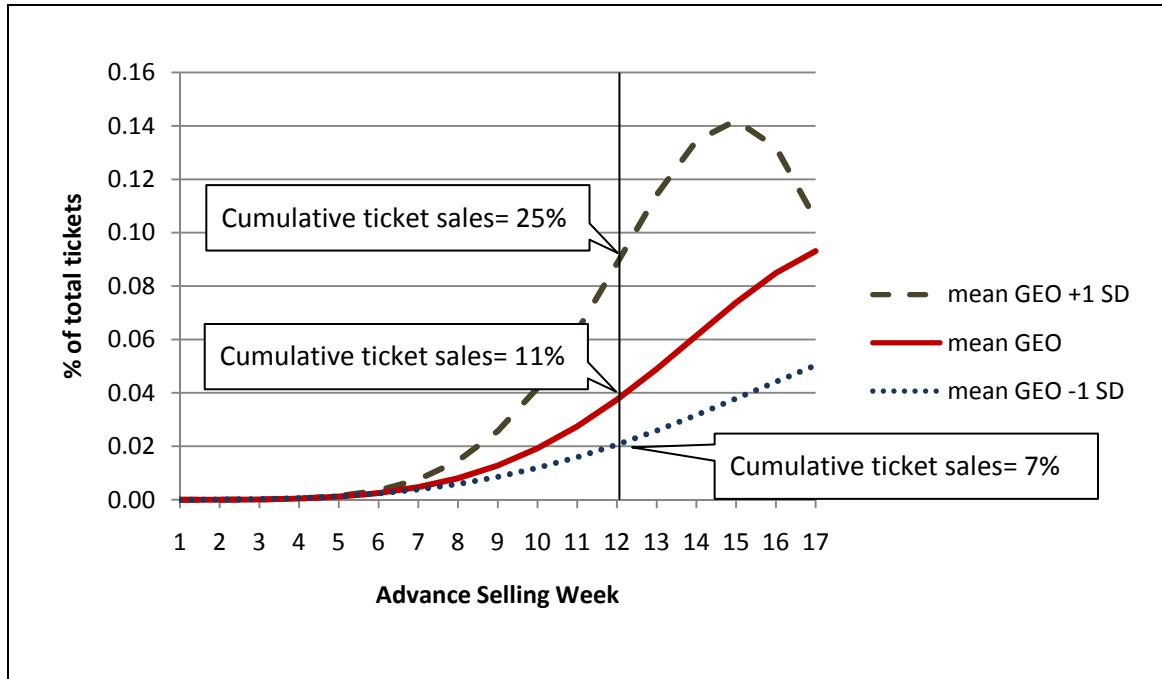


Figure 2-12: Effect of Schedule Changes on Ticket Sales

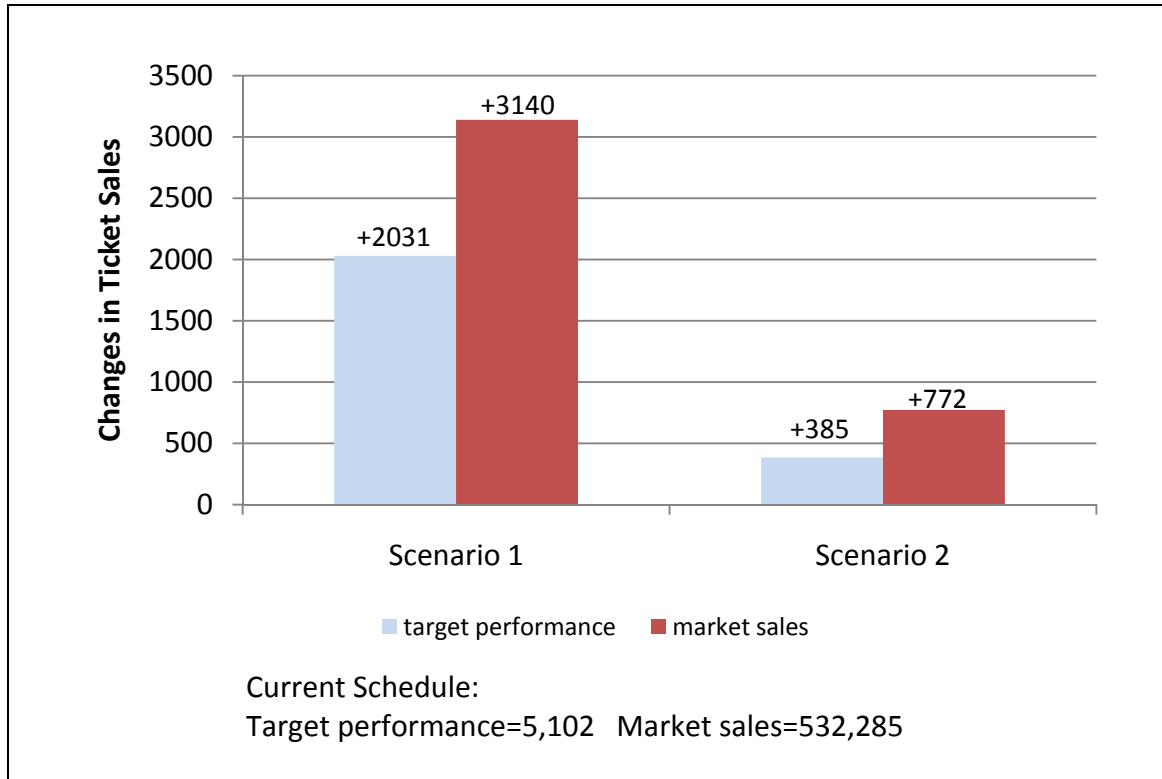
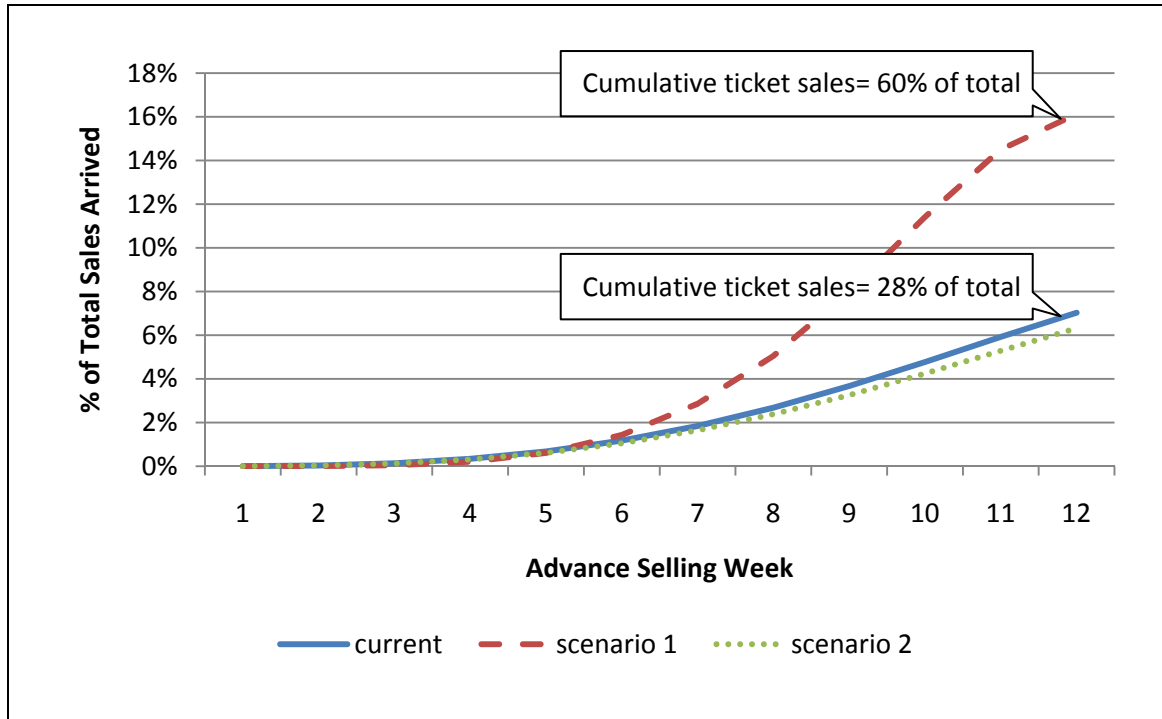


Figure 2-13: Effect of Schedule Changes on Timing of Ticket Sales



3 Essay 2: Heterogeneous Market Responses to Performance Schedules and Their Explanatory Factors

3.1 Introduction

In the first essay, we characterize multiple performances of a single event by their venue locations and performance dates to understand how their geographic and temporal scheduling characteristics influence their ticket sales. Using ticket sales of a live performing event in the New York metropolitan market, we find that the effect of geographic scheduling differs from the effect of temporal scheduling. Performances scheduled in nearby venues not only sell more tickets but also sell tickets at a faster rate. In contrast, performances scheduled distantly in time sell more tickets but do not have an impact on the timing of sales.

However, event marketers often need to make scheduling decisions for more than one market. Although our finding in essay one has rich implications for event marketers, it is unclear whether event marketers can apply this finding to all markets. For example, the event analyzed in essay one had 70 performances in four venues for 32 days in the New York metropolitan market. However, when it travelled to other markets such as Norfolk, Virginia, it had 19 performances in two venues for 10 days. It also had 21 performances in one venue for 10 days in the Atlanta area. Thus, performance schedules can vary across markets and these schedules may not have the same effect on ticket sales across markets. Even if a schedule is the same across markets, these markets may not respond to their schedule identically. This limitation in essay one hence motivates our second essay to examine the effect of performance schedules across markets.

Although several studies in the event tickets literature examine descriptive drivers for event ticket sales, very limited research focuses on examining heterogeneous market responses (Moore 1966; Weinberg and Shachmut 1978; Havlena and Holak 1988; Reddy et al 1998). Hence, the objective of essay two is to use all performance schedules of the same event to investigate heterogeneous market responses and identify explanatory factors. It is important because events do not always go to the same set of markets when they are on tour. A long lasting event may go on tour several times and travels to a different set of markets each time. Hence, once the heterogeneity in market responses and explanatory drivers are known, event marketers could infer a likely response in a new market or select markets for touring based on expected market responses.

To accomplish our research objective, we first conduct a preliminary analysis to analyze all performance schedules and examine their impact on the number of ticket sales. After applying the model developed in essay one to the entire dataset and estimating market responses iteratively across markets, we find that the effect of geographic scheduling differs from the effect of temporal scheduling and this difference is consistent across markets. In terms of the geographic scheduling, performances scheduled in close venues sell more ticket sales than sparsely scheduled ones, but this result only hold for markets that use multiple venues. Regarding the temporal scheduling, in contrast, performances scheduled distantly in time sell more than the densely scheduled ones.

Although we find consistent scheduling effects from the preliminary results, we also observe the market responses are of different magnitudes. In other words, some markets are more responsive to geographic (temporal) schedules than other markets. To identify the factors that explain these differences across markets, we extend the model developed in essay one to not

only examine market-specific response parameters but also investigate observed and unobserved heterogeneity via the hierarchical Bayesian approach. In addition, we also control for the possible endogeneity in the performance scheduling process. Among several marketing characteristics, we choose the size of market population as the first explanatory factor. We also examine characteristics of a touring event to understand whether participating markets that are adjacent to each other and the order that an event travels across affect the magnitude of scheduling effects.

We use the same family event mentioned in essay one and analyze all of its performance schedules in the dataset to test our model. Because this event sequentially performed 449 times in 50 cities in the U.S. domestic market between January and June 2004, we aggregate these 50 cities to 42 designated market areas (which will be discussed in detail in the data section). As a result, there are six markets where the event performed in multiple venues yet all 42 markets have some variations in their temporal schedules.

Our results show that market and additional scheduling characteristics can both explain the differences across market responses. First, when a market has a bigger population, the effects of days of week and baseline attractiveness are attenuated. Our explanation is that usually there are more events offered to a bigger market than to a smaller one. Consumers in a bigger market may be used to seeing several competing events offered simultaneously and having a variety of events to choose from. Hence, they are less responsive to an event no matter on which day of week it may be on as compared to consumers in a smaller market.

Second, we find the additional scheduling characteristics can partly explain heterogeneous market responses. With respect to a current market, after an event travels to more of its geographically adjacent markets, the current market is less responsive to its baseline

attractiveness and temporal schedule. A possible reason is that after an event has gone to more geographically adjacent markets, its newness wears out but its reputation might accumulate over time. As a result, consumers may refer to other measures such as word of mouth to make their purchase decisions rather than refer to the baseline attractiveness and its temporal schedule.

Moreover, after an event perform in several markets (whether these markets are adjacent or not), a market in which an event performs later tends to respond more favorably to a Sunday performance. Our explanation is that after an event has lasted longer and gone to more markets, its reputation, or word of mouth, accumulates over time (Reddy et al 1981) even though its newness may wear out. Because a Sunday performance tends to be the last performance in a market (at least in the case of our dataset), consumers might think Sunday as their “last opportunity” to enjoy this event before it leaves for another market. As a result, a market in a later temporal sequence has a stronger Sunday effect.

We also find that the nature of performance schedules is endogenous. Different from essay one that endogeneity is found only in a temporal schedule, we find in essay two that geographic and temporal schedules are both done endogenously after we pool all performances across markets for analysis. When event marketers expect high performance attractiveness, they schedule more performances in all venues and tend to allocate those performances around weekends or along a limited time span. As a result, on average, performances have a shorter geographic and temporal distance to others and have higher density values. Moreover, when event marketers understand that consumers prefer performances on dispersed dates because of uncertain timing of attendance, they decrease the number of weekend performances and/or disperse performance dates. Consequently, performances in a temporal schedule have lower

temporal density values. Since we have accounted for this endogeneity in the estimation process, the results we present here are unbiased.

The rest of essay two is organized as follows. First, we conduct a preliminary analysis using all performances observed across markets to show heterogeneous market responses to performance schedules. Second, we review extant literature to find possible reasons for heterogeneity and propose our conceptual framework. In the next section, we present the modeling structure extended from the first essay and discuss the dataset in details. After the model estimation and benchmark comparison, we present our results and conclude this essay with limitations and next steps.

3.2 Preliminary Analysis

As described in essay one, a family event went to 50 cities on 245 dates for 449 performances between January and June 2004 (see §2.4.1 Description of Events for more details). Among which, several cities are within the same metropolitan area and show richer variations in geographic and temporal schedules. To test whether markets have heterogeneous responses to their performance schedules, we conduct a preliminary analysis to run the model in equations (5), (6), and (14) for one market at a time and examine their market specific parameters.

More specifically, we use the designated market area (DMA) to aggregate 50 cities into 42 markets (see the data section for full descriptions) and summarize the market information in Table 3-1. As Table 3-1 shows, we sort markets by their first performance date and assign a unique market identification number. Every market has its information listed regarding its first and last performance dates, number of performances, length of performing period, and venue usage. Hence, for performances within a market, we characterize these performances by their

venue locations and performance dates. Then, we follow the equations (1) and (2) in essay one to compute their geographic and temporal density and understand how densely or sparsely these performances are scheduled. Consequently, for each market, we model ticket sales of its performances as a function of their density measures and performance attractiveness while controlling for a possible endogeneity in performance scheduling.

Table 3-1: Summary of Performance Schedules across Markets

After iteratively estimating the model across 42 markets, we find that the days of week represent performance attractiveness and increase ticket sales (α_0 ranges from -3.82 to -8.23; α_1 ranges from 0.10 to 0.95; α_2 ranges from 0.24 to 1.48; α_3 ranges from 0.13 to 1.09). Moreover, the effect of geographic scheduling differs from the effect of temporal scheduling. Performances scheduled in nearby venues sell more tickets than those scheduled in distant venues (θ_1 ranges from 0.92 to 4.29). However, this result only holds for markets that use multiple venues. On the other hand, performances scheduled dispersed across dates sell more than the those scheduled close in time (θ_2 ranges from -0.04 to -2.92). We summarize these market-specific parameters in Table 3-2.

Table 3-2: Summary of Market Responses to Performance Schedules

According to our preliminary analysis, we confirm consistent yet heterogeneous market responses to performance schedules. To understand why market responses are different, we review extant literature that suggests potential explanatory factors for this heterogeneity.

3.3 Literature Review and Conceptual Framework

3.3.1 Literature Review

Consumers are different individuals and their preferences and decisions often differ from one another. However, as the proverb says, “birds of a feather flock together.” It is very common to observe consumers who have similar tastes living in similar areas and making similar purchase decisions. Accordingly, when marketers offer a variety of products to consumers, they often expect heterogeneous consumer responses across zip codes, counties, states, or metropolitan markets.

Heterogeneity in the unit of analysis is commonly studied in marketing and the entities include individual consumers, products, firms, markets, and countries. For example, consumers who have different demographic characteristics or live in different zip codes make different choices regarding automobiles (Yang and Allenby 2002), book formats (i.e., Print vs. PDF; Jank and Kannak 2005), or adoptions of online grocer (Choi, Hui, and Bell 2009). Their shopping behaviors also differ across *product types* (e.g., motels of high, medium, or low quality, Mazzeo 2002; department stores of upscale, midscale, or discount, Vitorino 2007), *store formats* (e.g., supermarkets, hypermarkets, and discount stores, González-Benito 2005; discounted or regular retailers, Zhu et al 2007), and *brand names* (e.g., Wal-mart, K-mart, Target, Zhu and Singh 2009; Zhu et al 2009). Besides examining the heterogeneity at an individual level, researchers can also summarize consumer responses across zip codes (Yang and Allenby 2002; Jank and Kannan 2005), metropolitan statistical areas (Zhu and Singh 2009), or countries (Elberse and Eliashberg 2003) to study heterogeneity at an aggregate level.

One way to account for heterogeneity in empirical analyses is to specify individual-specific parameters (Corning and Levy 2002; González-Benito 2005; Mazzeo 2002; Vitorino

2007; Moe and Fader 2009; Zhu and Singh 2009; Zhu et al 2009). For example, Corning and Levy (2002) specified venue-specific parameters when examining ticket sales across venues to understand whether consumers of those venues have different responses to product offerings. In the retail locations, Mazzeo (2002) specified type-specific effects of spatial competition to study whether motels of low, medium, or high quality types have different spatial effects on profitability. In addition, Zhu and Singh (2009) used brand-specific parameters to examine asymmetric competition effects among Wal-mart, K-mart, and Target.

Although heterogeneity has been extensively studied in many contexts, most of prior studies in the event tickets literature have not yet examined heterogeneous market responses. In other words, researchers assume the effects of days of week, prices, and promotions are homogeneous across venues, events, or performances (Moore 1966; Weinberg and Shachmut 1978; Havlena and Holak 1988; Reddy et al 1998). Although Corning and Levy (2002) and Moe and Fader (2009) are the two exceptions where Corning and Levy (2002) allowed parameters to be venue specific and Moe and Fader (2009) specified parameters varied with events and price tiers, they did not identify explanatory factors for their proposed heterogeneity. Given that we have found the heterogeneous market responses in the preliminary analysis, the objective of essay two is to identify explanatory factors to explain the differences across markets.

3.3.2 Conceptual Framework

In our conceptual framework, we first discuss possible market characteristics that may explain differences across markets. Then, we discuss characteristics of a touring event that may provide context dependent reasons for response heterogeneity.

Market Characteristics

When the analysis is made at a market level rather than at an individual level, the first issue is to define what a market is. Depending on the context of interest, a market can be a metropolitan statistical area (MSA; Zhu et al 2007), a designated market area defined by A.C. Nielsen (DMA; Carlyle, Slater, and Chakroff 2008), or a retail trade area (Bronnenberg and Mela 2004). Then, researchers try to find the market characteristics that may explain the difference to some extent.

In general, metropolitan areas are assumed more similar to other MSAs than to rural areas, and the similarity or differences may be due to the population size, population density, income, education, household size, household values, commute time to work, etc. (Mazzeo 2002; Vitorino 2007; Zhu et al 2007; Zhu and Singh 2009; Zhu et al 2009). For this reason, we propose that market characteristics can explain the heterogeneous market responses in our preliminary analysis.

