Measurement of Competitive Issues in Product Entry Decisions

Jorge M. Gonzalez

Dedicado a papá y a mamá.

Al cielo y la tierra.

ABSTRACT

Measurement of Competitive Issues in Product Entry Decisions

This thesis aims to make two types of academic contributions. The first is the development of empirical models in situations of new product entry in the marketplace. The second type of contributions is to provide substantive results regarding the impact of launching new products in sectors such as the mobile telephony, pharmaceutical, and motion picture industries.

In Chapter 1, I develop a brand level diffusion model to measure the substitution and category expansion effects of the launching of a new product into an existing category. This model accounts for unobservable factors that have carry-over effects and influence the diffusion of the new product introduced in the market. I use the proposed model to analyze the differences in adoption of mobile phone services in France, Germany and the UK. I find that some of these differences can be explained by the changes in the adoption costs and the different impact of the launching of prepaid plans in the three countries. More specifically, I find that France, the least developed of the three markets in terms of total percentage of adoption, is the country where prepaid plans were less effective in terms of category expansion and where there was more substitution of mobile services with contract plans. This finding suggests that prepaid plans in France were less appealing for light users of mobile telephony than in the other two countries. Therefore, I claim that the lower penetration of mobile telephony in France can be explained by the customer acquisition policy of French mobile network operators, that was more conservative than the policies followed in Germany and the UK.

In Chapter 2, I analyze the impact on competitors of the launching of generic versions of a drug after patent expiry. Previous research on generic entry has focused on the impact of a

generic on the branded drug which lost patent protection (i.e. within molecule competition). In this study, I suggest that public officials need to look beyond within-molecule competition and study the full competitive landscape in the relevant therapeutic class. Such a competitive landscape will include also the actions of non-bioequivalent competitors (between molecule competition). In addition, I contend that public officials need to consider carefully the role of physicians and their prescribing behavior across all competing molecules, and study not only their reaction to prices but also to other marketing activity. To provide support for this contention, I studied the evolution of the market for selective serotonine reuptake inhibitors (SSRI) in the United Kingdom (UK) after generic versions of fluoxetine (brand name Prozac) were introduced. Using a data set on physician prescribing and competitive marketing activity, I found that the combined sales of the drug that was losing patent protection (branded + generic versions) decreased after patent expiration, despite the availability of generics at significant price discounts. This reduction occurred because a segment of physicians switched from the multi-source molecule to other drugs in the category after generic entry (between-molecule effect). These were physicians sensitive to the promotional activities of Prozac, which significantly reduced its marketing effort after generic entry. In addition, although a smaller segment of price sensitive physicians increased the use of fluoxetine, that was not sufficient to compensate for the previous reduction in fluoxetine prescribing behavior. These results suggest that generic adoption is influenced by the actions of all competitors, not just the original branded version. Therefore, to fully understand the impact of generics, it is important to account for the marketing activity of all pharmaceutical companies that are close substitutes and determine how physicians respond to the marketing actions and drug prices at the individual level.

Finally, in Chapter 3, I measure the effect of the retail channel on brand performance using data on consumer purchases across competing retailers in the context of the movie exhibition market. I develop a model to measure the relative performance of competing theaters that takes into account the differences in the assortment of movies. This model accounts for the temporal evolution of box-office revenues and the exhibitor decision to show a movie for another week or to change it for a new release. I use this model to compare the

relative performance of two chains of theaters in a Spanish city. I find that one of the theater chains performs, on average, consistently better than the other. As a result, a movie that is shown in this best performing chain is more likely to perform well, all else constant. However, brand strength plays a moderating role: differences in performance across the two chains are more important for less popular movies; strong movies present smaller differences across the two chains. From these results, I suggest that strong brands rely less than weaker brands on retailers for their performance. These results highlight further the importance of developing strong brands: not only will weaker brands be bought less often by consumers and carried less often by retailers, weaker brands will also have less bargaining power with channel members because their performance will depend more on the "quality" of the channel members.

Contents

List of Tables

List of Figures

Introduction

From the starting scene of *"Smoke"* (1995), directed by Wayne Wang and originally written by Paul Auster.

THE BROOKLYN CIGAR CO. The cigar shop from within. Near the counter are three local characters (TOMMY, JERRY and DENNIS), shooting the breeze with AUGGIE (Harvey Keitel), the owner of the cigar shop. PAUL BENJAMIN (William Hurt), another custom is also there talking to AUGGIE.