Additional Scheduling Characteristics

We refer to additional scheduling characteristics as characteristics of a touring event. For example, one characteristic is that its performing group travels from one market to another. Because this distribution mechanism follows the sequential distribution approach (Elberse and Eliashberg 2003; Bronnenberg and Mela 2004), we think sequential distribution literature may provide context dependent characteristics to explain why consumers in different markets react to performance schedules differently.

Extant works in sequential distribution have focused on the effect of geographic adjacency on market adoption (Bronnenberg and Mela 2004) and the effect of release timing on box-office revenues (Elberse and Eliashberg 2003). When Bronnenberg and Mela (2004)

studied the spatial evolution of a new product adoption across markets, they found manufacturers tend to enter markets that are geographically adjacent to a current market. In other words, the initial market serves as a lead market and its lead market effect rolls out sequentially to geographically adjacent markets.

On the other hand, the release timing in the distribution also influences how well a product sells. For example, Elberse and Eliashberg (2003) studied motion pictures to investigate the issue of release timing between the U.S. market and foreign markets. Although they only examined the effect of release timing between the initial market and following foreign markets rather than the effect of release timing along the entire sequence, they still found that shortening the time lag between two markets increases the revenues of a later market.

Therefore, the sequential distribution literature has traditionally discussed the roles of geographic adjacency and release timing as important covariates. Whether the geographic adjacency and release timing in the distribution explains different market responses still remains unknown and deserves further investigation. Similarly, a live performance event follows a temporal sequence to travel across markets. Each market along the sequence has different release timing and some of these markets are geographically adjacent to one another. It is important to evaluate its geographic adjacency and temporal sequence to understand whether these additional scheduling characteristics explain different markets responses to performance schedules. Therefore, we incorporate market characteristics and additional scheduling characteristics to explain different market responses across markets.

In short, we summarize our conceptual framework in Figure 3-1. Similar to essay one, we examine the impact of geographic and temporal scheduling on the number of ticket sales and control for the performance attractiveness through its days of week. In addition, we also control

for the possible endogeneity in performance scheduling. Finally, we examine whether and how market and additional scheduling characteristics explain response heterogeneity across markets.

Figure 3-1: Conceptual Framework

3.4 Model Development

3.4.1 Model Overview

Our model development consists of four steps. First, we use the geographic and temporal density measures to capture the scheduling characteristics of performances in their associated markets and understand how densely or sparsely these performances are scheduled. Second, within each market, we specify market-specific parameters and model ticket sales at a performance level as a function of these density measures and performance attractiveness. Third, we control for a possible endogeneity between performance schedules and expected market responses. Finally, we employ a hierarchical Bayesian (HB) approach to incorporate the heterogeneity in market responses. Among these four steps, the first three steps are adapted from essay one, yet the fourth step is the model extension in essay two.

Although the HB approach is not the only method to study heterogeneous market responses and the latent class analysis (Kamakura and Russell 1989) may be another appropriate alternative, we choose the HB approach because it can accommodate unobserved heterogeneity across markets (Rossi and Allenby 2003) in addition to the heterogeneity explained by market characteristics and additional scheduling characteristics.

3.4.2 Scheduling Characteristics and the Number of Ticket Sales

To begin with, we refer to equations (1) and (2) in essay one to capture the scheduling characteristics by their geographic and temporal density for all performances in their markets.

Then, we refer to equation (5) to rewrite the sales share of performances (and the share of non-buyers) within a market with market-specific parameters:

$$(16) \quad P_m(j) = \frac{\exp(V_{jm}) \cdot GEO_{jm}^{\theta_{1m}} TMP_{jm}^{\theta_{2m}}}{1 + \sum_{j'=1}^{J_m} \exp(V_{jm'}) \cdot GEO_{jm'}^{\theta_{1m}} TMP_{jm'}^{\theta_{2m}}}$$

where

$$V_{jm} = \alpha_{0m} + \alpha_{1m} \text{FRIDAY}_{jm} + \alpha_{2m} \text{SATURDAY}_{jm} + \alpha_{3m} \text{SUNDAY}_{jm} + \varepsilon_{jm}; \varepsilon_{jm} \sim N(0, \sigma_\varepsilon^2)$$

where $P_m(j)$ is the sales share of performance j in market m , V_{jm} is its performance attractiveness (which is a function of days of week), GEO_{jm} and TMP_{jm} represent the geographic and temporal density measures, and α_{0m} , α_{1m} , α_{2m} , α_{3m} , θ_{1m} , and θ_{2m} are market specific parameters. Therefore, among J_m performances in market m , their parameters are homogeneous within a market but heterogeneous across markets. Using the population size in a target market (POP_m) and the sales share of a performance, we can calculate the expected ticket sales of a performance (i.e., $Sales_m(j) = POP_m \times P_m(j)$), the market penetration rate of this event (i.e., $\sum_{j=1}^{J_m} P_m(j)$), and the size of non-buyer segment (i.e., $1 - \sum_{j=1}^{J_m} P_m(j)$).

3.4.3 Endogeneity in Performance Scheduling

Next, we account for a possible endogeneity in performance scheduling by revising equation (14) as follows:

$$(17) \quad \begin{bmatrix} \text{logit}(GEO_{jm}) \\ \text{logit}(TMP_{jm}) \end{bmatrix} = \boldsymbol{\phi}_0 + \boldsymbol{\phi}_1 E[V_{jm}] + \boldsymbol{\phi}_2 \begin{bmatrix} \theta_{1m} \\ \theta_{2m} \end{bmatrix} + \boldsymbol{\eta} \quad \text{where } \eta_i \sim N(0, \sigma_{\eta_i}^2 \mathbf{I}), i = 1, 2$$

where $E[V_{jm}]$ is the expected performance attractiveness of performance j in market m , θ_{1m} , and θ_{2m} represent the effects of geographic and temporal scheduling, and $\boldsymbol{\phi}_0$, $\boldsymbol{\phi}_1$, and $\boldsymbol{\phi}_2$ are the parameters of interest. When $\boldsymbol{\phi}_1$ or $\boldsymbol{\phi}_2$ is significant, scheduling is endogenous but has been taken into account. Note that the specification of equation (17) is the same as equation (14)

except that we specify an independent relationship between geographic and temporal density. In this way, when an event performs in a single venue within a market and only has variation in its temporal schedule, we can directly drop GEO_{jm} in equations (16) and (17) and just investigate a possible endogeneity in temporal scheduling.

3.4.4 Use of the HB Approach for Response Heterogeneity

Finally, we take the HB approach to explain differences of response parameters across markets and specify these market-specific parameters as a function of their unobserved heterogeneity and observed market characteristics and additional scheduling characteristics:

$$(18) \begin{bmatrix} \alpha_{0m} \\ \alpha_{1m} \\ \alpha_{2m} \\ \alpha_{3m} \\ \theta_{1m} \\ \theta_{2m} \end{bmatrix} = \Lambda_m = \beta \mathbf{X}_m + \epsilon \text{ where } \epsilon \sim N(0, \sigma_{\epsilon_i}^2 \mathbf{I}), i = 1, 2, 3, 4, 5, 6$$

where Λ_m is a 6-by-1 vector that contains the market-specific parameters (α_{0m} , α_{1m} , α_{2m} , α_{3m} , θ_{1m} , and θ_{2m}) in equation (16), \mathbf{X}_m is a k-by-1 vector that includes market characteristics and additional scheduling characteristics, β is a 6-by-k matrix that represents the effects for these characteristics, and ϵ is a vector of random errors for the unobserved heterogeneity.

3.5 Data

We contact a national ticket seller to obtain a dataset of two family events and analyze ticket sales for one event in this dissertation (see §2.4.1 for more information about this event). In short, this event sequentially performed 449 times in 50 cities in the U.S. domestic market between January and June 2004. In essay one, we only used ticket sales in the New York metropolitan market. In essay two, we analyze all performances in the dataset to investigate heterogeneity in market responses.

3.5.1 Definition of Markets

Among 50 venues in the dataset, some venues are in the same MSAs, some are the only venues in their MSAs, and others are in rural areas (i.e., non-MSAs). To avoid information losses after aggregating venues to MSAs, we aggregate venues by their designated market areas (DMAs) for urban and rural cities. The definition and classification of DMAs are proposed by Nielsen Media Research (Weiner 2000) where each DMA consists of several counties and consumers in the same DMA receive the same TV broadcasting and media messages (Carlyle, Slater, and Chakroff 2008). The advantage of aggregating data by DMAs is that, suppose marketing activities for an event are planned at a DMA level, consumers within the same DMA are potentially aware of this event even though they may live in a rural area far away from a venue.

Hence, we refer to a website by the Truck Ads[®] (www.truckads.com) that disaggregates the U.S. market into several DMAs and lists all individual counties within each DMA. Figure 3-2 provides an example of the Orlando DMA in Florida. As the map shows, there are nine counties within this DMA. According to the venue locations in our dataset (i.e., names of venues, cities, and states), we can identify in which DMA a venue is and which counties are in this DMA. As a result, we aggregate 50 venues into 42 DMAs in Table 3-3. Figure 3-3 also shows the locations of these DMAs. Each shaded area represents a DMA and a number in a box is its market identification number assigned in Table 3-1.

Figure 3-2: Example of a DMA and its county information

Table 3-3: Venue Locations and their Associated DMAs

Figure 3-3: DMA locations

3.5.2 Description of Performance Schedules across Markets

According to the DMAs and performance information in our dataset, we summarize the temporal schedule in each market into Table 3-1 by its first and last dates, length of performing period, total number of performances, and venue usage in a market. On average, there were 10.69 performances in a market, lasted for 5.79 days, and used 1.19 venues.

Temporal Sequence of the Event Distribution

In Table 3-1, we sort the temporal schedules by their first performance date and observe the temporal sequence of the event distribution. In general, this event first performed in Tallahassee in January (market ID= 1), Atlanta in February (market ID= 12), New York in March (market ID= 16), St. Paul in May (market ID= 33), and Tucson in June (market ID = 42)³. Table 3-1 also indicates a few incidences where two or three markets started performances on the same date or one to two days apart. For instance, the event had performances in Providence (market ID= 26) and Worcester (market ID= 27) between May 1 and May 9 while having performances in La Crosse (market ID= 25) between May 4 and May 5. Therefore, it is likely that there were up to three performing groups touring in the same period. Because we cannot identify which groups performed in which markets, we assume that the performing quality is constant across performing groups and do not affect how markets respond to their performance schedules. Hence, we analyze all 42 markets together regardless of their performing groups.

Venue Usage of the Event across Markets

In terms of the venue usage across markets, among 42 DMAs, only six markets had more than one venue in use. These markets were the Greenville-Asheville, Raleigh-Fayetteville, Norfolk-Hampton, Champaign-Springfield, New York, and Philadelphia DMAs. Moreover,

³ This event kept on travelling after performing in Tucson. However, the performance schedules available in the dataset were truncated up to June 2004. Thus, we examine the performance schedules of these 42 markets only.

except for the New York market that scheduled performances across four venues, the rest had performances scheduled in two venues. We also find that the event did not always perform in these venues consecutively within a market. Sometimes the event offered all performances in one market and then left for a new market, but sometimes it offered a few performances in one venue and then provided more after a period. Specifically, this event completed all scheduled performances consecutively in the markets of Norfolk-Hampton, Champaign-Springfield, and Philadelphia. However, in the market of Greenville-Asheville and Raleigh-Fayetteville, after the event performed in one venue, it left for other markets and then came back three to four months later. In the New York market, it performed in three venues consecutively, left for other markets, and then returned seven weeks later.

Geographic Adjacency of Markets

Upon a closer look of these markets and their locations in Figure 3-3, we also find that this event had an extensive tour in the East Coast and some of the Mid-West markets. Moreover, this event sometimes went to near or adjacent markets but occasionally traveled to an isolated market. For example, this event went to Orlando (market ID=2) and Tampa (market ID=3) in a consecutive order but went to an isolated market in Tucson (market ID=42).

Descriptions of Ticket Sales

Table 3-4 summarizes the average ticket sales at a performance level and its total ticket sales at a market level. Across all markets, a performance can sell an average of 3,825 tickets with a standard deviation being 1,162 tickets. However, depending on in which market a performance is, it can sell as many as 8,316 tickets in New York (market ID= 16) or as little as 585 tickets in Madison (market ID= 28). In terms of ticket sales at a market level, an event can sell an average of 51,905 tickets with a standard deviation being 90,992. Although it seems that

markets that use multiple venues experience more ticket sales (e.g., New York and Philadelphia are ranked as the top two best selling markets), markets of a single venue usage do not necessarily sell less. For example, the event performed in only one venue in Atlanta (market ID=12) had market sales ranked at the third place. Moreover, Miami is also a single venue DMA but its market sales exceeded the DMAs of Greenville-Ashville (market ID=9) and Champaign-Springfield (market ID=20). Because the focus of essay two is on sales at performance level and response heterogeneity across markets, we will address the issue of market sales in essay three.

Table 3-4: Summary of Ticket Sales across Markets

3.5.3 Covariate Specifications

Before we estimate our model, we still have to measure geographic and temporal density as scheduling characteristics, create the days of week indicators for performance attractiveness, and compute the population size of the target markets. Moreover, we need to select market characteristics and measure the geographic adjacency and temporal sequence for the additional scheduling characteristics. Hence, we discuss each covariate in turn.

Geographic and Temporal Density Measures

First, we calculate the geographic density for performances in markets (GEO_{jm}) where more than one venue is used. These markets are Greenville-Asheville, Raleigh-Fayetteville, Norfolk-Hampton, Champaign-Springfield, New York, and Philadelphia. We start with identifying venue locations on the Google Maps to compute the geographic distance (in miles) between venues in the same market. Then, we apply the equation (1) in essay one to compute the geographic density for each performance. As a result, depending on in which market a performance is, the average geographic density of a performance ranges between 0.368 and 0.556 with the average across markets being 0.476 and the standard deviation being 0.09.

Next, we use the equation (2) in essay one to calculate the temporal density for performances in their associated markets (TMP_{jm}). On average, a performance in a market has its temporal density ranging from 0.118 to 0.667 with the average across markets being 0.476 and the standard deviation being 0.09. Table 3-5 provides the descriptive statistics of these covariates.

Table 3-5: Descriptive Statistics of Covariates across Markets

Days of Week Indicators and Market Population

According to observed performance dates in the dataset, we further create the days of week indicators ($FRIDAY_{jm}$, $SATURDAY_{jm}$, and $SUNDAY_{jm}$) to measure performance attractiveness. On average, a market has 17% of performances on Friday, 38% on Saturday, and 25% on Sunday. However, there are markets without any Friday, Saturday, or Sunday performances, as shown in those blank cells in Table 3-5. We also summarize the descriptive statistics of days of week covariates in Table 3-5.

To compute a population size (POP_m) in a target market (i.e., family population with children under 10 years of age) across all DMAs, we refer to the Census Bureau to collect relevant population information at the county level and then aggregate the population size by DMAs, the same approach used in essay one. As a result, the average population size in a target market is 439,662 with a standard deviation being 647,091. Table 3-6 presents the summary information of the population size in each DMA.

Table 3-6: Descriptive Statistics of Market Characteristics

Market Characteristics

In addition to population size in a target market, we consider population density, family income, and average family size as other potential market characteristics to explain response

heterogeneity. Different from the extant literature, we choose the information at a family level rather than at a household level because our event targets at families with young children. Hence, we first download the U.S. 2000 Census data at the county level to match the counties of interest in our 42 DMAs. Because the population size in each county differs, we weight the market characteristics in each county by its population size to calculate the average value for each DMA. Table 3-6 presents the summary statistics across these DMAs.

Additional Scheduling Characteristics

We consider two additional characteristics of a performance schedule to explain the heterogeneity across markets. The first characteristic we examine reflects the order of markets that appear in a schedule. The second is the number of geographically adjacent markets with respect to a focal market. We refer to the previous covariate as the temporal sequence and the later as geographic adjacency.

To measure the temporal sequence, we refer to Table 3-1 that sorts markets by their first day of performance to check which market is in the earliest distribution timeline (Order=1). Then, we go down the list to assign an increasing number to markets in a later distribution timeline. For example, according to Table 3-1, Tallahassee is the first market and Orlando is the second market. We assign $Order_1=1$ and $Order_2=2$. For markets that had the first performance on the same date (e.g., Columbia and Greenville-Asheville), we assigned an equal rank to these markets (i.e., $Order_8=Order_9=8$). Table 3-7 summarizes the descriptive statistics of temporal sequence across markets.

Table 3-7: Descriptive Statistics of Additional Scheduling Characteristics

According to the lead market effect (Bronnenberg and Mela 2004), markets that are adjacent and adopt a new product first have an impact on adjacent markets that have not yet been

adopted. We follow this logic to measure the geographic adjacency among our participating DMAs. Hence, we first refer to Figure 3-3 to locate these 42 DMAs and check which markets are adjacent to one another. Then, we refer to the order of each market to count how many adjacent markets an event went to before it arrives to a focal market. Finally, we use this number to represent the extent of geographic adjacency of a participating market. As a result, an event went to an average of 0.95 spatially adjacent markets before it goes to a focal market. Table 3-7 summarizes the descriptive statistics of geographic adjacency across markets⁴.

The purpose of essay two is to explain heterogeneous market responses and propose explanatory factors. Thus, we use the same set of covariates in the HB approach in equation (18) and choose the population size in a target market, the order of markets that an event travels, and the number of geographically adjacent markets for a focal market. We also examined other market characteristics as shown in Table 3-6. Although population density is another significant explanatory factor, it has the same effect as the population size. On the other hand, we find the average family income and family size cannot explain any response heterogeneity across markets.

3.6 Model Estimation and Benchmark Comparison

3.6.1 Estimation

We choose the hierarchical Bayesian approach to estimate the number of ticket sales, heterogeneous market responses, and endogeneity in performance scheduling simultaneously. We specify appropriate and diffuse priors for our parameters in the WinBUGS program and estimate the model over 10,000 iterations. After checking the convergence criteria, we examine the autocorrelation plots for all covariates, discard the first 5,000 iterations for burn-in, and use

⁴ We also count how many adjacent markets a focal market has regardless of when the event performed in these markets. However, this alternative measure did not explain any of the response heterogeneity.

the remaining iterations as the posterior distribution. We specify the prior distributions of parameters below:

Priors for modeling performance attractiveness:

$$\sigma_{\varepsilon}^2 \sim IG(0.1, 0.1)$$

Priors for modeling the heterogeneity in market responses:

$$\beta_{ki} \sim N(0, 10) \quad \text{where } k=1, 2, 3, 4 \text{ and } i=1, 2, 3, 4, 5, 6$$

$$\sigma_{\varepsilon_i}^2 \sim IG(0.1, 0.1) \quad \text{where } i=1, 2, 3, 4, 5, 6$$

Priors for modeling the endogeneity in performance scheduling:

$$\phi_{ki} \sim N(0, 10) \quad \text{where } k=0, 1, 2 \text{ and } i=1, 2$$

$$\eta_i \sim N(0, 10) \quad \text{where } k=1, 2$$

3.6.2 Benchmark Comparison

Before presenting our model results, we compare the model fit between the proposed and benchmark models. Because our proposed model aims to explain the heterogeneous market responses to performance schedules, we think a homogeneous model that does not account for any heterogeneity to be an appropriate benchmark (i.e., Benchmark 1). In addition, we also compare the proposed model with the preliminary analysis (i.e., Benchmark 2). After comparing the model fit using the DIC measure (equation 15), we find that the DIC of the proposed model is 5590.63. This fit measure is lower than the heterogeneous model without explanatory factors (DIC=5613.94) and the homogeneous model (DIC=6927.14). Hence, our proposed model has incorporated the market heterogeneity and explained the differences across markets.

3.7 Results

3.7.1 Heterogeneous Market Responses to Performance Schedules

According to the market-specific parameters, we find that markets respond to performance schedules consistently. Although the effect sizes vary from markets to markets, all expected values of parameters (i.e., effects of baseline performance attractiveness, days of week, geographic density, and temporal density) are consistently positive or negative. Figure 3-4 visually presents these heterogeneous parameter values. Specifically, the parameter values of the baseline performance attractiveness is consistently negative across markets ($E[\alpha_{0m}]$ ranges from -4.43 to -7.10) and performances on Friday, Saturday, or Sunday have incremental attractiveness to generate more ticket sales ($E[\alpha_{1m}]$ ranges from 0.08 to 0.39; $E[\alpha_{2m}]$ ranges from 0.16 to 0.66; $E[\alpha_{3m}]$ ranges from 0.18 to 0.44).

Figure 3-4: Heterogeneous Market Responses

Moreover, markets have consistent responses to their geographic and temporal schedules. For markets where multiple venues are in use, densely scheduled performances across venues sell more tickets than sparsely scheduled performances ($E[\theta_{1m}]$ ranges from 0.81 to 2.13). In contrast, sparsely scheduled performances along a time span sell more than densely scheduled performances ($E[\theta_{2m}]$ ranges from -0.10 to -0.59). These results are consistent with results in essay one and our preliminary analysis. Hence, we confirm the consistent (yet heterogeneous) market responses to performance schedules.

3.7.2 Explanatory Factors for Market Heterogeneity

Our results in Table 3-8 report explanatory factors for the heterogeneity in market responses. First, when a market has a bigger population, the effects of days of week and baseline attractiveness are attenuated ($\beta_{11} = -0.25$; $\beta_{12} = -0.03$; $\beta_{13} = -0.05$; $\beta_{14} = -0.02$). Our explanation is that

usually there are more events offered to a bigger market than to a smaller one. Consumers in a bigger market may be used to seeing several competing events offered simultaneously and have a variety of events to choose. Hence, they are less responsive to an event (no matter on which days of week it is) than are consumers in a smaller market.

Table 3-8: Explanatory Factors for Market Heterogeneity

Second, we find that additional scheduling characteristics can partly explain heterogeneous market responses. With respect to a current market, after an event travels to more of its geographically adjacent markets, the current market is less responsive to its baseline attractiveness and temporal schedule ($\beta_{21} = -0.14$; $\beta_{26} = 0.10$). A possible reason is that after an event has gone to more spatially adjacent markets, its newness wears out but its reputation might accumulate over time. As a result, consumers may refer to other measures such as word of mouth to make their purchase decisions rather than refer to the baseline attractiveness and its temporal schedule.

Moreover, after an event follows its temporal sequence to perform in several markets (whether these markets are adjacent or not), a current market in a late distribution sequence tends to respond more favorably to a Sunday performance ($\beta_{34} = 0.10$). This result is also graphically shown in Figure 3-4 (d). Our explanation is that after an event has lasted longer and gone to more markets, its reputation or word of mouth accumulates over time (Reddy et al 1981) even though its newness may wear out. Because a Sunday performance tends to be the last performance in a market (at least it is the case in our dataset), consumers might think Sunday as their “last opportunity” to enjoy this event before it leaves for another market. As a result, a market in a later temporal sequence has a stronger Sunday effect.

3.7.3 Endogenous Scheduling Decision

We also find an endogeneity in performance schedules. Different from essay one where only endogeneity is found in a temporal schedule, in essay two we find that geographic and temporal schedules are both done endogenously after we pool all performances across markets for analysis. When event marketers expect high performance attractiveness, they schedule more performances in all venues ($\phi_{11}= 0.18$) and tend to allocate those performances around weekends or along a limited time span ($\phi_{12}= 0.84$). As a result, on average, performances have a shorter geographic and temporal distance to others and have higher density values. Moreover, when event marketers understand that consumers prefer performances on dispersed dates because of uncertain timing of attendance, event marketers decrease the number of weekend performances and/or disperse performance dates ($\phi_{22}= 1.30$). Consequently, performances in a temporal schedule have lower temporal density values. Since we have accounted for this endogeneity in the estimation process, the results we present here are unbiased. Table 3-9 summarizes the results of the endogeneity in performance scheduling.

Table 3-9: Endogenous Performance Schedules

3.8 Conclusions

3.8.1 Summary

In the first essay, we observe multiple performances of a single event and examine them by their venue locations and performance dates to understand how their geographic and temporal scheduling characteristics influence their ticket sales. However, event marketers often need to make scheduling decisions for more than one market. Although our finding in essay one has rich implications for event marketers, it is unclear whether event marketers can apply this finding to

all markets. Hence, the objective of essay two is to use all performance schedules of the same event to investigate heterogeneous market responses and identify explanatory factors.

To accomplish our research objective, we first conduct a preliminary analysis and find consistent scheduling effects. However, we also observe the market responses are of different magnitudes. To identify the factors that explain these differences across markets, we extend the model developed in essay one to not only examine market-specific response parameters but also investigate observed and unobserved heterogeneity via the hierarchical Bayesian approach. Among several marketing characteristics, we choose the size of market population as the first explanatory factor. We also use additional scheduling characteristics along the distribution of this event to examine whether geographic adjacency between markets and temporal sequence along the distribution affect the magnitude of scheduling effects.

We use the same family event mentioned in essay one and aggregate the 50 cities it travelled to 42 designated market areas. Our results show that market characteristics and additional scheduling characteristics can both explain the differences across market responses. First, when a market has a bigger population, the effects of days of week and baseline attractiveness are attenuated. Second, with respect to a current market, after an event travels to more of its geographically adjacent markets, the current market is less responsive to its baseline attractiveness and temporal schedule. Moreover, after an event follows its temporal sequence to perform in several markets, a current market in a late distribution sequence tends to respond more favorably to a Sunday performance. We also find an endogeneity in performance schedules. Since we have accounted for this endogeneity in the estimation process, the results we present here are unbiased.

3.8.2 Limitations and Next Steps

This essay examines heterogeneous market responses to performance schedules and contributes to the event tickets literature by investigating explanatory factors. Results of this essay provide a more generalizable scheduling guideline for event marketers and assist event marketers in anticipating potential market response based on market characteristics and additional scheduling characteristics.

However, the limitation of this essay is that we allow the additional scheduling characteristics to explain the heterogeneity in market responses (i.e., parameter effects) but have not yet directly examined whether additional scheduling characteristics in an event distribution affect ticket sales across markets. As the sequential distribution literature suggests, preceding markets tend to have some effects on later markets through their spatial adjacency (Bronnenberg and Mela 2004) or time lag between release timing (Elberse and Eliashberg 2003). It is important to examine whether sales in different markets are independent or not. We continue discussing this issue in essay three.

Tables and Figures

Table 3-1: Summary of DMA markets

Market ID	Market	First Date	Last Date	Number of Performances	Number of Show Dates	Number of Venues
1	Tallahassee	1/1	1/4	6	4	1
2	Orlando	1/2	1/4	6	3	1
3	Tampa	1/7	1/11	8	5	1
4	Miami	1/8	1/18	16	10	1
5	Jacksonville	1/14	1/18	9	5	1
6	Birmingham	1/21	1/25	10	5	1
7	Nashville	1/22	1/25	8	4	1
8	Columbia	1/28	2/1	9	5	1
9	Greenville-Asheville	1/28	6/13	19	10	2
10	Raleigh-Fayetteville	2/5	5/23	17	9	2
11	Richmond	2/11	2/16	11	6	1
12	Atlanta	2/12	2/22	21	10	1
13	Norfolk-Hampton	2/18	2/29	19	10	2
14	Cincinnati	2/25	2/29	9	5	1
15	Charlotte	3/3	3/7	11	5	1
16	New York	3/3	6/6	70	32	4
17	Wheeling	3/17	3/20	7	4	1
18	Louisville	3/24	3/28	7	5	1
19	Terre Haute	4/6	4/7	4	2	1
20	Champaign-Springfield	4/9	4/25	11	6	2
21	Carbondale	4/13	4/14	3	2	1
22	Philadelphia	4/14	5/2	31	16	2
23	Charleston	4/15	4/18	8	4	1
24	Albany	4/29	5/2	8	4	1
25	La Crosse	5/4	5/5	4	2	1
26	Providence	5/5	5/9	9	5	1
27	Worcester	5/5	5/9	8	5	1
28	Madison	5/7	5/9	6	3	1
29	Hartford	5/12	5/16	9	5	1
30	Dayton	5/13	5/16	7	4	1
31	Mankato	5/18	5/19	3	2	1
32	Rochester	5/19	5/23	8	5	1
33	St. Paul	5/21	5/23	6	3	1
34	Cedar Rapids	5/25	5/26	4	2	1
35	Hershey	5/26	5/31	9	6	1
36	Sedalia	5/29	5/31	5	3	1
37	Memphis	6/2	6/5	6	4	1
38	Evansville	6/3	6/6	6	4	1
39	Wilkes-Barre	6/9	6/13	8	5	1
40	North Little Rock	6/16	6/20	8	5	1
41	Macon	6/23	6/27	8	5	1
42	Tucson	6/24	6/27	7	4	1
Average (STD)				10.69 (10.81)	5.79 (4.97)	1.19 (0.55)

Table 3-2: Summary of Market Responses to Performance Schedules

Market ID	α_0	α_1	α_2	α_3	θ_1	θ_2
1	-5.5 **	0.3	1.32 **	0.15		-1.8 **
2	-5.76 **		1.19 **	0.58 **		-0.79 **
3	-6.32 **	0.75 **	1.48 **	0.88 **		-1.33 **
4	-6.97 **	0.3	0.79 **	0.61 **		-1.24 **
5	-5.96 **	0.9 **	1.33 **	0.7 **		-1.69 **
6	-5.42 **	0.62 **	0.89 **	0.22		-2.04 **
7	-5.99 **	0.86 **	1.42 **	0.73 **		-1.4 **
8	-5.92 **	0.95 **	1.36 **	0.59 **		-1.81 **
9	-7.17 **	0.66 **	0.94 **	0.6 **	0.96 **	-1.8 **
10	-6.16 **	0.5 **	0.81 **	0.41 **	4.29 **	-2.92 **
11	-5.66 **	0.9 **	1.3 **	1.09 **		-2.38 **
12	-6.72 **	0.24	0.5 **	0.34 **		-1.2 **
13	-7.23 **	0.54 **	0.75 **	0.48 **	0.92 **	-0.84 **
14	-5.68 **	0.4 *	0.91 **	0.41 **		-1.74 **
15	-5.78 **	0.69 **	0.96 **	0.53 **		-1.67 **
16	-8.23 **	0.1	0.24 **	0.2 **	0.51 **	-1.16 **
17	-5.4 **	0.94 **	1.19 **			-2.22 **
18	-6.17 **	0.56 *	1.21 **	0.22		-1.18 **
19	-3.82 **					-2.22 **
20	-6.03 **		0.40 **	0.35 **	2.09 **	-2.04 **
21	-4.43 **					-1.17 **
22	-7.18 **	0.28 **	0.37 **	0.24 **	0.99 **	-1.3 **
23	-5.68 **	0.83 **	1.27 **	0.61 **		-1.8 **
24	-5.62 **	0.89 **	1.4 **	0.79 **		-2.1 **
25	-4.79 **					-0.66 **
26	-5.63 **	0.34 *	0.85 **	0.27 *		-1.71 **
27	-6.82 **	0.53 **	1.27 **	0.71 **		-0.37 **
28	-6.1 **		0.98 **	0.29		-0.04
29	-5.86 **	0.35	0.84 **	0.29 *		-1.32 **
30	-6.2 **	0.7 **	1.46 **	0.9 **		-1.25 **
31	-3.83 **					-2.12 **
32	-6.19 **	0.66 **	1.34 **	0.87 **		-1.41 **
33	-6.44 **		1.05 **	0.5 **		-0.59 *
34	-4.59 **					-0.98 **
35	-6.83 **	0.45 **	1.11 **	0.71 **		-0.34 **
36	-6.35 **		0.65 **	0.77 **		0.08
37	-6.13 **	0.59 *	1.24 **			-1.08 **
38	-6.04 **	0.35	1.16 **	0.13		-0.88 **
39	-6 **	0.51 **	1.13 **	0.6 **		-1.47 **
40	-6.06 **	0.58 **	1.19 **	0.6 **		-1.51 **
41	-6.14 **	0.48 *	1.22 **	0.57 **		-1.34 **
42	-5.79 **	0.54 **	1.36 **	0.82 **		-1.7 **

** : significant at the 95% highest posterior density

* : significant at the 90% highest posterior density

Table 3-3: Venue Locations and their Associated DMAs

Venue	City	State	DMA Market
Pepsi Arena	Albany	NY	Albany
Philips Arena	Atlanta	GA	Atlanta
Bjcc Arena	Birmingham	AL	Birmingham
Southern Illinois University	Carbondale	IL	Carbondale
Us Cellular Center	Cedar Rapids	IA	Cedar Rapids
Assembly Hall	Champaign	IL	Champaign-Springfield
Prairie Capital Convention Center	Springfield	IL	Champaign-Springfield
Charleston Civic Center	Charleston	WV	Charleston
Charlotte Coliseum	Charlotte	NC	Charlotte
Us Bank Arena	Cincinnati	OH	Cincinnati
Colonial Center	Columbia	SC	Columbia
Ej Nutter Center	Dayton	OH	Dayton
Roberts Municipal Stadium	Evansville	IN	Evansville
Asheville Civic Center	Asheville	NC	Greenville-Asheville
Bi-Lo Center	Greenville	SC	Greenville-Asheville
Hartford Civic Center	Hartford	CT	Hartford
Giant Center	Hershey	PA	Hershey
Jacksonville Veterans Memorial Arena	Jacksonville	FL	Jacksonville
La Crosse Center	Lacrosse	WI	Lacrosse
Louisville Gardens	Louisville	KY	Louisville
Macon Centreplex	Macon	GA	Macon
Alliant Energy Center Coliseum	Madison	WI	Madison
Midwest Wireless Civic Center	Mankato	MN	Mankato
Pyramid Arena	Memphis	TN	Memphis
American Airlines Arena	Miami	FL	Miami
Gaylord Entertainment Ctr	Nashville	TN	Nashville
Continental Arena	East Rutherford	NJ	New York
Madison Square Garden	New York	NY	New York
Sovereign Bank Arena	Trenton	NJ	New York
Nassau Coliseum	Uniondale	NY	New York
Hampton Coliseum	Hampton	VA	Norfolk-Hampton
Norfolk Scope Arena	Norfolk	VA	Norfolk-Hampton
Alltel Arena	North Little Rock	AK	North Little Rock
Td Waterhouse Centre	Orlando	FL	Orlando
Boardwalk Hall	Atlantic City	NJ	Philadelphia
Wachovia Spectrum	Philadelphia	PA	Philadelphia
Dunkin' Donuts Center	Providence	RI	Providence
Crown Center Of Cumberland	Fayetteville	NC	Raleigh-Fayetteville
Rbc Center	Raleigh	NC	Raleigh-Fayetteville
Richmond Coliseum	Richmond	VA	Richmond
Blue Cross Arena	Rochester	NY	Rochester
Mathewson Center	Sedalia	MO	Sedalia
Xcel Energy Center	St Paul	MN	St Paul
Tallahassee Leon County Civic Center	Tallahassee	FL	Tallahassee
St Pete Times Forum	Tampa	FL	Tampa
Hulman Center	Terre Haute	IN	Terre Haute
Tcc Arena	Tucson	AZ	Tucson
Wesbanco Arena	Wheeling	WV	Wheeling
Wachovia Arena	Wilkes-Barre	PA	Wilkes-Barre
Worcester Centrum Centre	Worcester	MA	Worcester

Table 3-4: Summary of Ticket Sales

Market ID	Market	Ticket Sales per Performance				Market Sales
		Mean	STD	Min	Max	
1	Tallahassee	2362	1236	1659	4858	14174
2	Orlando	4348	396	3893	4952	26088
3	Tampa	6660	2056	2644	9294	53277
4	Miami	5192	2499	2150	10635	83075
5	Jacksonville	5038	1148	3357	6766	45341
6	Birmingham	8072	2048	5237	11214	80720
7	Nashville	6359	1944	3897	9274	50869
8	Columbia	3571	1147	2511	5707	32136
9	Greenville-Asheville	3475	2306	800	7716	66024
10	Raleigh-Fayetteville	5481	3480	1376	12747	93171
11	Richmond	6355	1240	3863	7703	69901
12	Atlanta	6611	1908	2499	9969	138827
13	Norfolk-Hampton	5209	1433	3095	8093	98977
14	Cincinnati	7788	2501	2638	10228	70092
15	Charlotte	7457	2647	2935	11459	82030
16	New York	8316	3525	1827	15810	582099
17	Wheeling	1848	450	993	2469	12939
18	Louisville	2734	317	2326	3173	19137
19	Terre Haute	3031	422	2545	3563	12124
20	Champaign-Springfield	1045	527	491	1910	11500
21	Carbondale	3182	1321	1838	4478	9546
22	Philadelphia	4497	2182	1548	8915	139421
23	Charleston	4407	651	3434	5442	35258
24	Albany	6489	1489	3456	8084	51914
25	La Crosse	907	219	603	1096	3629
26	Providence	5088	1065	2803	6216	45795
27	Worcester	3233	995	1521	4838	25864
28	Madison	585	210	278	914	3508
29	Hartford	5137	1258	2768	6925	46237
30	Dayton	2704	614	2011	3669	18928
31	Mankato	869	321	646	1237	2608
32	Rochester	2314	588	1472	3322	18513
33	St. Paul	1855	337	1516	2324	11130
34	Cedar Rapids	2037	287	1689	2356	8149
35	Hershey	758	147	574	982	6825
36	Sedalia	1088	203	855	1304	5442
37	Memphis	3135	321	2624	3539	18811
38	Evansville	972	429	507	1780	5834
39	Wilkes-Barre	2921	933	2018	4583	23369
40	North Little Rock	2879	827	2044	4281	23029
41	Macon	1183	369	735	1691	9461
42	Tucson	3465	824	2437	4379	24257
Market average		3825	1162	2098	5712	51905 (STD= 90992)

Table 3-5: Descriptive Statistics of Covariates across Markets

Market ID	FRIDAY		SATURDAY		SUNDAY		GEO		TMP		Population of Target Market
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	
1	0.167	0.41	0.500	0.55	0.167	0.41			0.539	0.14	104326
2	0.167	0.41	0.500	0.55	0.333	0.52			0.611	0.11	477402
3	0.125	0.35	0.375	0.52	0.250	0.46			0.470	0.11	578505
4	0.125	0.34	0.375	0.50	0.250	0.45			0.299	0.04	741879
5	0.222	0.44	0.333	0.50	0.222	0.44			0.476	0.10	282479
6	0.200	0.42	0.300	0.48	0.200	0.42			0.470	0.07	321845
7	0.250	0.46	0.375	0.52	0.250	0.46			0.530	0.09	430888
8	0.222	0.44	0.333	0.50	0.222	0.44			0.476	0.10	169819
9	0.211	0.42	0.316	0.48	0.263	0.45	0.482	0.03	0.232	0.05	344151
10	0.235	0.44	0.353	0.49	0.176	0.39	0.492	0.09	0.245	0.05	463117
11	0.182	0.40	0.273	0.47	0.273	0.47			0.457	0.10	183972
12	0.190	0.40	0.286	0.46	0.286	0.46			0.307	0.04	1074597
13	0.211	0.42	0.316	0.48	0.263	0.45	0.497	0.03	0.296	0.04	345541
14	0.111	0.33	0.333	0.50	0.222	0.44			0.463	0.08	435717
15	0.182	0.40	0.273	0.47	0.273	0.47			0.473	0.07	466459
16	0.157	0.37	0.300	0.46	0.286	0.46	0.368	0.18	0.118	0.02	4100325
17	0.286	0.49	0.429	0.53					0.520	0.11	53729
18	0.143	0.38	0.429	0.53	0.143	0.38			0.470	0.13	298428
19									0.667	0.00†	66486
20	0.273	0.47	0.545	0.52	0.182	0.40	0.461	0.05	0.318	0.06	156173
21									0.667	0.14	155322
22	0.129	0.34	0.290	0.46	0.258	0.44	0.556	0.17	0.221	0.03	1321626
23	0.250	0.46	0.375	0.52	0.250	0.46			0.530	0.09	211135
24	0.250	0.46	0.375	0.52	0.250	0.46			0.530	0.09	225057
25									0.667	0.00†	86726
26	0.111	0.33	0.333	0.50	0.222	0.44			0.463	0.08	287211
27	0.125	0.35	0.375	0.52	0.250	0.46			0.470	0.11	1126579
28	0.167	0.41	0.500	0.55	0.333	0.52			0.611	0.11	147178
29	0.111	0.33	0.333	0.50	0.222	0.44			0.463	0.08	463979
30	0.143	0.38	0.429	0.53	0.286	0.49			0.532	0.12	240286
31									0.667	0.14	17074
32	0.125	0.35	0.375	0.52	0.250	0.46			0.470	0.11	186215
33	0.167	0.41	0.500	0.55	0.333	0.52			0.611	0.11	802661
34									0.667	0.00†	140908
35	0.111	0.33	0.333	0.50	0.222	0.44			0.438	0.11	316530
36			0.400	0.55	0.400	0.55			0.567	0.09	423202
37	0.167	0.41	0.500	0.55					0.506	0.13	347835
38	0.167	0.41	0.500	0.55	0.167	0.41			0.539	0.14	128297
39	0.125	0.35	0.375	0.52	0.250	0.46			0.470	0.11	227157
40	0.125	0.35	0.375	0.52	0.250	0.46			0.470	0.11	230179
41	0.125	0.35	0.375	0.52	0.250	0.46			0.470	0.11	109799
42	0.143	0.38	0.429	0.53	0.286	0.49			0.532	0.12	174998
Market Average	0.172	0.40	0.382	0.51	0.250	0.46	0.476	0.09	0.476	0.09	439662

Note:

1. Markets without any observations in days of week are shown in blank cells.

2. Markets without any variation in their geographic schedules are shown in blank cells.

† Performances in market 19, 25, and 34 had equal temporal distance to other performances in the same market.