PAUL

"Did you ever hear of Sir Walter Raleigh?

TOMMY

Sure. He's the guy who threw his cloak down over the puddle.

JERRY

I used to smoke Raleigh cigarettes. They came with a free gift coupon in every pack.

PAUL

That's the man. Well, Raleigh was the person who introduced tobacco in England, and since he was a favorite of the Queen's -- Queen Bess, he used to call her -- smoking caught on as a fashion at court. ... Once, he made a bet with her that he could measure the weight of smoke.

DENNIS.

You mean, weigh smoke?

PAUL

Exactly. Weigh smoke.

TOMMY

You can't do that. It's like weighing air.

PAUL

I admit it's strange. Almost like weighing someone's soul. But Sir Walter was a clever guy. First, he took an unsmoked cigar and put it on a balance and weighed it. Then he lit up and smoked the cigar, carefully tapping the ashes

into the balance pan. When he was finished, he put the butt into the pan along with the ashes and weighed what was there. Then he subtracted that number from the original weight of the unsmoked cigar. The difference was the weight of the smoke."

Radical innovations, me-too products, copycats, flankers, line extensions and new entrants are constantly redefining the competitive market arena. Again and again, new products are launched targeting new markets, segments, niches or just the old competitor's market share. This shifting scenario can be a challenging environment in which to measure both the impact of a new product launch and the reactions of competitors. Interactions among multiple variables come often into play, and yet, disentangling their influences can become as complex as measuring the weight of smoke.

This thesis focuses on the launching of new products and the impact they have on the competitive landscape. Overall, I aim to provide two types of contributions. The first is methodological insights into the application of quantitative methods when studying the impact of the launch of new products into a market. The second, substantive results concerning economic sectors such as the mobile phone, pharmaceutical and movie industries.

Although the chapters of this dissertation each deal with different problems, they all share a common research goal. This goal is to measure the impact on sales of the launch of a new product in the marketplace. The measurement is not straightforward because it requires a disentanglement of the several effects going on simultaneously. The modeling challenge consists precisely in determining how to overcome this measurement problem and how to analyze the results in order to achieve a better understanding of the market or take more appropriate managerial decisions. I will now briefly outline the focus of the analysis, the

methodological contributions, the empirical context and the key findings of the study for the three chapters of this dissertation.

In the first chapter, I analyze how to measure the **substitution** and **category expansion** effects of launching a new product. A new product introduced into an existing category can draw its sales from two sources. Firstly, from consumers who would have bought the product from other competitors in so far as the new product was not available (the substitution effect) and, secondly, from consumers who buy the category for the first time because of the availability of the new product (the category expansion effect). The disentanglement of both effects can be useful in different contexts, for example, in the case of measuring the cannibalization effects of the launch of a brand extension in the firm's product line or to evaluate the impact on the sales of an incumbent product of the launching of a new product of a competitor. For these reasons in Chapter 1, I develop a utility-based brand diffusion model in order to analyze categories where growth is influenced by the launching of different products and where disentangling substitution from category expansion effects can help to better understand the evolution of the market.

The methodological contribution of this study entails the development of a micro-level model of new product adoption that explains diffusion as the outcome of consumer choice in situations where there is an evolution of both observable variables (e.g. price reductions) and unobservable variables with carry-over effects. The influence of unobservable variables in a utility model are included in the random error. Some of these unobservable variables may be random shocks but others may have an influence that remains, at least partially, as time goes by. In this sense, these variables have carry-over effects. It is important then to account for them in a random utility model to avoid biasing the estimates of the model parameters.

The proposed model has the following characteristics: (1) being a choice model, it frames situations where differentiated products are available (2) being utility-based, it can be used to run counterfactual analyses. I analyze the substitution and category expansion effects through policy experiments such as simulating the evolution of the market without the launching of the new product. Traditional diffusion models (Bass 1969) are more limited for performing this type of analysis. The modeling approach combines insights from existing micro-models of new product adoption (Song and Chintagunta 2003), with the measurement of time-varying parameters in choice models (Sriram et al. 2006).