Table 3-6: Descriptive Statistics of Market Characteristics

Market Characteristics	N	Mean	STD	Min	Max
POP _m Population of target market	42	439662	647091	17074	4100325
POP_Density _m Population density (in the log term)	42	5.717	0.85	3.787	7.615
Income _m Family income (in the log term)	42	10.594	0.15	10.260	10.883
Family_Size _m Average family size	42	3.028	0.09	2.857	3.276

Table 3-7: Descriptive Statistics of Additional Scheduling Characteristics

Additional Scheduling Characteristics	N	Mean	STD	Min	Max
ADJ _m Number of geographically adjacent markets performing prior to a focal market	42	0.95	1.00	0	4
ORDER _m Distribution order in the temporal sequence	42	21.43	12.3	1	42

Table 3-8: Sources of Heterogeneous Market Responses

Parameter	Description	Median	(Std Dev)
<i>Effect of Baseline performance attractiveness: $E[\alpha_{0m}]$</i>			
β_{01}	Intercept	-4.30	(0.21)**
β_{11}	Population size in a target market	-0.25	(0.06)**
β_{21}	Num. of geographically contiguous markets	-0.14	(0.09)*
β_{31}	Num. of preceding markets in temporal sequence	-0.12	(0.16)
<i>Effect of Friday performances: $E[\alpha_{1m}]$</i>			
β_{02}	Intercept	0.31	(0.73)**
β_{12}	Population size in a target market	-0.03	(0.01)**
β_{22}	Num. of geographically contiguous markets	0.00	(0.03)
β_{32}	Num. of preceding markets in temporal sequence	0.03	(0.06)
<i>Effect of Saturday performances: $E[\alpha_{2m}]$</i>			
β_{03}	Intercept	0.51	(0.07)**
β_{13}	Population size in a target market	-0.05	(0.01)**
β_{23}	Num. of geographically contiguous markets	0.01	(0.02)
β_{33}	Num. of preceding markets in temporal sequence	0.06	(0.05)
<i>Effect of Sunday performances: $E[\alpha_{3m}]$</i>			
β_{04}	Intercept	0.21	(0.07)**
β_{14}	Population size in a target market	-0.02	(0.01)**
β_{24}	Num. of geographically contiguous markets	0.00	(0.03)
β_{34}	Num. of preceding markets in temporal sequence	0.10	(0.05)**
<i>Effect of Geographic density: $E[\theta_{1m}]$</i>			
β_{05}	Intercept	1.22	(0.85)*
β_{15}	Population size in a target market	-0.18	(0.32)
β_{25}	Num. of geographically contiguous markets	-0.25	(1.19)
β_{35}	Num. of preceding markets in temporal sequence	0.86	(1.53)
<i>Effect of Temporal density: $E[\theta_{2m}]$</i>			
β_{06}	Intercept	-0.61	(0.15)**
β_{16}	Population size in a target market	0.04	(0.04)
β_{26}	Num. of geographically contiguous markets	0.10	(0.06)**
β_{36}	Num. of preceding markets in temporal sequence	0.09	(0.11)

* significant at the 90% highest posterior density

** significant at the 95% highest posterior density

Table 3-9: Results of Performance Schedule Model

Parameter	Description	Median	(Std Dev)
<i>Expected geographic density: m_1</i>			
ϕ_{01}	Intercept	-0.06	(0.47)
ϕ_{11}	Expected performance attractiveness	0.18	(0.06)**
ϕ_{21}	Effect of geographic density	0.09	(0.14)
<i>Expected temporal density: m_2</i>			
ϕ_{02}	Intercept	3.35	(0.27)**
ϕ_{12}	Expected value of performance	0.84	(0.05)**
ϕ_{22}	Effect of temporal density	1.30	(0.18)**

** significant at the 95% highest posterior density

Figure 3-1: Conceptual Framework of Heterogeneous Market Responses

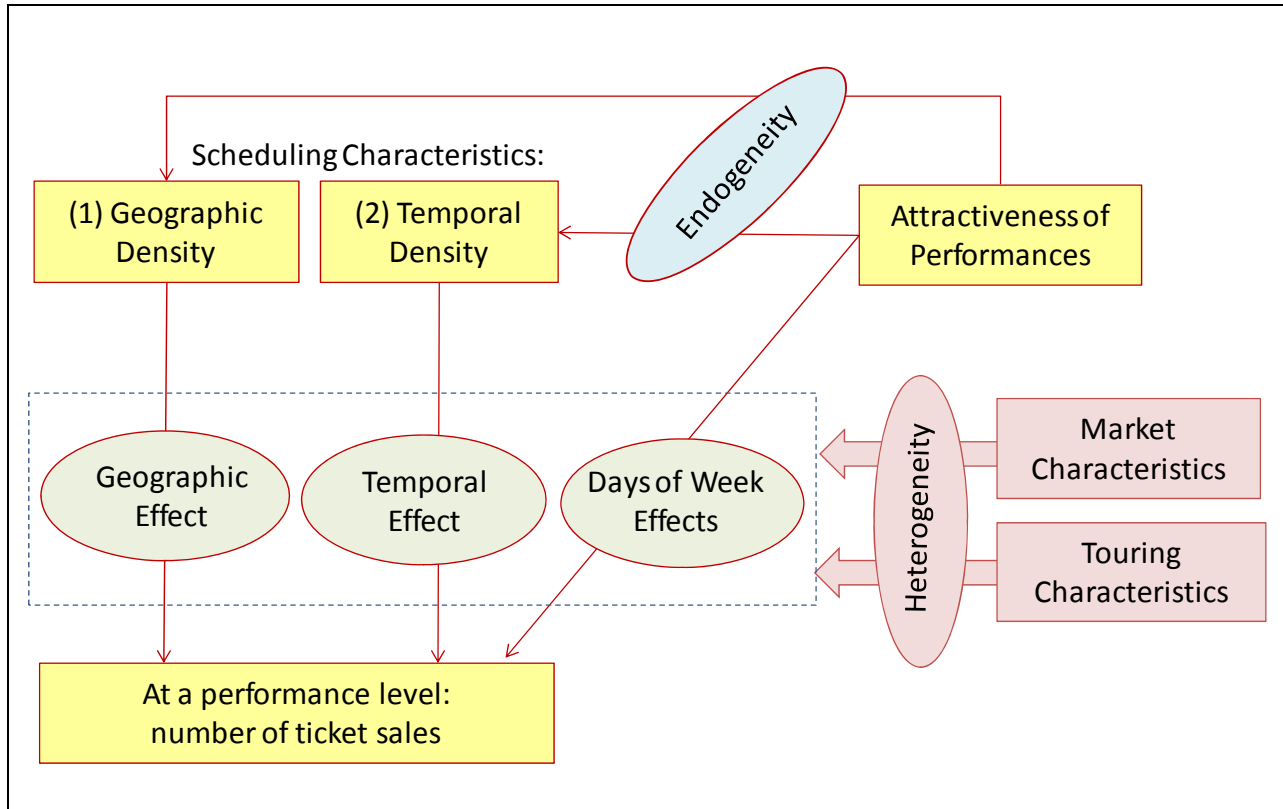


Figure 3-2: Example of a DMA and its county information

TRUCKADS® | Orlando Daytona Beach Melbourne DMA | Truckside Advertising ~ Mobile Billboards ~ Fleet Graphics | CALL 1 800 TRUCK ADS® - Mozilla Firefox

File Edit View History Bookmarks Tools Help

http://www.truckads.com/Affiliate/Orlando_Daytona_Beach_Melbourne.htm

Most Visited Getting Started Latest Headlines

Advertising in the Fast Lane®

9 COUNTIES IN THIS DMA
 Brevard, FL ~ Flagler, FL ~ Lake, FL ~ Marion, FL ~ Orange, FL ~ Osceola, FL ~ Seminole, FL ~ Sumter, FL ~ Volusia, FL

▲ up

Banner Sign Store

[Truck Ads® Banners and Frames Inc.](#)

MULTI-MARKET TRUCK SIDE ADVERTISING INQUIRIES CALL 800 TRUCKADS
 Toll free number in the U.S., Canada and Puerto Rico

Figure 3-3: Locations of DMA Markets and Performing Sequence

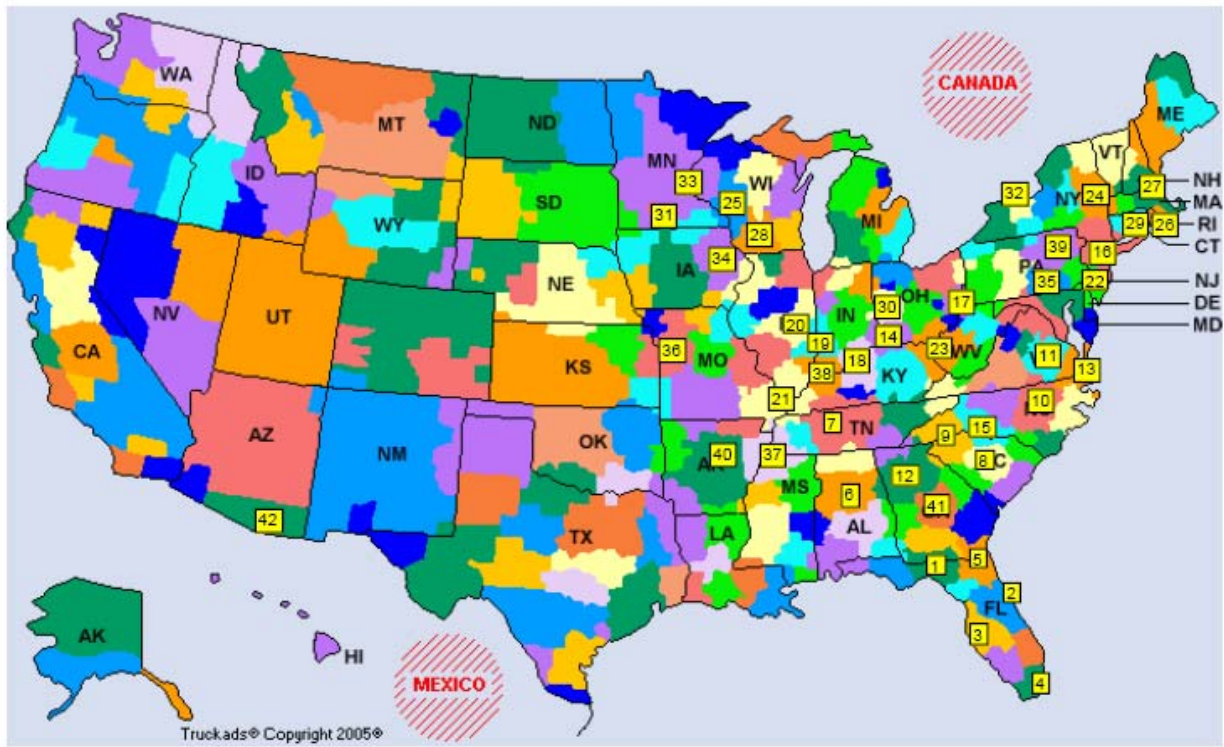
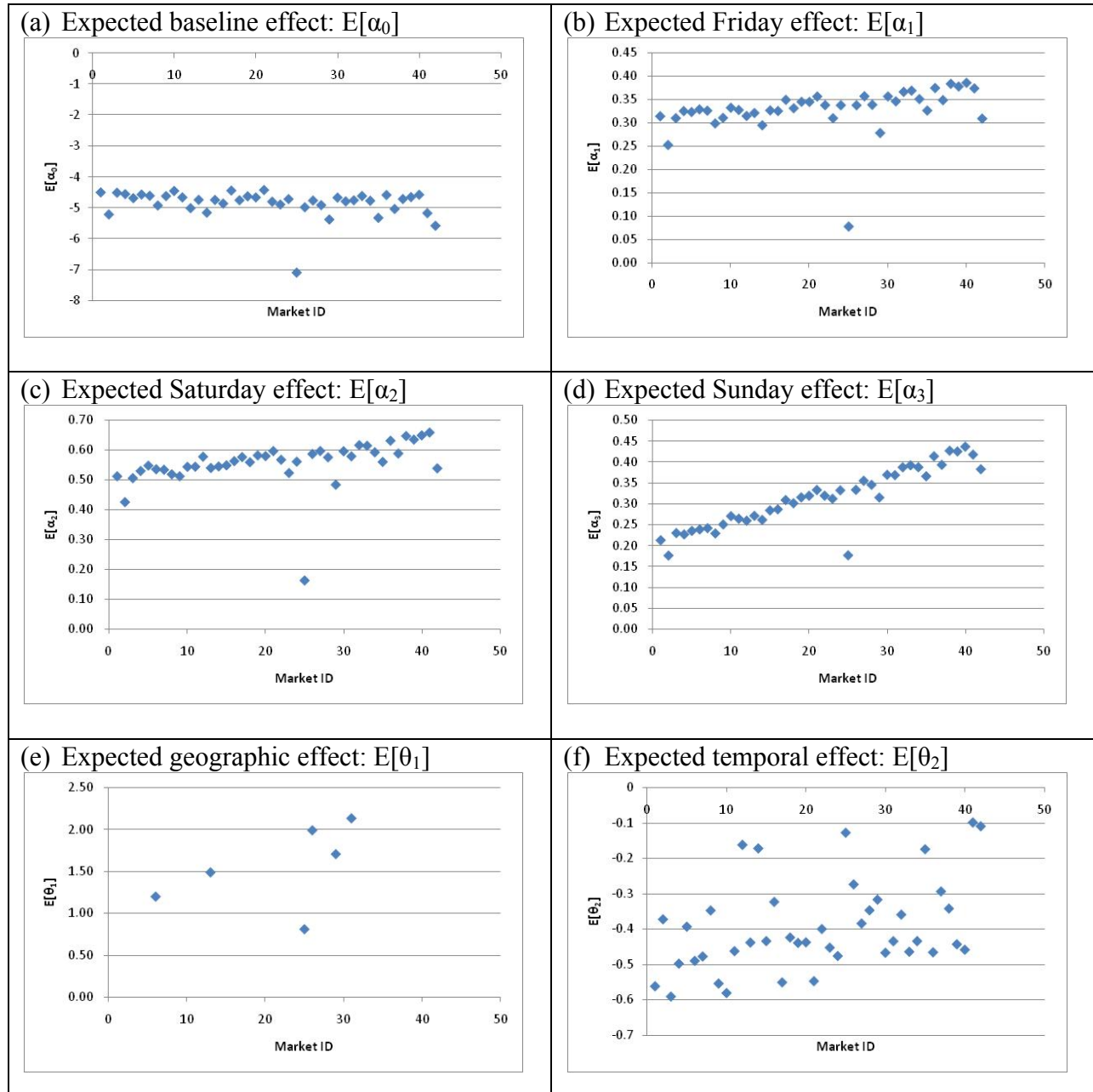


Figure 3-4: Heterogeneous Market Responses



4 Essay 3: Sequential Distribution of a Live Performance Event

4.1 Introduction

When and where to schedule performances are two of the most important decisions facing event marketers in the live entertainment industry. When event marketers schedule a tour for an event, they have to design a performance schedule within each participating market and determine an overall travel sequence across markets. Therefore, their scheduling decisions are within and across markets and may have different effects on ticket sales.

In the first two essays, we have shown the effect of within-market scheduling and identified explanatory factors for heterogeneous market responses. Specifically, we find that venue locations in a geographic schedule influences ticket sales differently from do performance dates in a temporal schedule. Densely scheduled performances across venues sell more tickets, yet densely scheduled performances across times sell fewer tickets. Moreover, the population size, geographic adjacency between markets, and temporal sequence in an event distribution can explain heterogeneous market responses to some extent.

Because essays one and two have studied the effect of within-market scheduling and left the impact of across-market scheduling unknown, essay three examines an event distribution across markets and its impact on market sales. Specifically, an event distribution involves scheduling across markets. Event marketers first decide a touring sequence at one time. Then, a performing group follows this sequence to travel from one market to another. This group performs in one market at a time, provides a few shows within a venue, and then leaves for another market. Therefore, the mechanism of an event distribution is the same as the sequential distribution.

Sequential distribution has been studied in marketing literature where researchers study the market roll out of a new product (Bronnenberg and Mela 2004) and movie releases across markets or channels (Lehmann and Weinberg 2000; Elberse and Eliashberg 2003; Chintagunta, Gopinath, and Venkataraman 2009). These works show a dependent relationship between preceding and following markets and indicate the effect of sequential distribution on sales or profitability. In addition, they suggest the underlying reasons for the effect of sequential distribution to be the lead market effect from geographically adjacent markets (Bronnenberg and Mela 2004), word of mouth effect from previous markets (Elberse and Eliashberg 2003; Chintagunta et al 2009), or effect of release timing between channels (Lehmann and Weinberg 2000). Hence, it is common to observe how well a new product sells in previous markets to influence whether other markets adopt this product, when following markets launch this product, and how well this product sells.

Similarly, when an event is distributed across markets, it is likely to see preceding markets influencing following markets. This influence may come from geographic adjacency, word of mouth, or release timing. Although essay two uses geographical adjacency between markets and temporal sequence in a distribution to explain heterogeneous market responses, it has not yet explored the possibility that markets may have a more direct dependent relationship. Consequently, the objective of essay three is to examine whether an event distributed sequentially across markets has an effect such that ticket sales in preceding markets can influence sales in those following markets. We refer to such an effect as the carryover effect in this essay.

To achieve this objective, we model ticket sales of each market as a function of its performance schedule within a market and potential carryovers from an event distribution.

However, one modeling challenge is that scheduling decisions are correlated and endogenous with the demand. For instance, the number of performances, the number of venues booked, and the number of days scheduled may be highly correlated with one another. If we simply use these scheduling decisions to explain market demand, these scheduling variables will be highly correlated and suffer from the issue of collinearity.