I use the proposed model to study the adoption of mobile telephony services in France, Germany and the UK. I focus my analysis on explaining how the diffusion of mobile telephone services was influenced by the launch of prepaid plans and changes in adoption costs. The introduction of prepaid plans in Europe increased dramatically the adoption of mobile phone services but it also slowed down the rate of increase of mobile users with contract phones. The results suggest that the launch of prepaid plans had its main effect through category expansion in the three countries studied. That is, most consumers that adopted a prepaid phone would not have adopted a mobile phone with a contract payment plan if prepaid services had not been available. This cross-country analysis also suggests that the impact of category expansion of prepaid plans relative to that of substitution was greater in the UK and Germany than in France. These results, together with the fact that light users in the French market faced higher call costs, indicate that the slower diffusion of mobile telephony in France has been motivated not only by socio-demographic or cultural factors alone but also by the more conservative customer acquisition policy of the country's mobile network operators.

In Chapter 2, I analyze the effects of the **introduction** of a **generic drug** after patent expiry on the evolution of the market. Previous research on generic entry has focused on the impact of the launching of a generic on the branded version of the drug going out of patent (Grabowski and Vernon 1996). This is known as intra- or **within-molecule competition.** However, little is known about the impact of the launching of a generic drug on the sales of non-bioequivalent competitors (i.e. other drugs that deal with the same condition or illness but are not bio-equivalent to the drug going out of patent) In this study, I incorporate non-bioequivalent competitors into the analysis to analyze **between-molecule competition** in markets where there is generic enty.

Patent expiration represents a turning point for the brand which is losing patent protection, as generic versions of the drug, certified to be bio-equivalent, quickly enter the market at reduced prices. With cheaper versions becoming available, it would be reasonable to think that, after generic entry, the combined market share of all the drugs selling the molecule going out of patent (generic+branded versions together) would increase since some price sensitive physicians would decide to increase the level of prescription of the drug now available at cheaper prices instead of using other drugs in the same category that are close substitutes. Surprisingly, I found that the market share of several molecules after patent expiry decreased even though generics entered the market at prices discounted up to a 40%. Looking for an explanation to this puzzling result I discovered that brands losing patent protection reduce their marketing effort significantly. The reason being that after patent expiration, the manufacturer of the original brand cannot be certain that its marketing efforts are going to generate branded prescriptions. Therefore, the launching of a generic drug is a situation where two simultaneous marketing actions take place. First, a price reduction due to the entry of generics, and second, a reduction in marketing investments. Hence, it is not clear a priori whether

the introduction of a generic will increase or decrease between-molecule competition. This aspect can be of interest for both pharmaceutical companies and policy makers

From a methodological point of view, we face the challenge of measuring the impact of two marketing actions that occur simultaneously and are likely to have different directional impact. The key factor in unraveling a situation like this is to exploit the physician cross-sectional heterogeneity in their response to both variables, in order to show that market evolution is the outcome of the combination of these two factors. Some physicians may be sensitive to price and increase the level of prescription of the molecule going out of patent. Others may be sensitive to the promotional efforts of the pharmaceutical companies and decrease the level of prescription once the company stops promoting the branded drug.

I develop these ideas studying the evolution of the selective serotonine reuptake inhibitors (SSRIs) in the United Kingdom, after generic versions of fluoxetine (brand name Prozac) were introduced. Using a data set on physician prescribing behavior and competitive marketing activity, I study how the prescribing decisions of physicians and their characteristics impact the competition among all molecules after generic entry. For example, I discover that the combined market share of all the version of fluoxetine declined after patent expiration, despite the availability of generics at significant price discounts. This reduction occurs because a segment of physicians switch from fluoxetine (the molecule going out of patent) to other drugs with a different active principle in the category after generic entry (between-molecule effect). These are physicians sensitive to promotional activities of Prozac. In addition, a smaller segment of price sensitive physicians increased the use of fluoxetine but was unable to compensate for the previous reduction of fluoxetine being prescribed.

These results suggest that final generic adoption is influenced by the actions of all competitors. In addition, to fully understand the impact of generics it is important to account for the marketing activity of pharmaceutical companies and determine how physicians respond to marketing actions and drug prices at the individual level. Hence, governments and drug companies interested in assessing the diffusion of generic drugs might want to monitor: (1) how physicians prescribe the molecules expected to lose patent protection and their non-bioequivalent competitors, and (2) the size of physician segments sensitive to pharmaceutical marketing activity and/or prices.

In the last chapter of the dissertation, I focus the analysis on the **interaction between retailers and manufacturers in the motion picture industry.** Specifically, I study how the impact of a retailer (exhibitor) can benefit manufacturers (film distributors) with products (movies) with different brand equity (audience appeal). The main finding of this study is that more popular movies (i.e. the ones with a higher audience) perform more closely in exhibitors of different quality than less popular movies. Less popular movies benefit more of being available in good exhibitors than movies with higher audience.

I think that the movie exhibition market is an excellent empirical setting to assess how different retailers (i.e. theaters) impact the level of sales of products (i.e. movies) with different brand preferences. The abscence of price competition at the theater level and the fact that theaters charge the same price for all the movies regarldless the quality of the film, make it possible to assess brand equity by total box office revenue.

I develop a Bayesian type II Tobit model (see for example Bucklin and Sismeiro 2003) to analyze the relative performance of theaters competing in the same area. The proposed type II Tobit model jointly considers the decision to keep showing the movie for another week and

the box office revenue of each theater. The model accounts for the temporal evolution of sales through the adapted Gamma model of Ainslie et al. (2005). This model is applied to measure the relative performance of two theater chains in a Spanish city during a period of one year. The analysis of the results shows that the proposed modeling approach provides diagnostic information and can correct for differences in assortment, whilst measuring the relative level of performance of both theaters. The results also show that the decision to stop or continue showing a particular movie by an individual theater is influenced by expectations about future audiences and hence contains valuable information for modeling box-office revenue at the level of the individual theater.

I use the proposed model to check if there is an interaction between theater quality and movie popularity. I find that theater performance differences are smaller for popular movies (i.e. blockbusters) when compared to less successful movies. This suggests that the enhancing effect of a better theater could be more salient for movies in which quality is less certain. There are several potential explanations for this phenomenon: For example, there is a percentage of movie goers that might be customers of the theater. In other words, they decide first what theater they are going to visit and then, what movie they watch from the assortment of films in the given location. A "better" theater, (i.e. the one that attracts a higher number of people for its better facilities, location or with more interesting movies) will attract more of this type of customers On the other hand, when the movie goer has decided in advanced which movie to watch, then the theater selection comes as a second step. Another explanation for this could be signaling: releasing a movie in a more popular venue might signal to a movie goer that the movie is also of higher quality. In contrast, if the movie is well known because it has been supported with a large advertising campaign or has famous actors, then this effect will be smaller. These findings can be extrapolated to other

retail settings different from movie audiences and point out how critical is for manufacturers to develop strong brands to compete more successfully in an environment with increasing powerful retailers.

In summary, the three chapters of this dissertation cover different measurement problems associated with product entry decisions. They explore the above themes as self-contained research essays. The positioning of the chapters focuses the analysis around the substantive problems. The empirical focus of this thesis is, therefore, much more salient than any attempt to develop a rigorous and exhaustive theoretical framework about the topic. However, the research method has been an iterative process where I have tried to develop my analytical toolbox with different methodologies whilst trying to answer the questions under study. None of the models of this dissertation is as ingenious as the one proposed by Sir Walter Raileigh to weigh smoke. Despite my admiration for Sir Walter I do not consider him a role model. I believe he also committed mistakes in life, such as being beheaded and failing on his expedition to the Orinoco River in the quest for El Dorado. Instead, I plan to keep on working on marketing problems.

CHAPTER 1

Impact of Pre-Paid Services on the Diffusion of Mobile Telephony: A Consumer Level Approach to the Study of Cross-Country Diffusion.

1.1. Introduction

The increasing globalization of the markets for products and services has spurred interest among marketers and academics in improving their understanding of the adoption of new products in countries with different characteristics. As pointed out by Kumar and Krishnan (2002), there are two main streams of research in cross-national diffusion. The first stream explores the impact of social and cultural differences on the pattern of adoption across different countries (Talukdar et al. 2002; Kumar et al. 1998). The second stream focuses on modeling the interaction between the diffusion processes in different countries, typically captured through lead-lag effects (Kalish et al.1995). However, in these previous analyses, cross-country diffusion studies have rarely included relevant aspects of firm behavior that could be crucial in understanding market evolution. For example, brand-level diffusion studies have shown the importance of assessing the impact of launching new brands (Krishnan et al. 2000), or new models of the same brand (Song and Chintagunta 2003) in an existing category, in order to understand the diffusion process. Thus, while acknowledging that cultural, economic, and sociological factors can be relevant for understanding cross-country adoption differences, it can be even more important to assess how marketers' actions have influenced market evolution. In this article, I present a cross-national diffusion study where I model the impact of the decisions of some firms on the diffusion of a new product and show how

this can help to enhance our understanding of the differences in the diffusion process in the countries analyzed.