To solve this issue, in addition to modeling supply and demand simultaneously to account for the endogeneity, we have to use variables that are independent of one another yet still represent the scheduling influences. Thus, in the demand model for event tickets, we use the size of trading areas of booked venue(s) in a market as one instrumental variable for the scheduling influence. We also use the distribution of performance dates in a schedule as the second instrumental variable for the supply of an event on different dates.

On the other hand, we capture carryovers from an event distribution from the beginning of its tour. Because an event travels to markets at different times and each market along the distribution has different release timing, we employ the spatially weighted approach to account for ticket sales of preceding markets as well as their release timing.

To specify the supply decisions simultaneously with the demand, we assume that event scheduling within a market consists of three related decisions. First, event marketers consider how many seats they have to provide in order to sell an expected number of tickets. We call this decision an overall supply in a market. Next, they decide how many venues they need to reserve given the number of seats needed in a market. This is the decision of *venue usage*. In the meantime, they have to determine how many days they need to book given the number of seats needed and the size of a venue capacity. We refer to this decision as the *day usage* decision. In

this way, we take into account the influence of expected demand on the supply decisions and use variables to incorporate the scheduling influences on demand.

We contact a national ticket seller to obtain a dataset of live performance events and use ticket sales for one event to test our model. This particular event sequentially performed 449 times in 50 cities in the U.S. domestic market between January and June 2004. Because we aggregated these cities into 42 DMAs in essay two, we proceed to analyze ticket sales at a market level in essay three.

The first finding of our demand model is that an event experiences more market sales when more consumers are within the primary trading area of its venue(s). The intuition behind is that when an event is more accessible to consumers and has more consumers within its primary trading area, it provides more convenience to consumers due to a shorter travel distance. As a result, an event with a larger trading area because of using more venues in a market can accommodate more consumers and increase ticket sales.

Second, we show that an event sells more tickets when it has performances on various dates in a market. In other words, when an event has more performances available to a market and has a dispersed temporal schedule, it provides more flexibility to consumers especially for those who have higher uncertainty about whether they could attend at a particular time. Therefore, an event with a bigger variance in the distribution of performance dates sells more tickets in a market.

Third, we show that an event distribution has a carryover effect on ticket sales. However, the influence is across multiple venues within the same market but not across different markets. In other words, when an event performs from one market to another, its ticket sales in preceding markets do not affect sales in following markets. Yet, when this event performs in more than

one venue, its ticket sales in a preceding venue carry over to a later venue and influence its overall market sales.

We think the nature of the family event analyzed in this essay is the underlying reason for a carryover effect significant within a market but not across markets. Because this family event targets young children and their parents, it is easier to observe children and parents discussing event information within a market than across markets. Moreover, this family event travels within the U.S. and often goes to a similar set of markets after a year or longer. Thus, these markets do not have to depend on other participating markets but can rely on their own historical experience to determine the quality of this event.

Finally, we show the endogeneity in the supply of an event. Event marketers use the expected market demand to determine how many seats they need to provide, and this overall supply further influences the number of venues and days they schedule the event.

The rest of essay three is organized as follows. We start with reviewing relevant literature and constructing the conceptual framework. Next, we introduce our model development and describe our data. After the model estimation and benchmark comparisons, we discuss our results and conclude this essay.

4.2 Literature Review and Conceptual Framework

Essay three centers on literature in sequential distribution. Although we have reviewed some relevant works in essay two, we discuss this literature in depth to show its mechanism and possible effects in turn.

4.2.1 Sequential Distribution

Sequential distribution has been studied in movie and retailing contexts. The concept of sequential distribution is that a new product starts in one channel or market and then gradually

distributes to another. Hence, as time passes by, the product availability increases and reaches more consumers (Lehmann and Weinberg 2000). Based on where sequential distribution takes place, we categorize extant works into two mechanisms: (1) sequential distribution across channels and (2) sequential distribution across markets.

Sequential Distribution across Channels

Sequential distribution across channels refers to a new product released from one channel to another, and it is a very common mechanism in the movie industry. One key objective of research in this stream is to understand the impact of release timing of a new movie title on its box-office revenues (Lehmann and Weinberg 2000; Hennig-Thurau et al 2006; Hennig-Thurau, Houston, and Walsh 2007). In this way, researchers can suggest the optimal release timing of a movie to another channel.

Specifically, Lehmann and Weinberg (2000) examined the optimal release timing from movie theaters to video rental stores, and they found shortening the release timing (compared with current practice) leads to increases in profits. On the other hand, Hennig-Thurau et al (2006) studied revenue drivers in different movie channels (i.e., theater and video). They found that release timing has a stronger influence on short-term box-office revenues than on long-term revenues. Yet, release timing does not affect how well a movie sells on the video channel.

Another work by Hennig-Thurau et al (2007) examined the optimal release timing across four distribution channels (i.e., theater, video purchase, video rental, and video on demand) and further indicated that changing the order of distribution or shortening the release timing increases profits for movie studios. To sum up, studies in this category emphasize the effect of time lags between channels and show higher profitability due to a shortened time lag between channels.

Sequential Distribution across Markets

Sequential distribution across markets refers to a new product distributed from one market to another, and it is observed in the movie and retailing industries. A primary objective of this research stream is to investigate whether and how previous market success carries over to later markets and influences market entry decisions or product sales in later markets (Elberse and Eliashberg 2003; Bronnenberg and Mela 2004; Chintagunta et al 2009).

In terms of the movie industry, no matter whether movies are of limited or wide release within a market, a common approach is to distribute movies sequentially across markets. For instance, Elberse and Eliashberg (2003) investigated the relationship between the U.S. domestic and a foreign market. Within a market, they concluded that box-office revenues of a movie title and the number of screens in a theater in a preceding week affect the supply and demand in a following week. They also found that total box-office revenues in the U.S market tend to carry over to a foreign market and influence the supply and demand for the same movie in the opening week. However, when they tested an interaction effect between the U.S. box-office revenues and the time lag on a foreign market, they found this carryover effect only significant for the screen management decision but insignificant for market demand.

Similarly, Chintagunta et al (2009) studied a sequentially released movie across the U.S. local markets and examined the effect of online word of mouth (measured by the valance of online reviews) from previous markets on the box-office revenues on the opening day in a new market. They found that a time lag between an initial market and a current market negatively affects sales, yet the average user rating of online reviews positively influences sales. However, reviews are accumulated from the opening of a movie up to a current market. Researchers did

not incorporate the joint effect between the release timing and user rating generated in different markets.

On the other hand, in the retailing context, Bronnenberg and Mela (2004) examined manufacturers' market entry decisions and retailers' chain adoption decisions for newly introduced frozen pizzas. They suggested that past market entry decisions influence whether a manufacturer enters a new market, and past chain adoption decisions affect whether a chain in a new market adopts this product. However, because the focus of this paper was on the supply side, researchers did not investigate the effect of previous market entry or retail adoption on demand in following markets.

Rationale for the Effect of Sequential Distribution

One primary reason for retailers or movie studios to practice sequential distribution is to prevent financial losses of a failing launch (Lehmann and Weinberg 2000). Moreover, there are several underlying reasons to explain why sequential distribution would be effective and influence sales in later markets or channels.

For example, the success-breed-success effect (Elberse and Eliashberg 2003; Hennig-Thuran et al 2006) shows a previous success in preceding markets or channels may be replicated more easily in later entities. The word-of-mouth effect (Elberse and Eliashberg 2003; Hennig-Thuran et al 2007; Chintagunta et al 2009) suggests that people exchange opinions and their experiences influence how other people think. Moreover, the lead market effect (Bronnenberg and Mela 2004) posits that similar behaviors tend to take place in spatially adjacent markets. Thus, it is easier for adjacent markets to observe a focal market and imitate behaviors in this focal market.

Summary

To sum up, studies in sequential distribution show a dependent relationship between preceding and following markets and indicate the effect of sequential distribution on sales or profitability. However, one limitation is that some, if not all, of these papers assume the decision of sequential distribution is made one at a time rather than simultaneously (Lehmann and Weinberg 2000; Elberse and Eliashberg 2003; Bronnenberg and Mela 2004; Hennig-Thuran et al 2006; Hennig-Thuran et al 2007). In other words, decisions of release timing, market entry, chain adoption, and screen management are made sequentially *after* managers observe outcomes (i.e., adoption decisions, box-office revenues, or profitability) from previous adoptions.

When managers have to plan a new product launch simultaneously for all participating markets, it is not clear whether these markets still have a dependent relationship such that sales in preceding markets carry over to following markets and influence their sales. Accordingly, essay three contributes to this literature by studying an event distribution and its impact while a touring sequence has to be planned at one time for an event to travel sequentially across markets.

4.2.2 Conceptual Framework

The objective of essay three is to examine whether markets along an event distribution have a dependent relationship such that ticket sales of preceding markets have a carryover effect to influence ticket sales in following markets. Hence, in our conceptual framework, we first discuss how a performance schedule in a market influences its ticket sales. Then, we discuss why preceding markets along an event distribution could influence following markets and what the possible impact might be. Finally, we discuss the endogeneity between supply and demand for an event.

Effects of Performance Schedule within a Market

When an event provides many performances in a market, its performance schedule is of a relatively larger scale, compared with an event providing fewer performances. Among these performances, if event marketers choose to book multiple venues and each venue is surrounded by densely populated consumers, this event will be able to reach more consumers and have a bigger primary trading area (Huff 1964) due to its enhanced spatial accessibility (Betancourt 2004). On the other hand, if these performances are at different times of day across various days of week, this event will provide more flexibility to consumers and can deliver the performing contents at consumers' desired times (Betancourt 2004). In this way, the supply of a performance schedule within a market influences how well an event sells in this market.

Effects of Carryovers from an Event Distribution

Moreover, as an event travels across markets and incurs a varying number of ticket sales, it is possible to see preceding markets influencing following markets due to the effect of event distribution. In other words, how well an event sells in a market may influence its sales in adjacent markets via the lead market effect (Bronnenberg and Mela 2004). Addition, it is possible that when an event sells well in one market, event marketers try to replicate this success in another market because of the success-breed-success effect (Elberse and Eliashberg 2003; Hennig-Thuran et al 2006).

On the other hand, it is also likely that consumers who have attended an event talk about this event online or offline thus influencing people who have not yet attended. In this way, the word of mouth of this event may travel across markets and influence people in different areas (Elberse and Eliashberg 2003; Chingatunga et al 2009). Hence, the more ticket sales an event

experiences from previous markets, the higher is its volume of word of mouth, and the more likely an event will sell well.

One special case occurs when an event travels to multiple venues of the same market. It is possible that people who have gone to an event in a preceding venue express their opinions about this event and influence other people in the same market. If so, an event distribution will not only influence ticket sales across markets but also affect ticket sales across venues within the same market. Consequently, the carryover effect from an event distribution may be across markets as well as within a market (but across multiple venues).

Finally, although the population size of a market may influence the baseline market demand, once we control for this market characteristic, a sequentially distributed event may still influence its market sales through its performance schedule within a market and carryovers from an event distribution.

Endogenous Supply and Demand of an Event Distribution

Meanwhile, because supply is often endogenous with demand, it is likely that the supply of an event in a market influences its market sales, and the expected demand in this market affects the supply of the same market. Therefore, our conceptual framework for an event distribution must consider supply and demand simultaneously and allow the expected demand and other scheduling constraints to influence the supply decision. Figure 4-1 below indicates the endogenous relationship and summarizes the effects of performance schedule and event distribution on market sales.

Figure 4-1: Conceptual Framework of Essay Three

Specifically, we assume event marketers make several scheduling decisions for a touring event. Similar to the screen management decision in the movie industry (Elberse and

Eliashberg 2003; Basuroy, Desai, and Talukdar 2006; Eliashberg et al 2007), the first scheduling decision is to determine the total number of seats an event needs to provide in individual markets. Because the total number of seats is the maximum possible seats that an event can sell within a market, we call this an *overall supply* decision. To endogenize the overall supply with market sales, we assume event marketers rely on a size of market population and expected market demand to set a desirable amount of supply. Hence, they may increase the overall supply when they expect higher demand in a bigger market. In addition, after setting an overall supply of an event, other scheduling issues are deciding how many venues to use and how many days to book for this event. We call these decisions as *venue usage* and *day usage* and assume these decisions are as a result of the market characteristics (e.g., population size or population density) and scheduling constraints (e.g., venue capacity, venue availability, or facility rental fees).

4.3 Model Development

4.3.1 Overview

To test our conceptual framework, we model the supply and demand for an event simultaneously. At the supply side, we model the total number of seats, venues, and days needed. At the demand side, we specify ticket sales of each market as a function of its performance schedule within a market and potential carryovers from an event distribution. However, one modeling challenge is that scheduling decisions are correlated and endogenous with market demand. For instance, the number of performances, the number of venues booked, and the number of days scheduled in a market may be highly correlated with one another. If we simply use these scheduling decisions to explain market demand, these covariates will be highly correlated and suffer from the issue of collinearity.

To solve this issue, in addition to modeling supply and demand simultaneously to account for the endogeneity, we have to use variables that are independent of one another yet still represent the scheduling influences. Thus, in the demand model for event tickets, we use the size of trading areas of booked venue(s) in a market as one variable for the scheduling influence. We also use the distribution of performance dates in a schedule as the second variable for the supply of an event on different dates.

Although our modeling approach is similar to that of Elberse and Eliashberg (2003) who specified the number of screens and box-office revenues simultaneously for a sequentially distributed movie, our approach differs from theirs because we model several elements in the scheduling decisions in addition to just the capacity decision.

As such, we model the linerized supply and demand to follow the multivariate normal distribution.

$$(19) \quad \mathbf{Y} = \begin{bmatrix} \ln(\text{Sales}_m) \\ \ln(\text{Seats}_m) \\ \ln(\text{Venues}_m) \\ \ln(\text{Days}_m) \end{bmatrix} \sim MVN \left(\begin{bmatrix} y_{1m} \\ y_{2m} \\ y_{3m} \\ y_{4m} \end{bmatrix}, \boldsymbol{\Sigma} \right)$$

where Sales_m is the number of ticket sales in market m (i.e., market demand), Seats_m is the total number of seats supplied in market m (i.e., overall supply), Venues_m is the number of venues used in a market (i.e., venue usage), and Days_m is the number of days available in a schedule (i.e., day usage). These dependent variables have expected values \mathbf{y}_m and a variance-covariance matrix $\boldsymbol{\Sigma}$. In this way, the correlations between supply decisions and the correlation between supply and demand are controlled in the variance-covariance matrix.

4.3.2 Demand Equation: Market Sales

According to equation (19), we model expected market sales as a function of its performance schedule within a market and potential carryovers from an event distribution:

$$(20) \quad y_{1m} = \alpha_0 + \mathbf{X}_{1m}\alpha_1 + \mathbf{X}_{2m}\alpha_2 + \mathbf{Z}_m\alpha_3$$

where y_{1m} is the expected ticket sales (in the log term) in market m , \mathbf{X}_1 is a vector of variables to represent the scheduling influences, \mathbf{X}_2 represents potential carryovers from an event distribution, \mathbf{Z}_m is a vector of market characteristics used as control covariates, and α is the vector of associated parameter effects. We discuss the operationalization of these covariates in variable specification.

4.3.3 Supply Equations: Overall Supply, Venue Usage, and Day Usage

Although some studies assume an exogenous supply decision (Swami et al 1999; Eliashberg et al 2005; Eliashberg et al 2007; Chintagunta et al 2009), we propose an endogenous and positive relationship between overall supply and market demand (Elberse and Eliashberg 2003; Basuroy et al 2006).

We assume that event scheduling within a market consists of several related decisions. First, event marketers consider how many seats they have to provide in order to sell an expected number of tickets. Hence, we specify the expected number of seats as a function of its expected market demand and market characteristics:

$$(21) \quad y_{2m} = \beta_0 + \beta_1 y_{1m} + \mathbf{Z}_m\beta_2$$

where y_{2m} is the expected number of seats (in the log term) provided, y_{1m} is the expected market sales (in the log term), \mathbf{Z}_m is a vector of market characteristics used as control covariates, and β is the vector of associated parameter effects.

Second, we assume the following decisions are to decide how many venues to reserve and how many days to book. Specifically, given the amount of supply event marketers have to provide, they can also refer to market characteristics such as market land area and population density in a market to determine how many venues to book. They can also refer to the size of

venue capacity and the cost of venue rental to decide how many days are needed in order to be cost effective. For example, if a market is densely populated and its land area is big, event marketers may consider booking more venues to increase the spatial accessibility of this event. On the other hand, if the average venue capacity is small and the daily cost of renting a venue is high, event marketers may consider booking fewer days but scheduling more performances in a day. We specify the expected venue and day usage as follows:

$$(22) \quad y_{3m} = \gamma_0 + \gamma_1 y_{2m} + \mathbf{Z}_m \boldsymbol{\gamma}_2$$

$$y_{4m} = \theta_0 + \theta_1 y_{2m} + \mathbf{Z}_m \boldsymbol{\theta}_2$$

where y_{2m} is the expected number of seats (in the log term) provided, y_{2m} is the expected number of venues (in the log term) needed, y_{3m} is the expected number of days (in the log term) needed, \mathbf{Z}_m is a vector of market characteristics, and $\boldsymbol{\gamma}$ and $\boldsymbol{\theta}$ are the vectors of associated parameter effects.

Similar to Elberse and Eliashberg (2003), the advantage of specifying supply and demand equations in the way above is that parameters in equations (20), (21), and (22) represent elasticity of covariates. These parameter values suggest how changes in their covariates result in changes in demand and supply. We can also compare $\boldsymbol{\alpha}$ in equation (20) to rank the importance of these covariates on market sales.

4.3.4 Variable Specifications

Because of the endogenous and correlated scheduling decisions, we aim to find representative variables that are correlated with a performance schedule but do not have a severe collinearity in the demand equation. Among several possible measures, we find the size of trading area of venues and the flexibility in a temporal schedule may serve the modeling purpose. The rationale is that when an event uses multiple venues in its performance schedule, it has a

bigger primary trading area and is more accessible for consumers within this area. In addition, when this event has more performances at different times of day and on various days of week, it provides consumers with higher flexibility to attend at their own convenience. Since these benefits are relevant with a performance schedule but are not highly collinear, we propose three variables and discuss how we operationalize these variables in turn.

Size of Trading Area

We follow the retail trading area in the retail location literature (Huff 1964; Applebaum 1966; Cliquet 1998) to compute the size of trading area of booked venue(s) in a market. Specifically, we measure the size of trading area by referring to the population density around each venue of a performance schedule. Because population density can determine the size of a potential market (Huff 1964) yet it is not uniformly distributed (Donthu and Rust 1989), we assume the zip code of each venue as its primary trading area and consumers living in the same zip code to be the potential consumers. Therefore, the proxy of total consumers within the primary trading areas is as follows:

$$(23) \quad Size_m = \sum_{v=1}^{Venue_m} Density_v$$

where $Size_m$ is the size of trading area of selected venues, x_{1m} is the total number of consumers within the primary trading areas and $Density_v$ is the population density around the zip code of venue v .

However, the level of people's willingness to travel can expand or shrink the trading area of a venue (Huff 1964; Applebaum 1966). In other words, when people have higher tolerance to travel, a venue is able to reach more people and has a bigger trading area. To consider the factor of travel tolerance, we further include an adjustment term and rewrite equation (23) as follows:

$$(24) \quad Size_m = \sum_{v=1}^{Venues_m} density_v \cdot \lambda_v$$

where λ_v is an adjustment term to represent consumers' willingness to travel.

To approximate consumers' willingness to travel, we use the average commute time as a proxy. Our assumption is that consumers who spend more time commuting on a daily basis are more willing to travel and have higher travel tolerance. Hence, we compute λ_v as an index relative to the average (Mazzeo 2002):

$$(25) \quad \lambda_v = \frac{commute_v}{mean(commute_v)}; \forall v \in \{m = 1, 2, \dots, M\}$$

where $commute_v$ is the average commute time (in minutes) for people living in zip code v and $mean(commute_v)$ is the average. In this way, if $\lambda_v > 1$, people are willing to travel farther, and venue v has an expanded trading area to reach more people. In contrast, if $\lambda_v < 1$, the trading area of venue v shrinks. Finally, if $\lambda_v = 1$, the trading area of a venue is as it is.