The objective of this study is to understand the adoption of mobile services in three countries of the European Union (France, Germany and the UK). These three countries have similar economic backgrounds, but exhibit substantially differing rates of adoption by the general population. For example, the penetration rate of mobile telephony in the UK in 2004 was higher than 85%, while in France it was around. 69% (Herzog 2005). Part of that difference might be attributed to exogenous factors such as cultural characteristics or differences in the regulatory environment. However, as I will demonstrate, mobile service providers have also played an important role in the adoption of mobile telephony. Reductions in mobile service pricing, the availability of prepaid plans, and the deployment of technologies such as GPRS and UMTS have been critical for the rapid and, in some ways, unexpected diffusion of cellular phones across the world (Van Veen and Lussanet 2005). An assessment of how these factors have influenced adoption rates in different countries can lead to a better understanding not only of the evolution of those markets, but also of the evolution of markets where there are still considerable prospects for growth.

I focus my analysis on the two main pricing decisions of mobile network operators (MNO) in defining their customer acquisition strategy. The first is the issue of how much to charge for the adoption of the service. The second considers how to structure pricing plans. Originally, MNOs marketed mobile telephony using contracts with a two-part tariff comprising a monthly fee and a usage-based call rate. Later, prepaid plans were launched allowing customers - once they had purchased a handset, SIM card, and a calling card voucher- to make calls up to a given value without having to enter into a contract. In this article, I show how the availability of prepaid plans dramatically increased the total number of mobile users (i.e.

a category expansion effect), and how it reduced the rate of mobile contract subscriptions (i.e. a substitution effect). Disentangling the effects of category expansion from those of substitution between contract and prepaid payment plans will allow us to understand more accurately the adoption of mobile telephony in the different countries under study.

To perform this analysis, I develop a micro-model of new product adoption. I model the adoption process as a stopping problem, using a discrete-choice approach, even though estimation can also be performed using aggregate level data as in Song and Chintagunta (2003). There are two reasons for using this approach. First, it allows me to model a market where substitutes are available. Hence, a choice model provides the proper framework to represent the consumer decision. Second, a demand model based on a structural specification of utility can be used for simulations and policy analyses, because the estimated parameters of such models are invariant under equilibrium assumptions (Reiss and Wolak 2007). One of the objectives of this analysis is to assess the impact of prepaid phones in terms of market expansion, and in terms of their substitution of contract phones. I estimate this by means of a counterfactual experiment which simulates a market that has not launched any prepaid plans. Aggregate level diffusion models (Bass 1969), therefore, would prove restrictive for this type of analysis, even though variations of the Bass model have been developed to analyze both brand-level adoption (Krishnan et al. 2000) and successive generations of the same product (Norton and Bass 1987; Danaher et al. 2001).

One of the main challenges in modeling adoption in a utility-based framework lies in how to account for unobservable variables with "carry-over" effects, which significantly influence the consumer's valuation of the product. In the early stages of the product cycle, it is commonly observed that the initial offer of the product becomes more attractive: for example, the new product becomes available with more features, or from more outlets, and there are

fewer doubts about how the product will perform. Some of these improvements will be unobservable to the researcher, and hence included in the model as part of the random error. However, these variables do not affect the consumer's decision in a random fashion because their effects are very likely to remain in the following periods. In this sense, I will refer to them as variables with "carry-over" effects. A failure to acknowledge the existence of carry-over effects on the adoption decision would result in a misspecification in the random utility model, if the observed variables in the model have time trends. This misspecification would affect the value of the estimates of the effects of these observed variables. Therefore, they must be accounted for in order to avoid biasing the estimates. In most cases it will be impossible to give a structural specification of the unobserved errors. Therefore, we have to make some assumptions about how these errors evolve. In this study, I assume that the carry-over effects follow an autoregressive process, and I use a Kalman filter to estimate them, as has been proposed in a similar setting by Sriram et al. (2006).