Flexibility in a Temporal Schedule

Because the flexibility in a temporal schedule represents how easily consumers can attend an event at different times of day and across various days of week, we use the distribution of performance dates in a schedule as other variables. Specifically, we compute the average number of performances per day for the flexibility during a day. In addition, among all performances available to a market, we use its distribution and calculate its variance to represent the flexibility during a week. Therefore, if an event has more performances per day and has a bigger variance, consumers will have more flexibility to attend this event at their own convenience.

Carryovers from an Event Distribution

As we mentioned in the conceptual framework, carryovers from an event distribution may affect sales in later markets. Moreover, when an event performs in multiple venues within a market, the carryover effect may also exist across venues but within this market. Therefore, we measure across-market carryovers and within-market carryovers in this section.

To measure across-market carryovers since the beginning of an event distribution, we use ticket sales from preceding markets as a proxy (Elberse and Eliashberg 2003; Bronnenberg and Mela 2004). In this way, various amounts of ticket sales from preceding markets represent different magnitudes of carryovers from these markets. However, because an event travels to markets at a different time and each market along the distribution has different release timing, we employ the spatially weighted approach to account for ticket sales of preceding markets as well as their release timing (Yang and Allenby 2003; Bronnenberg and Mela 2004; Choi, Hui, and Bell 2009).

$$(26) \quad AC_m = \mathbf{W}_1 \mathbf{Sales}_m = \sum_{\substack{m'=1 \\ m' \neq m}}^M W_{1mm'} Sales_{m'}$$

where

$$W_{1mm'} = \frac{1}{\exp(d_1(m, m'))}$$

where AC_m represents the amount of across-market carryovers up to market m , \mathbf{Sales}_m is a vector of ticket sales that market m' has occurred up to the beginning of market m ($m' \neq m$), and \mathbf{W}_1 is a spatial weight matrix where each element ($W_{1mm'}$) is an exponentially weighted distance measure between a preceding market m' and a current market m ($d_1(m, m')$).

Although it is arguable that our across-market measure only considers the temporal sequence of participating markets but not considers the geographic adjacency between markets, we think our measure is better because this essay focuses on understanding the effect of an entire

distribution rather than the effect of spatially adjacent markets only. However, it is possible to include the geographic adjacency between markets as an extension and study the effect of spatial adjacency.

Therefore, before measuring d_1 in equation (26), we observe markets are temporally adjacent in several ways. Figure 4-2 below illustrates various possibilities of market connectedness, where a darker color represents a preceding market m' , a lighter color indicates a current market m , and the width of a box is the length of a performing period. In our dataset, we observe several ways of market connectedness. We classify them into three cases and discuss each one in turn.

Figure 4-2: Illustration of Market Connectedness

Specifically, in the first case, *Apart*, performances in two markets are apart from each other in a few days or are tightly connected. *Case 1.a* and *Case 1.b* in Figure 4-2 illustrates these situations, respectively. In the second case, *Overlap*, performances in two markets have an overlapped performing period. This overlapped period may be for a few days or for a longer period. *Case 2.a* and *Case 2.b* in Figure 4-2 illustrates these situations, respectively. Note that in the first two cases, an event only employs one venue to provide performances. If there are multiple performing groups touring in the U.S. at the same time, it is possible to observe markets without any time lag in between or markets have performances at the same time. *Case 1.b*, *Case 2.a*, and *Case 2.b* in Figure 4-2 represent these situations.

On the other hand, when an event performs in two markets and uses multiple venues in one of the markets, it is likely that performances in a current market are in between two venues of another market or overlaps with one of the venues. *Case 3.a*, *In between a break*, and *Case 3.b*, *Overlap with one venue*, in Figure 4-2 are examples of these situations. However, when an

event performs in two markets and both employ multiple venues, it is possible to see performing periods overlapping in some venues yet apart in others (i.e., Figure 4-2, *Case 3.c: between and overlap*). Therefore, *Case 3.b* and *Case 3.c* in Figure 4-2 exist if an event has more than one performing group touring at the same time.

According to these different situations, we measure d_1 (in weeks) differently. In *Case 1* (*Apart*), we measure d_1 by calculating the time lag (in days) between two markets and then converting this value to week:

$$(27) \quad d_1(m, m') = \#apart / 7$$

where $\#apart$ indicates the time lag between two markets in days.

Case 2 represents a situation that markets have an overlapped performing period.

Because there are performances showing concurrently in two markets, we assume the carryovers from these markets should have no decay but a stronger effect. In other words, markets of some overlapped performing periods should have stronger influence on each other than markets that are apart from each other. Therefore, overlapped markets should have higher spatial weights. To do this, we allow $d_1(m, m')$ in equation (26) to be negative such that its associated spatial weight ($W_{1mm'}$) is larger:

$$(28) \quad d_1(m, m') = -1 \times \#overlap / 7$$

where $\#overlap$ indicates the number of days that two markets have overlapped performances.

This specification ensures overlapped markets in *Case 2* have higher weights than markets in *Case 1*.

Finally, in *Case 3*, venues are either *in between a break* (*Case 3.a*), *overlap with one venue* (*Case 3.b*), or *between and overlap* (*Case 3.c*). We consider each condition separately and measure d_1 accordingly:

- *Case 3.a In between a break*

Case 3.a is when performances in market m are in between the first and second venue of market m' . Because by the time of market m , sales in the second venue of market m' have not yet occurred. Hence, $d_1(m, m')$ is the time lag between performances in the first venue of market m' and those in the venue of market m . That is, *Case 3.a* is similar to *Case 1.a*. We measure d_1 using equation (27). However, the associated market sales ($Sales_m$) in equation (26) are up to the end of first venue of market m' only.

- *Case 3.b Overlap with one venue*

Case 3.b is when performances in market m overlap with the first venue of market m' . This is a similar case to *Case 2*. Therefore, we measure d_1 using equation (28) yet sales for market m' are up to the end of first venue only.

- *Case 3.c Between and overlap*

Because *Case 3.c* is a combination of *Case 1* and *Case 2*, we need to consider the number of days markets are apart and overlapped at the same time. Hence, we allow $\#apart$ and $\#overlap$ to cancel each other and measure d_1 accordingly:

$$(29) \quad d_1(m, m') = [\#apart + (-1 \times \#overlap)]/7$$

To measure within-market carryovers from preceding venues in a market, we take the same spatially weighted approach and assign a different weight based on the time lag to a current venue v :

$$(30) \quad WC_m = \mathbf{W}_2 \mathbf{Sales}_v = \sum_{v, v' \in m} W_{2vv'} Sales_{v'}$$

where

$$W_{2vv'} = \frac{1}{\exp(d_2(v, v'))}$$

where WC_m is the within-market carryovers for market m (if it is a market that uses multiple venues), $Sales_{v'}$ is a vector of ticket sales that a preceding venue v' has occurred up to the beginning of venue v , and W_2 is a spatial weight matrix to measure the temporal difference (d_2) between a current venue v and its preceding venue v' in market m .

In a market where an event employs multiple venues, performances tend to take place sequentially with a number of days apart from one another. Hence, we measure d_2 in a similar way to Case 1 in equation (27):

$$(31) \quad d_2(v, v') = \#apart / 7$$

4.3.5 Model Summary

To sum up, we model the supply and demand simultaneously. At the demand side, we use three variables and two spatially weighted measures to represent the scheduling influences from a performance schedule and carryovers from an event distribution. We also use the population size as a market characteristic to control for the baseline effect on market demand. At the supply side, we model the total number of seats, venues, and days an event needs to provide for each market. We allow the expected market demand to influence the total number of seats and assume event marketers book venues and days based on their overall supply. Meanwhile, we take into account the potential effects of market characteristics and scheduling constraints in the supply decision.

Finally, in case there are omitted yet correlated variables to affect supply and demand jointly, we allow correlated error terms and estimate supply and demand simultaneously. We rewrite our model specification as follow and present the relationships among these covariates in Figure 4-3:

$$(32) \quad \mathbf{Y} = \begin{bmatrix} \ln(\text{Sales}_m) \\ \ln(\text{Seats}_m) \\ \ln(\text{Venues}_m) \\ \ln(\text{Days}_m) \end{bmatrix} \sim MVN \left(\begin{bmatrix} y_{1m} \\ y_{2m} \\ y_{3m} \\ y_{4m} \end{bmatrix}, \boldsymbol{\Sigma} \right)$$

$$y_{1m} = \alpha_0 + \alpha_1 \ln(\text{Size}_m) + \alpha_2 \ln(\text{Intensity}_m) + \alpha_3 \ln(\text{Variance}_m) \\ + \alpha_4 \ln(\text{AC}_m) + \alpha_5 \ln(\text{WC}_m) + \alpha_6 \ln(\text{POP}_m)$$

$$y_{2m} = \beta_0 + \beta_1 y_{1m} + \beta_2 \ln(\text{POP}_m)$$

$$y_{3m} = \gamma_0 + \gamma_1 y_{2m} + \gamma_2 \ln(\text{Area}_m) + \gamma_3 \ln(\text{Density}_m)$$

$$y_{4m} = \theta_0 + \theta_1 y_{2m} + \theta_2 \ln(\text{Capacity}_m) + \theta_3 \ln(\text{Fees}_m)$$

where

M	= market 1,2,...,M market
Sales _m	= Number of ticket sales (market demand)
Seats _m	= Number of seats supplied (overall supply)
Venues _m	= Number of venues booked (venue usage)
Days _m	= Number of days scheduled (day usage)
Size _m	= Size of trading area of venues
Intensity _m	= Average number of performances per show day
Variance _m	= Variance in the distribution of performance dates
AC _m	= Across-market carryovers up to market m
WC _m	= Within-market carryovers in market m
POP _m	= Size of market population
Area _m	= Size of market land area (in square miles)
Density _m	= Population density in market m
Capacity _m	= Avg. capacity of selected venues in market m
Rental _m	= Avg. rental fees in market m

Figure 4-3: Overview of Model Development

4.4 Data

We contact a national ticket seller to obtain a dataset of live performance events and use ticket sales for one event to test our model. This event sequentially performed 449 times in 50

cities in the U.S. domestic market between January and June 2004. We have aggregated the data into 42 DMAs in essay two and analyze this aggregated dataset in essay three⁵.

4.4.1 Touring Sequence

We have discussed how the event travels across markets in essay two. Table 3-1 lists the first and last dates of performances and the venue usage for each DMA and Figure 3-3 shows the touring sequence graphically. Among these 42 DMAs, the event performed in multiple venues in six DMAs where we observe two ways of within-market touring.

One approach is that the event first performed in one venue in a focal DMA, left for other DMAs, and then returned to the focal DMA again but performed in a different venue. Specifically, the event took this approach in the Greenville-Asheville DMA (market ID= 9), the Raleigh-Fayetteville DMA (market ID= 10), and the Champaign-Springfield DMA (market ID=20). In the Greenville-Asheville DMA, the event first performed in Greenville between January 28 and February 1, left for other DMAs, and then returned to Asheville on June 9, 2004. In the Raleigh-Fayetteville DMA, it performed in Raleigh between February 5 and February 9, left for other DMAs, and then returned to Fayetteville on May 20, 2004. Finally, in the Champaign-Springfield DMA, it performed in Springfield between April 9 and April 11 and then in Champaign on April 23.

The other approach is that the event performed in venues within a market consecutively and then left for other DMAs. For example, when it performed in the Norfolk-Hampton DMA (market ID= 13), it first stayed in Norfolk between February 18 and February 22 and then went to Hampton on February 25. In the Philadelphia DMA (market ID= 22), it first performed in Philadelphia between April 14 and April 25 and then went to Atlantic City on April 28.

⁵ Essay one provides detailed discussion about the event and essay two describes how we aggregate sales data into 42 DMAs.

However, the tour for the New York DMA (market ID= 16) is a combination of these two approaches. The event first performed in East Rutherford, Uniondale, and New York consecutively between March 3 and April 11. Then, it left for other DMAs and finally returned to Trenton on June 3.

4.4.2 Covariates in the Demand Model

Venue Usage and Size of Trading Area

In terms of the venue usage within a market, we find that a selected venue may not be in the center of a DMA but it is often located in a densely populated area. For example, Figure 4-4 illustrates the venue locations of the six DMAs discussed above and shows the population density around each venue. Therefore, it is reasonable to assume that the zip code of a venue is the primary trading area for this venue and consumers living in this zip code are the potential consumers in the trading area. As such, it is meaningful to use the population density to measure the size of potential market.

Figure 4-4: Venue Locations and Surrounding Population Density

Specifically, to calculate the size of trading area for selected venues in a market, we refer to the data collected from the U.S. Census Bureau for population, land area (in square miles), and consumers' travel time to work (in minutes) at a zip code level for all venues observed in the dataset. We further divide the population by the size of land area for the population density of each venue ($Venue_v$). On average, there are 3,289 consumers in the same zip code of a venue with the standard deviation being 4,239.

In addition, the average travel time to work across all observed venues is 20.70 minutes with the standard deviation being 5.71. We divide travel time to work for each venue ($Commute_v$) by the sample average to get the index of travel tolerance (λ_v). Hence, the mean

travel tolerance across venues is 1 with its standard deviation being 0.28. Using the new information above, we compute the size of trading area at a venue level. Then, for DMAs that have multiple venues, we aggregate across venues to conclude that an average size of trading area in a market is about 4,291 consumers with the standard deviation being 9,968. Table 4-1 indicates the descriptive statistics of the size of trading area across markets (in the log term).

Table 4-1: Descriptive Statistics of Covariates (in the log term)

Day Usage and Flexibility Measures

We summarize the touring dates across markets in Figure 4-5. On average, it took an event 5.79 days performing in a market with the number of show days ranging from two to 32. In terms of days of week for performances, we find that most markets (32 out of 42 DMAs) tend to offer the last performance on Sunday. However, depending on the number of performances offered in a market, some markets started the first performance on Wednesday (22 out of 42 DMAs), some on Thursday (10 out of 42 DMAs), and the rest on Tuesday or Friday. In other words, the flexibility that an event provides with consumers to attend on various days of week is heterogeneous across markets. Descriptively, nine DMAs have performances for two to three days in a week, nine DMAs have performances across four days, 14 DMAs have performances across five days, and 10 DMAs have performances more than six days.

Figure 4-5: Touring Dates across Markets

After examining the distribution of performance dates for each market, we find an average market has its variance in the distribution of performance dates to be 199.71 days with the standard deviation being 831.68. This skewed distribution is due to four DMAs that have performances in multiple venues and have a long lag between venues. Therefore, if we exclude

these four DMAs, the average value of variance is 2.325 days with its standard deviation being 3.37.

In addition, on average, there are 1.79 performances available during a show day with the standard deviation being 0.21. Although we do not know the specific times for day of our performances, we still find the flexibility that an event provides with consumers to attend at different times of day to be heterogeneous across markets. Table 4-1 indicates the descriptive statistics of the flexibility in days of week and for times of day (in the log term).

Across-Market and Within-Market Carryovers

Figure 4-5 also illustrates how markets are temporally connected with one another. According to venue usage and the first and last dates of performances, we classify 42 DMAs into markets that are completely apart from one another (*Case 1* in Figure 4-2), overlapped (*Case 2*), or are in between multiple venues (*Case 3*). We further apply equations (27), (28), or (29) to compute the time lag between markets to ensure all preceding markets have different spatial weights in equation (26) and calculate across-market carryovers accordingly. Hence, the average across-market carryovers are 73,963.88 with the standard deviation being 65,688.67.

Figure 4-5: Touring Dates across Markets

Similarly, we use equation (31) to calculate the time lag between venues within a market for those six DMAs that have multiple venues. As a result, we have an average within-market carryovers being 51,564.62 and its standard deviation being 73,673.07. Table 4-1 indicates the descriptive statistics of the across-market and within-market carryovers (in the log term).

Population Size

The last covariate in the demand equation is the population size in each market. Because we have computed the target market population in essay two, we include the descriptive statistics

in Table 4-1. The average population size in a market is 439,662 and the standard deviation is 647091.

4.4.3 Covariates in the Supply Model

Venue Capacity and Market Capacity

Before we study the overall supply in each market ($Seat_m$) as the first supply decision, we need to know the number of performances and the seating capacity for each venue. However, we do not have information regarding venue capacity in our dataset, so we refer to venue websites and the Wikipedia to collect seating capacity data.

According to venue websites, venues have various configurations for different events (e.g., basketball games, hockey games, concerts, etc.). Hence, we choose the format that is the closest to the setting of a family event and record the associated capacity as the venue capacity ($Capacity_v$). Using all venue capacity in the same market, we further compute the average venue capacity in a market ($Capacity_m$) for equation (32) and observe heterogeneity in venue capacity. On average, a venue has 13,612 seats with standard deviation being 4,682. Fifty percent of venues have capacity between 10,423 seats (quartile 1) and 17,315 seats (quartile 3).

Next, we multiply the venue capacity by the number of performances in this venue to know the total number of seats supplied by this venue and then sum across all venues in the same market to get the market capacity ($Seats_m$). On average, an event offers 156,747 seats in a market with its standard deviation being 184,537. Some markets only supplied a few seats (e.g., Mankato DMA offered 14,496 seats in a total) but some markets provided as many as 1,159,059 seats (i.e., New York DMA).

According to the market sales and market capacity, we find that at most 50% of market capacity was filled. On average, only 24% of total capacity was filled in a market. Figure 4-6

presents the rate of filled capacity across markets. Table 4-1 also indicates the descriptive statistics of the overall market supply (in the log term).

Figure 4-6: Capacity-Filled Rate across Markets

Market Land Area and Population Density

To study the number of venues a market needs to book in equation (32), we still need information about the market land area and population density at a market level. Hence, we use the U.S. Census Bureau statistics to obtain the market land area (in square miles) and the size of population at a county level.

After we divide the county population by its land area, we understand the population density at a county level. Then, we sum across all counties within the same DMA to get the population density ($Density_m$) at a market level. We also compute the land area in a market ($Area_m$) by summing the land area across counties in the same DMA. Therefore, an average market has 3,846 square miles of land and its population density is 422 people per square mile. Table 4-1 indicates the descriptive statistics of the market land area and population density (in the log term).

Facility Rental Fees

We also use the facility rental fees ($Fees_m$) to study the number of days event marketers need to book in a market. However, because this information is not publicly available, we assume rental fees of a venue are positively correlated with housing values in the same zip code. In other words, when a median value of a single-family house is high, it is very likely that rental fees of a venue in this zip code are also high. Hence, we collect housing market data from the U.S. Census Bureau based on this assumption. The distribution of the housing value across markets is skewed. The average value (in thousands) is 2055 and the standard deviation is 4855.

The median of the housing value is 94.2. Table 4-1 also summarizes the descriptive statistics of this covariate (in the log term).

Correlation

Finally, before we estimate the proposed model, we also check the correlation among our covariates and the correlation among all dependent variables. Table 4-2 reports the correlation between covariates in the demand model and Table 4-3 indicates that dependent variables are moderate or highly correlated. Hence, our proposed model that correlates all error terms among dependent variables has accounted for this issue.

Table 4-2: Correlation Coefficient of Demand Covariates

Table 4-3: Correlation Coefficient of Dependent Variables

4.5 Estimation and Results

4.5.1 Model Estimation

We estimate demand and supply equations simultaneously using the Bayesian approach where parameters are specified to follow diffuse prior distribution as follows:

Priors for model of market sales:

$$\alpha_0 \sim N(10,10) \text{ and } \alpha_i \sim N(0,100) \text{ where } i=1, 2, 3, 4, 5, 6$$

Priors for model of overall supply:

$$\beta_0 \sim N(11,10) \text{ and } \beta_i \sim N(0,100) \text{ where } i=1, 2$$

Priors for model of venue usage:

$$\gamma_0 \sim N(0.11,10) \text{ and } \gamma_i \sim N(0,100) \text{ where } i=1, 2, 3$$

Priors for model of day usage:

$$\theta_0 \sim N(1.5,10) \text{ and } \theta_i \sim N(0,100) \text{ where } i=1, 2, 3$$

Priors for the variance-covariance of Supply and Demand:

$$\Sigma^{-1} \sim Weibull(I_4, 4)$$

We run 30,000 iterations in WinBUGs. After checking the convergence criteria, we check the autocorrelation plots for all covariates, discard the first 20,000 iterations for burn-in, and use the remaining iterations as the posterior distribution.

4.5.2 Results of Demand Equation

Scheduling Influence in a Performance Schedule

First, we show that the size of trading area of selected venues in a market has a positive effect on market sales. When an event performs in multiple venues in a market or when its venues are located in densely populated areas, this event sells more tickets in this market ($\alpha_1=0.160$). Our explanation is that scheduling performances in multiple venues or selecting venues in densely populated area can improve the spatial accessibility of this event (Huff 1964; Donthu and Rust 1989; Betancourt 2004). In this way, consumers living within the trading area do not have to travel a longer distance to attend an event. When there are more consumers within the trading area of a market, it is more likely for this market to sell more tickets (Huff 1964; Applebaum 1966; Cliquet 1988).

Second, we find the flexibility of performance dates in a schedule has a positive effect on ticket sales. When the variance in the distribution of performance dates increases, an event provides consumers with higher flexibility to attend on various days of week (Betancourt 2004) and sell more tickets in a market ($\alpha_3=0.235$). However, when there are more performances in a show day, the flexibility for times of day does not contribute to ticket sales.

Carryovers in an Event Distribution

Moreover, we show that a sequentially distributed event has an effect on ticket sales. However, the influence is across multiple venues within the same market but not across different markets. In other words, when an event performs from one market to another, its ticket sales in

preceding markets do not affect sales in following markets. Yet, when this event performs in more than one venue within a market, its ticket sales in a preceding venue can carry over to a later venue and influence its overall market sales ($\alpha_5=0.083$).

We think the nature of the family event analyzed in this essay is the underlying reason for a carryover effect significant within a market but not across markets. Because this family event targets young children and their parents, it is easier to observe children and parents discussing event information within a market than across markets. Moreover, this family event travels within the U.S. and often goes to a similar set of markets after a year or longer. Thus, these markets do not have to depend on other participating markets but can rely on their own historical experience to determine the quality of this event.

Our results are consistent with the results in Elberse and Eliashberg (2003). Specifically, they used sales in a preceding week as the volume of word of mouth and found a significant effect on box-office revenues in a following week within the same market. This is similar to our carryover effect within a market except that our carryover effect is across venues but not over time. On the other hand, when Elberse and Eliashberg (2003) measured the interaction effect between market sales in a domestic market and the time lag between a domestic and foreign market, they found this interaction, or weighted word of mouth, effect insignificant across markets. Although our spatially weighted measure for the carryovers across markets is similar to their measure except that we take into account all of the participating markets instead of just the initial market, our results are consistent with their work and support their results.

Elasticity

Another advantage of our model specification is that parameter estimates in our demand model suggest the elasticity for all covariates. After comparing elasticity across significant

covariates, we conclude that the variance in the distribution of performance dates is more important than the size of trading area of selected venues and the carryovers of an event distribution within a market, respectively in this order. Although market population has a higher elasticity ($\alpha_6 = 0.264$), this is a market characteristic that event marketers cannot manipulate in their scheduling decisions. Furthermore, these elasticity values suggest event marketers which factors to strengthen. If trade-offs among these factors have to be made, they can make rational decisions based on the elasticity. We summarize the parameter estimates in our demand model in Table 4-4.

Table 4-4: Results of the Demand Model

4.5.3 Results of Supply Equations

From the results of the supply model, we confirm the endogeneity between the supply and demand for an event. Event marketers use the expected market demand to determine how many seats they need to provide ($\beta_1 = 0.771$) but not the size of market population. Moreover, in terms of the venue usage, when event marketers need to increase their overall supply, they tend to schedule performances in more venues ($\gamma_1 = 0.473$) but do not consider the size of market land area or population density in this market.

On the other hand, when event marketers evaluate how many days to book for an event, they consider how many seats they need to supply ($\theta_1 = 0.929$) and the average venue capacity in a market ($\theta_2 = -0.703$). In other words, when they need to provide more seats to a market, they book more days for this event and have a longer performing duration. However, the number of days needed decreases with the venue capacity. Although we do not find average housing value influences the decision of day usage, it is possible that this variable is not an appropriate proxy

for the rental facility fees in a market. Table 4-5 below summarizes the parameter values in the supply equations.

Table 4-5: Results of the Supply Model

4.5.4 Correlated Demand and Supply

Finally, we find correlated error terms in the supply and demand models. In other words, there are unspecified covariates affecting both supply and demand at the same time. The correlation between the market sales and overall supply is 0.549 and the correlation between the market sales and day usage is 0.499. On the other hand, the decisions of overall supply and day usage are also correlated ($\text{corr}(\varepsilon_{\text{Seats}}, \varepsilon_{\text{Days}})=0.823$). Hence, it is necessary to assume correlated error terms in our model to avoid biased parameter estimates. Table 4-6 below indicates the correlation coefficients among our supply and demand models.

Table 4-6: Correlation between Supply and Demand Models

4.6 Conclusions

4.6.1 Summary

When an event travels across markets and has its distribution sequence planned at one time, it is not clear whether and how the sequential distribution of this event influences ticket sales in each participating market. The objective of essay three is to examine whether markets along an event distribution have a dependent relationship and whether ticket sales of preceding markets have a carryover effect to influence ticket sales in following markets.

To achieve this objective, we model ticket sales of each market as a function of its performance schedule within a market and potential carryovers from an event distribution. Specifically, we employ three variables to represent the scheduling influences from various venues and performance dates, and take the spatially weighted approach to capture carryovers of

participating markets that have different ticket sales and release timing. We also specify the supply and demand for this event simultaneously to account for a likely endogeneity. At the supply side, we model separate but correlated decisions of overall supply, venue usage, and day usage. In this way, our proposed model provides better understanding of scheduling effects on demand and control for the endogenous supply and demand.

We contact a national ticket seller to obtain a dataset of a live performance event and analyze ticket sales at a market level. The first result indicates that an event experiences more market sales when it plays in several venues and has a bigger trading area to accommodate more potential consumers. Second, an event sells more tickets when its performances are dispersed across days of week but not during many times a day. In other words, the flexibility in a temporal schedule is along the days of week to attract more consumer attendance.

Third, we find a significant effect of carryovers from an event distribution. When an event performs in multiple venues within a market, ticket sales in a preceding market carry over to later venues and influence its market sales although this carryover effect does not exist across participating markets. Finally, we find supply and demand for an event to be endogenous. Event marketers use the expected market demand to determine how many seats they need to provide, and this overall supply further influences how many venues they reserve and how many days they book in a schedule.

4.6.2 Conclusion

This essay contributes to the sequential distribution literature by studying an event distribution where its touring sequence is set at one time rather than sequentially. We show that the impact of sequential distribution exists locally but not across markets. In other words, although markets along a tour do not have a dependent relationship, venues of the same market

have a dependent relationship and preceding venues can influence ticket sales in later venues and ticket sales in this market.

The methodological contribution of this essay is to employ variables for an endogenous and correlated performance schedule. By modeling the supply and demand simultaneously and having the variables in the demand equation, we ensure unbiased scheduling effects and provide actionable implications for event marketers.

To sum up, the first implication of essay three lies in the decision of venue usage. After event marketers decide how many venues to book, they can refer to the size of trading area of each alternative venue and select among these venues accordingly. Moreover, they can add or drop venues based on the size of trading area if the desirable number of venues is not feasible in a market. The second implication lies in the decision of day usage. Event marketers should consider not to allocate multiple performances in a day but to disperse performances across various days of week. However, event marketers should still evaluate the overall costs for such scheduling changes in any venue or day usage.

Finally, when a touring sequence has to be planned simultaneously, it is not necessary for event markets to consider any dependent relationship across markets. However, if this event performs in multiple venues in a specific market, it is preferred that event marketers schedule this event in a more important venue prior to other venues. In other words, the scheduling objective for a touring event should be to minimize the travel distance across markets but maximize the within-market carryovers for venues in the same market.

Tables and Figures

Table 4-1: Descriptive Statistics of Covariates (in the log term)

Variable	Label	N	Mean	Std Dev	Min	Max
<i>Covariates in the demand equation</i>						
Sales	Number of ticket sales	42	10.18	1.15	7.87	13.27
Size	Size of trading area	42	7.54	1.26	4.78	11.08
Intensity	Avg. number of performances in a show day	42	0.58	0.12	0.34	0.79
Variance	Variance in the distribution of performance dates	42	1.02	2.20	-1.10	8.44
AC	Across-market carryovers	42	10.93	0.74	9.52	12.75
WC	Within-market carryovers	6	5.16	8.33	-7.45	12.13
POP	Population size	42	12.46	0.92	9.75	15.23
<i>Covariates in the supply equations</i>						
Seats	Number of seats supplied	42	11.59	0.85	9.58	13.96
Venues	Number of venues booked	42	0.12	0.30	0	1.39
Days	Number of days supplied	42	1.57	0.56	0.69	3.47
Area	Size of market land area (in square miles)	42	7.90	0.80	6.55	9.81
Density	Population density of a market	42	5.72	0.85	3.79	7.62
Capacity	Avg. capacity of selected venues in a market	42	9.45	0.42	8.06	10.09
Rental	Avg. housing value of a market (in thousands)	42	5.24	1.85	3.60	9.71

Table 4-2: Correlation Coefficient of Demand Covariates

	ln(Size)	ln(Intensity)	ln(Variance)	ln(AC)	ln(WC)	ln(POP)
ln(Size)	--					
ln(Intensity)	0.41	--				
ln(Variance)	0.52	0.22	--			
ln(AC)	-0.02	0.08	-0.00	--		
ln(WC)	0.44	0.22	0.20	0.11	--	
ln(POP)	0.63	0.28	0.45	-0.23	0.16	--

Table 4-3: Correlation Coefficient of Dependent Variables

	ln(Sales)	ln(Seats)	ln(Venues)	ln(Days)
ln(Sales)	--			
ln(Seats)	0.87	--		
ln(Venues)	0.51	0.57	--	
ln(Days)	0.80	0.86	0.73	--

Table 4-4: Results of the Demand Model

Parameter	Effect	Median (Std Dev)		
<i>ln(Sales): Expected ticket sales in a market</i>				
α_0	Intercept	5.329	(1.164)	**
α_1	Effect of geographic coverage	0.161	(0.073)	*
α_2	Effect of intensity	0.128	(0.168)	
α_3	Effect of variance	0.235	(0.038)	**
α_4	Effect of across-market carryover	0.002	(0.063)	
α_5	Effect of within-market carryover	0.083	(0.021)	**
α_6	Effect of population size	0.264	(0.086)	**

** significant at the 95% highest posterior density

Table 4-5: Results of the Supply Model

Parameters		Median (Std Dev)		
<i>ln(Seats): Expected number of seats supplied in a market</i>				
β_0	Intercept	4.766	(0.832)	**
β_1	Effect of expected market sales	0.771	(0.086)	**
β_2	Effect of population	-0.073	(0.050)	
<i>ln(Venues): Expected number of venues needed</i>				
γ_0	Intercept	-4.621	(0.709)	**
γ_1	Effect of planned overall supply	0.473	(0.067)	**
γ_2	Effect of market land area	-0.042	(0.046)	
γ_3	Effect of market population density	-0.087	(0.050)	
<i>ln(Days): Expected number of days needed</i>				
θ_0	Intercept	-2.169	(1.097)	**
θ_1	Effect of planned overall supply	0.929	(0.070)	**
θ_2	Effect avg. venue capacity	-0.703	(0.098)	**
θ_3	Effect of housing value	-0.024	(0.028)	

** significant at the 95% highest posterior density

Table 4-6: Correlation between Supply and Demand Models

Σ	ϵ_{Sales}	ϵ_{Seats}	ϵ_{Venues}
ϵ_{Sales}	--		
ϵ_{Seats}	0.549 **	--	
ϵ_{Venues}	-0.169	-0.280	--
ϵ_{Days}	0.499 **	0.823 **	-0.273