Results obtained from the analysis of the mobile telephony market in France, Germany, and the UK, shows that the category expansion effect of prepaid plans was greater in the UK, while being less significant in France. The results suggest that in the UK around. 86% of prepaid users would not have adopted mobile telephone services, had prepaid services not been launched. This percentage is 68% in Germany, and 52% in France. Or in other words, in France, the level of substitution of contracts by prepaid phones was much higher. A potential explanation for these results is that prepaid phones were less appealing to light users in France than in the UK. Adoption of prepaid services is greater among light users. Hence, the higher level of substitution or lower level of category expansion of prepaid phones in France could be the outcome of a pricing strategy that excluded a higher proportion of light users than in Germany or the UK. While this study does not assess the optimality of

this decision from the standpoint of maximizing profit, the analysis does suggest that one reason for the differences in levels of adoption between France and its European neighbors could be the decision of French MNOs to avoid higher investment in handset subsidies and launching less appealing prepaid plans.

In summary, cross-country diffusion studies have shown how demand factors, such as demographics and sociological characteristics, are important in explaining why markets evolve over time in different ways. The findings of this study point out that supply factors, such as firm behavior, are also important and, if taken into account, can be useful in deepening the understanding of the reasons behind market evolution.

The contribution of the present research is three-fold. First, I show how using a consumer-level approach in cross-national studies can help us to compare the outcome associated with the behavior of firms in different countries. Second, I discuss the impact of prepaid plans and adoption costs in the diffusion of mobile telephony in different countries. This empirical example shows the critical importance that pricing menus might have on the adoption of some products or services that follow non-linear pricing structures. Third, I contribute to the existing literature on micro-models of new product adoption, by proposing how to account for carry-over effects in these models. Previous models of new product adoption have assumed a specific mechanism that leads the diffusion process: uncertainty reduction, improvements of the performance of the product (Roberts and Urban 1988), and consumers who are forward-looking (Song and Chintagunta 2003). In this study, I present a methodology to be used in situations where it is impossible to disentangle the different mechanisms contributing to the diffusion process.

The paper is structured as follows. I begin by describing the main features of the mobile phone industry in France, Germany, and the UK. This is followed by presenting previous research in developing the model used to perform the proposed analysis. Then, I describe the model and the most relevant estimation issues. Next, I present the results for the three countries, and perform several policy simulations. Finally, I discuss the implications of this study and make suggestions for further research.

1.2. The Mobile Phone Industry

For some years now, the importance of mobile telephony in an economy, as well as the availability of data have motivated academic interest in the subject (see Fildes and Kumar (2002) for a review). In the area of international diffusion, Dekimpe et al. (1998) show how various country characteristics affect diffusion patterns and how they can enhance the quality of mobile adoption forecasts for different countries. Some authors deal with the specific topic of substitution between the various options for adopting mobile services. Krishnan et al. (2000) develop a brand diffusion level model and analyze the impact of a new mobile operator on the diffusion of other brands. Another interesting area for researchers has been the analysis of successive generations of mobile technology (e.g., analog, GSM-900, GSM-1800, GPRS). In these contexts, substitution and competitive effects between technologies are highly relevant both for forecasting (Jun et al. 2002; Islam and Meade 1997), and for estimating changes in the effectiveness of a marketing mix (Danaher et al. 2001). The present study differs from those papers in that its main focus is not forecasting. To my knowledge, there is no study that analyzes how various actions by the MNOs, such as the launching of prepaid payment plans, have driven category growth.

Country	Operator	Service Launched	Prepaid Offered
FRANCE	France Telecom	Oct-85	Mar-97
	Cegetel	Apr-93	Nov-97
	Bouygues	Oct-96	Nov-97
GERMANY	T-Mobile	Sep-85	Feb-97
	Mannesmann Mobilfunk	Jul-92	Sep-97
	E-Plus Mobilfunk	May-94	Jul-97
	Viag Interkom	Oct-98	Jul-99
UK	Vodafone	Jan-85	Sep-96
	O2*	Jan-85	Sep-98
	T-Mobile**	Sep-93	Aug-97
	Orange	Apr-94	Oct-97
	Virgin Mobile***	Nov-99	Nov-99

* Previously, BT Cellnet ** Previously, One2One *** MVNO, joint venture with T-Mobile

Table 1.1. Mobile operators in France, Germany and the UK on June 2001

To better understand the issues under analysis, I will provide a brief description of the mobile industry in France, Germany, and the UK, and some background information about how pricing structure affects the adoption of a usage-based service such as mobile telephony.