** significant at the 95% highest posterior density

Figure 4-1: Conceptual Framework

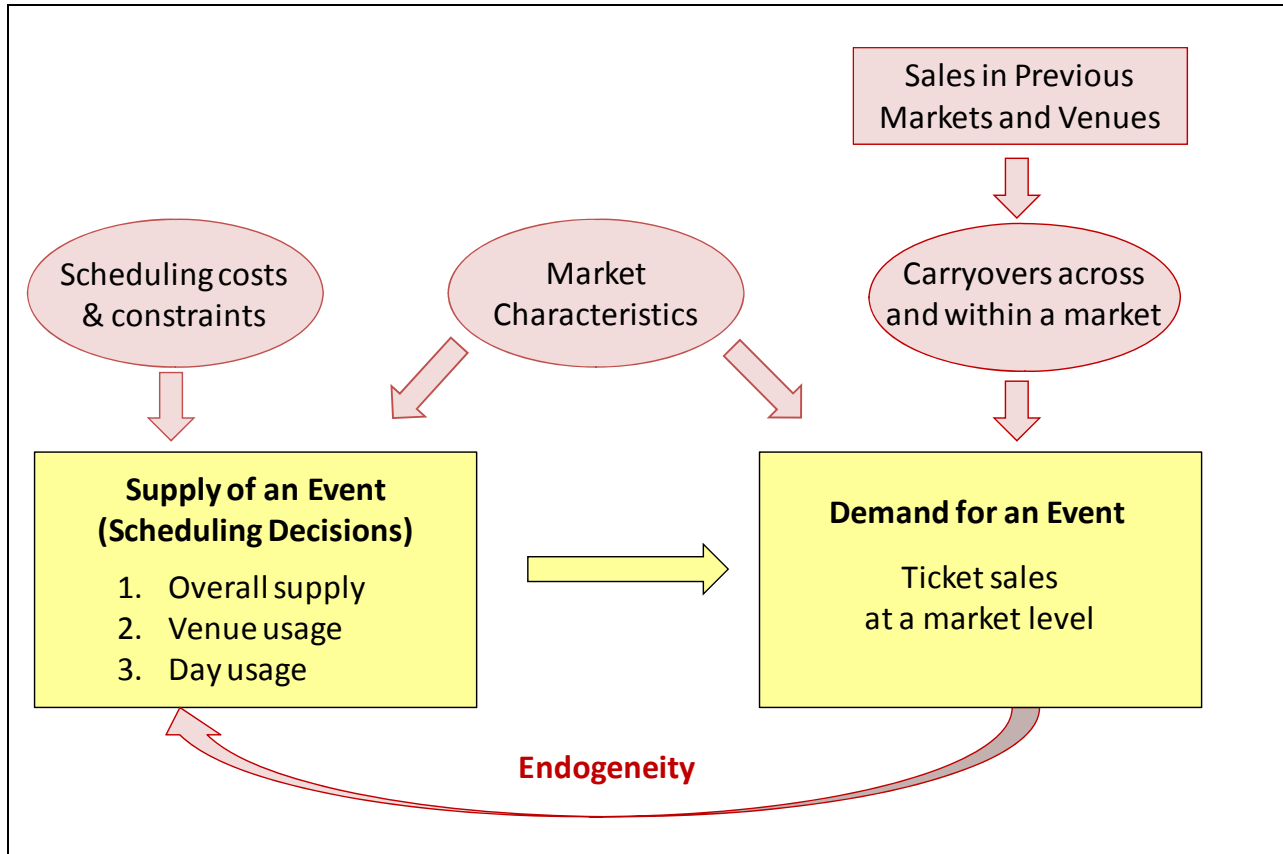


Figure 4-2: Illustration of Market Connectedness

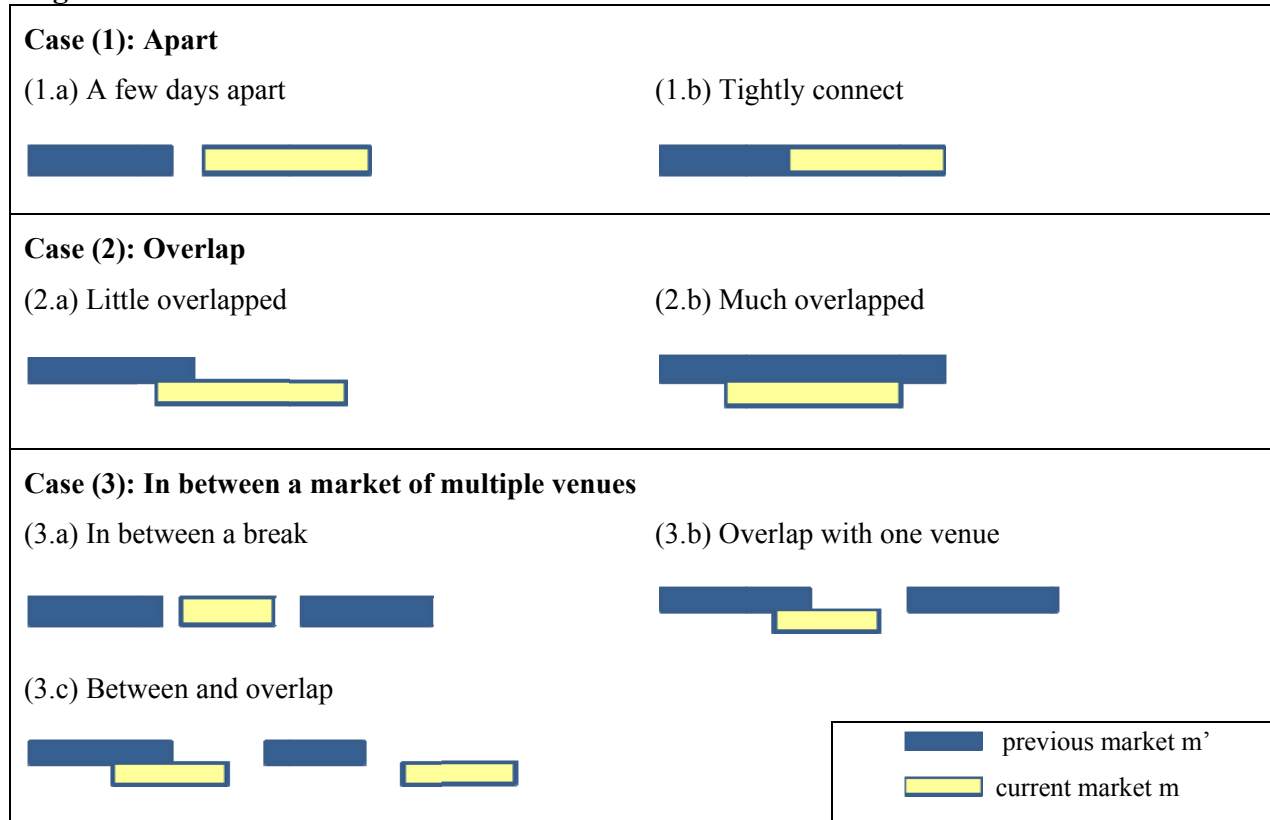


Figure 4-3: Overview of Model Development

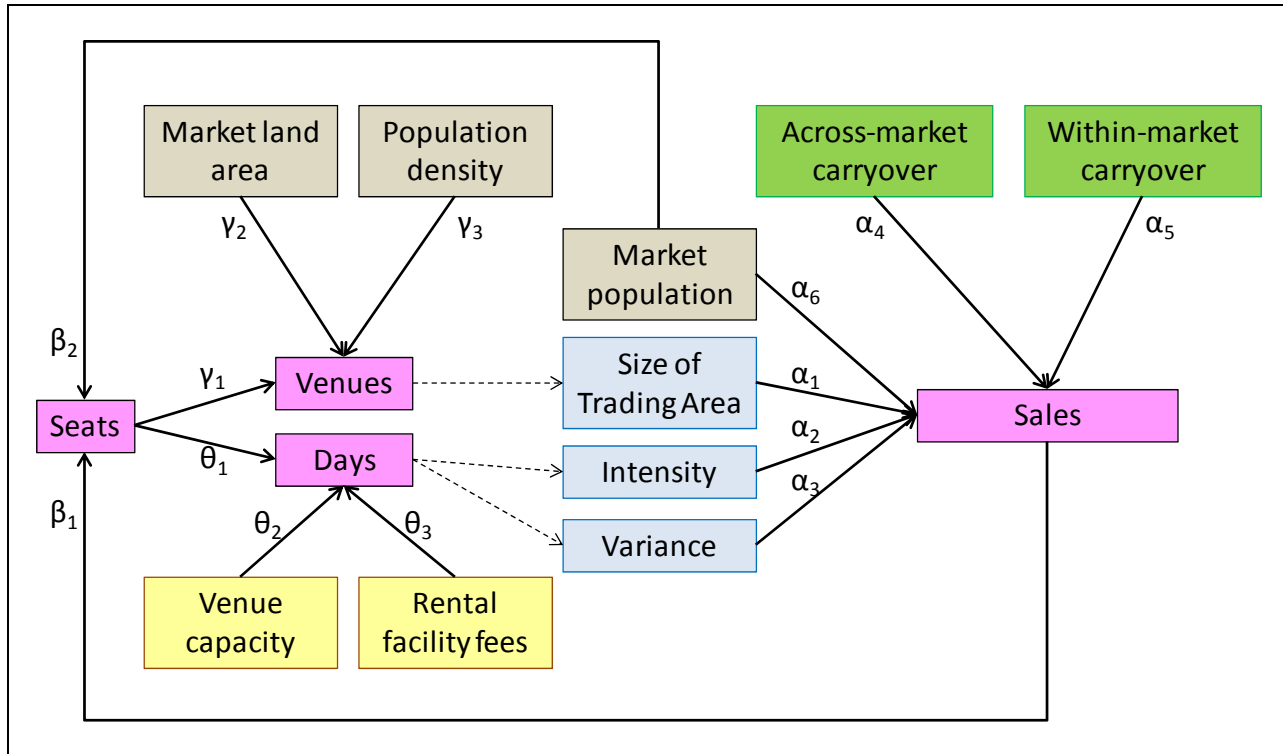


Figure 4-4: Venue Locations

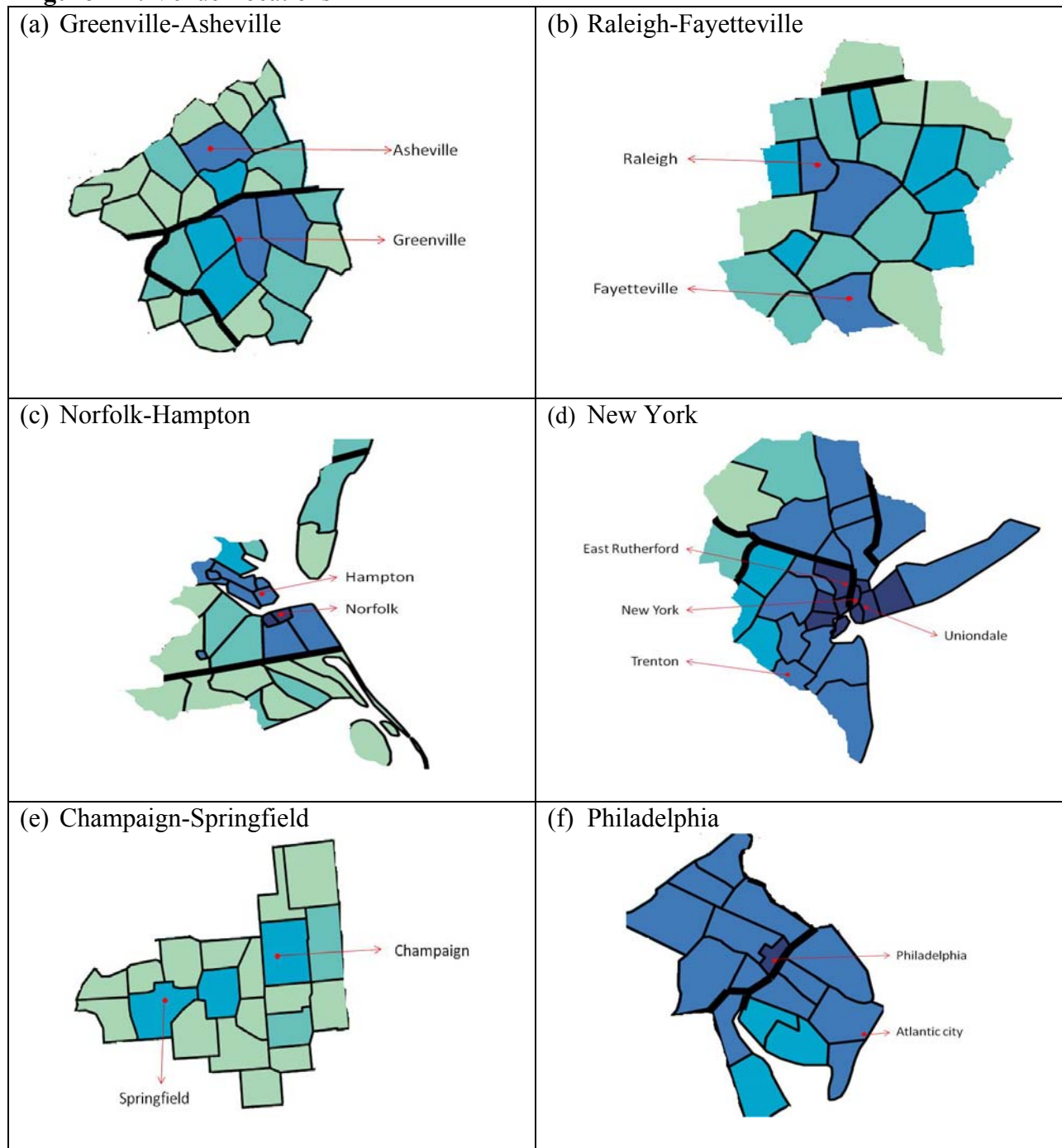


Figure 4-5: Touring Dates across Markets

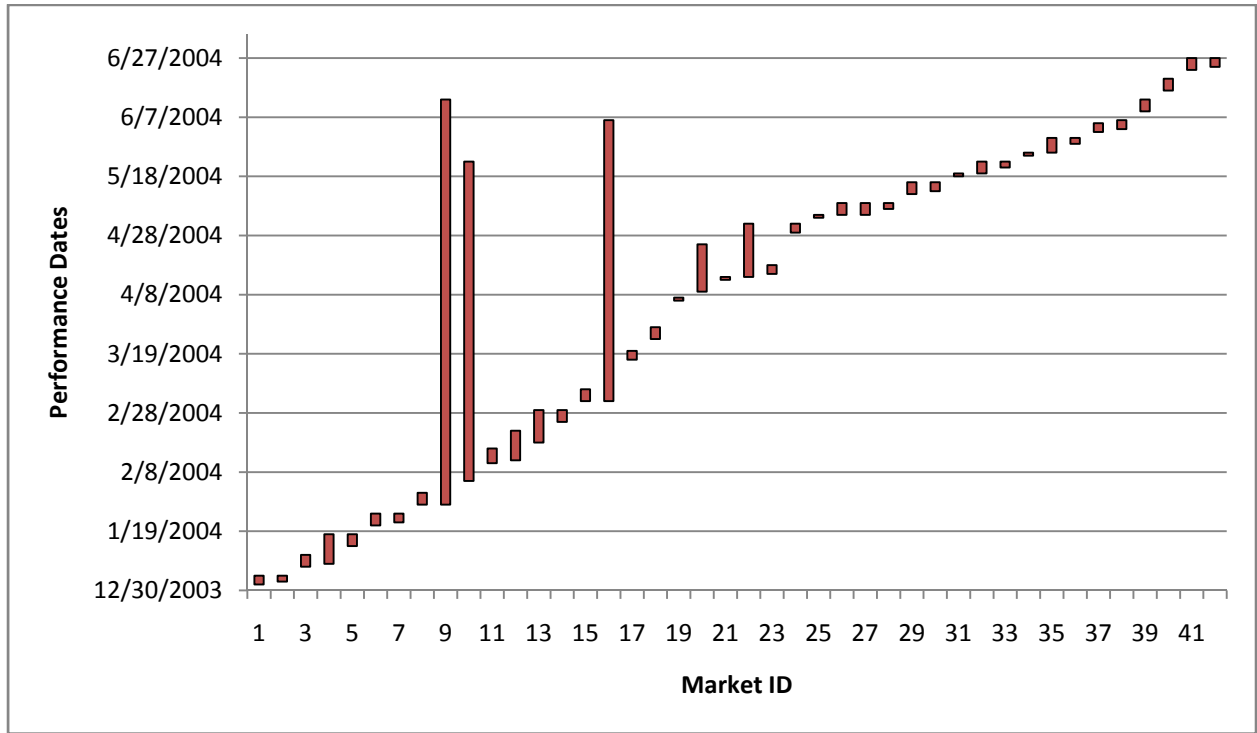
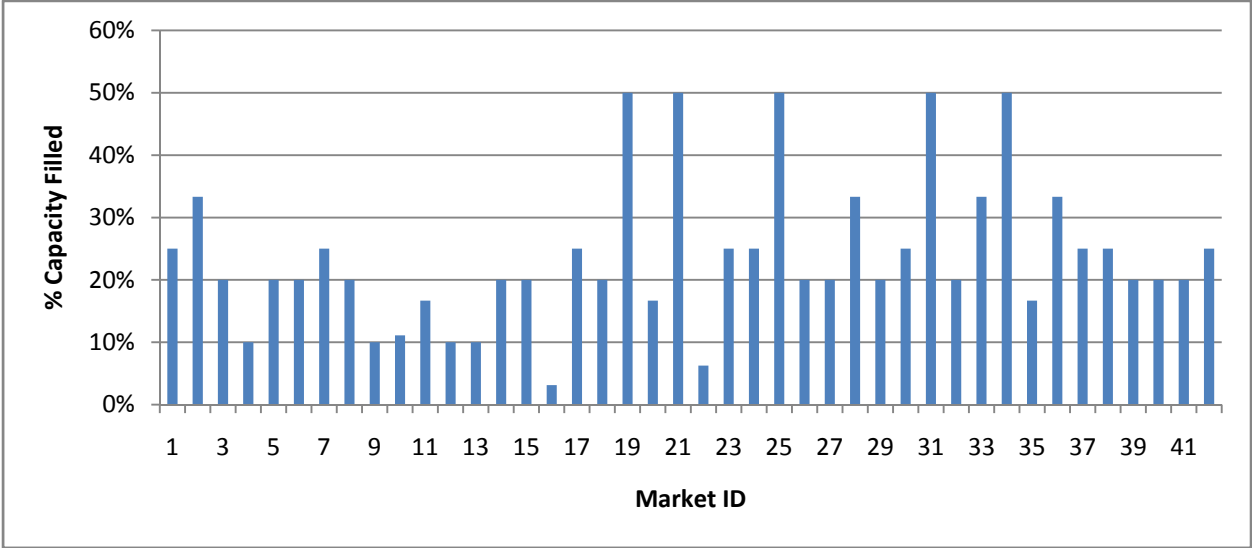


Figure 4-6: Capacity-Filled Rate across Markets



5 Conclusion

5.1 Summary

Scheduling is an important decision facing event marketers in the live entertainment industry. When they schedule a tour for an event, they have to design a performance schedule within each participating market and determine an overall travel sequence across markets. Therefore, their scheduling decisions are within and across markets, which may have different effects on ticket sales.

Although marketing research in the live entertainment industry has focused on identifying drivers for ticket sales, researchers have not evaluated whether the scheduling decisions influence how markets respond. In other words, researchers treat the supply and demand for an event as two separate problems and they have not yet investigated the relationship between supply and demand.

As such, this dissertation analyzes performance schedules of a live performance event and examines the effects on ticket sales within and across markets. Specifically, essay one investigates whether and how performances of similar scheduling characteristics sell differently in terms of how many tickets each performance sells and when ticket sales arrive. We use the venue locations and performance dates as the scheduling characteristics for each performance and measure the similarity in these scheduling characteristics by the geographic distance between venues and the temporal distance between performance dates.

Methodologically, we use the competing destination model to examine the number of ticket sales and the Weibull hazard model for the timing of ticket sales. In addition, we also control for a possible endogeneity between a performance schedule and its demand effect. Using

70 performances in the New York market, we show that performances sell differently depending on how similar their venue locations and performance dates are.

In other words, when performances are in the same or nearby venues, they have higher similarity in a geographic schedule. From consumers' perspective, they may perceive nearby venues to be more attractive due to this similarity in venue locations. As a result, more consumers purchase tickets for those performances and they are more willing to purchase these tickets early. On the other hand, when performances are on the same or closer dates, they have higher similarity in a temporal schedule. Because consumers often have uncertainty about their consumption state and prefer various attendance timing for choices, shorter temporal distance between performances result in higher competition and sales cannibalization.

Since results in essay one are limited in the New York metropolitan market, essay two analyzes performance schedules across 42 markets and examines whether the results in essay one are heterogeneous across markets and if there are any explanatory factors to explain differences across markets. We first conduct a preliminary analysis using the same model developed in essay one and compare the effects of scheduling characteristics across markets. After confirming the heterogeneous market responses to performance schedules, we employ the hierarchical Bayesian approach to identify explanatory factors for differences across markets.

Our results show that market population, geographic adjacency between markets, and temporal sequence in an event distribution can explain different market responses. First, when a market has a bigger population, the effects of days of week and baseline attractiveness are attenuated. Second, with respect to a current market, after an event travels to more of its geographically adjacent markets, the current market is less responsive to its baseline attractiveness and temporal schedule. Third, after an event follows its temporal sequence to

perform in several markets, a current market in a late distribution sequence tends to respond more favorably to a Sunday performance.

As such, essay one examines the impact of a performance schedule in a single market, and essay two analyzes all performance schedules observed in the dataset and uses market and additional scheduling characteristics to explain different market responses. However, the event in our dataset is sequentially distributed across its participating markets. It is important to understand whether the carryover effect exists due to an event distribution and how this carryover effect influences ticket sales of participating markets.

Therefore, essay three analyzes the distribution of this live performance event and examines whether ticket sales of preceding markets carry over to following markets and influence ticket sales in those following markets. Besides controlling for the effect of a performance schedule within a market, we model ticket sales of each market as a function of its potential carryovers from an event distribution. We also model the supply and demand for an event simultaneously to account for a possible endogeneity. Specifically, we use the size of trading area(s) of scheduled venue(s) in a market and flexibility in the distribution of performance dates in a schedule to represent the scheduling influences and employ the spatially weighted approach to incorporated carryovers of preceding markets and their different release timing.

Our results show that when an event has a larger trading area in a market and/or offers more performances along a dispersed time span, it tends to sell more tickets in this market. Moreover, we show that an event distribution has an effect on ticket sales. However, the effect of carryovers is significant across venues of the same market but not across markets. When an

event performs in more than one venue, its ticket sales in a preceding venue carry over to a later venue and influence its overall market sales.

5.2 General Discussions

In general, this dissertation indicates several scheduling effects. We classify these effects into effect of within-market scheduling and effect of across-market scheduling. Moreover, we study the effect of within-market scheduling into two aspects. Essays one and two focus on the effect of within-market scheduling at a performance level, yet essay three addresses the same effect at a market level. We sum up these scheduling effects and discuss the differences in turn.

First, for the effect of within-market scheduling at a performance level in essays one and two, we find that the effect of a geographic schedule differs from the effect of a temporal schedule. The similarity in venue locations benefit ticket sales at a performance level but the similarity in performance dates cannibalizes ticket sales. Moreover, market responses to performance schedules are heterogeneous and can be explained via the market and additional scheduling characteristics. Second, for the effect of within-market scheduling at a market level in essay three, we find that an event sells more tickets when it employs more venues in its geographic schedule and serve a bigger trading area. It also sells more when the distribution of its performance dates in a temporal schedule has a big variance to offer consumers greater flexibility in attendance timing. Third, for the effect of across-market scheduling in essay three, we find that markets are not dependent on one another, but venues within the same market have a dependent relationship to influence ticket sales in this market.

Although the effect of a geographic schedule at a performance level seems contradictory to the effect at a market level, these results are in fact complimentary. Although the first two essays suggest event marketers to decrease the geographic distance between performances and

increase the similarity in venue locations, this suggestion is for markets that employing multiple venues only. When an event performs in just one single venue, event marketers can follow the learning in essay three to select a venue that has the biggest trading area. In other words, if event marketers decide to schedule an event in multiple venues, they can apply their learning in essay three to select venues and then allocate performances to these venues based on the first two essays.

Consequently, the order of these essays allows us to understand the scheduling effects from a performance level to a market level. Essay one starts with examining the effect of a performance schedule at a performance level in a single market and concludes that performances scheduled closely in distance but distantly in time can experience more ticket sales. In addition, essay one also suggests performances experiencing earlier timing of ticket sales when these performances are scheduled in nearby venues. To test the generalizability of these results and explain the heterogeneity across markets, essay two expands the scope of analysis and confirms the scheduling impact in all participating markets of a touring event.

Finally, essay three examines whether an event has a carryover effect when it sequentially distributes across markets. This essay concludes that markets do not influence one another on their ticket sales yet their venues within the same market have such an effect. Although one may argue that the third essay does not have to be conducted after the first two essays, we choose this sequence to investigate the carryover effect after we can understand and control for the effect of a performance schedule within a market.

Finally, although it is arguable that essay three could have used the density measures developed in essay one, we choose to use three variables for the following reasons. First, the scheduling characteristics represent the similarity between performances in a schedule. They do

not represent how well an event is able to serve its trading area at a market level or express the flexibility in attendance timing in a temporal schedule. Second, the measure of geographic density in essay one is applicable only when an event performs in multiple venues in a market. For markets where an event performs in one venue only, there is no variation in its geographic distance yet the trading area of this single venue could still influence ticket sales. Therefore, it is necessary to use different measures to differentiate the effect of scheduling characteristics at a performance level from the effect of a performance schedule at a market level.

5.3 Contributions

This dissertation has both empirical and academic contributions to the marketing field. Empirically, we show that performance schedules do affect ticket sales. Managers can use performance schedules to estimate ticket sales at a performance or market level. Event marketers can use these estimates as benchmarks to monitor a pattern of ticket sales and even allocate marketing resources accordingly.

Academically, the findings in this dissertation enrich literature in event tickets and sequential distribution. We introduce new drivers of ticket sales to the event tickets literature such that researchers can use new differential measures to explain variations in the number and timing of ticket sales. Moreover, we examine a sequential distribution problem in a new context where simultaneous planning is needed and find the effect of sequential distribution only within a local market but not across markets.

5.4 Limitation and Future Research

The primary limitation in this dissertation is that we do not have access to consumer identification data. Although individual transactions are observed, we cannot model a consumer's decision process to understand the effect of a performance schedule at a finer level.

To resolve this issue, we could apply an agent based modeling approach. Using our model results as aggregated parameter values, we can further simulate individual consumers in a market using the U.S. Census data and allow variations in agents' preferences. This future direction will better assist event marketers in performance scheduling and allow researchers to study marketing problems using a complexity system.

Another future research lies in the pricing structure of event tickets. As our data suggest, the total price that a consumer pays includes the face value, facility fees, and convenience charges, where face value represents the highest share in the total price paid, followed by convenience charges and facility fees. When summarizing consumers' channel usage, we find that consumers tend to purchase in box offices to avoid paying for convenience fees. However, convenience fees are the major revenue source for ticket sellers. If ticket sellers and event promoters could collaborate and re-structure the pricing breakdowns (e.g., the merger between Ticketmaster, a primary ticket seller, and Live Nation, an event promoter), it is likely that consumers' ticket purchases will migrate to the Internet or other channels. This new topic involves pricing and channel strategies and we leave it for a future direction.

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