1.2.1. Mobile Telephony Evolution in France, Germany and the UK from 1985 to 2002

Vodafone became the first UK mobile operator in 1985, when it launched a "Total Access Control System" (TACS) analog network. Later that year, France Telecom and Deutsche Telekom (T-Mobile) followed suit in their respective countries. Seventeen years later, in 2002, the UK had five operators, Germany had four, and France had three (See Table 1.1). In September 1996, Vodafone launched the first prepaid plan. With the introduction of prepaid plans, market growth began to speed up. For example, in the UK, the rate of subscriber penetration grew from 17% in 1997 to more than 80% by the end of 2002 (Figure 1.1). The differences between countries are remarkable, especially if we compare France's penetration rate of 61% with the UK's rate of 83%.

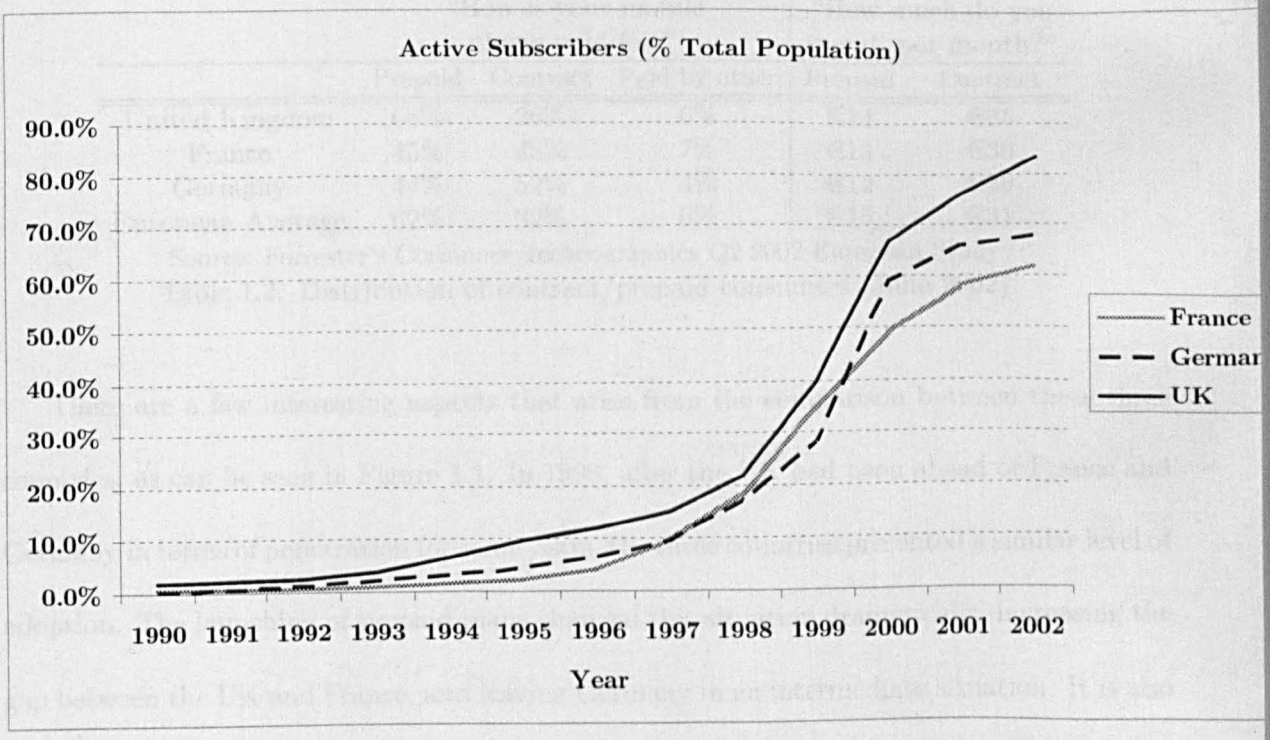

Figure 1.1. Penetration of mobile telephony in France, Germany and the UK. (Source: Forrester Research, Inc.(Lussanet 2004))

In 2002, the ratio between prepaid and contract customers in Germany and France was approx. 50-50 (See Table 1.2), while in the UK the percentage of prepaid customers was significantly higher (68-32). This suggests that, aside from differences in demographic and sociological characteristics that might or might not be present, prepaid plans were marketed more aggressively in the UK than in the other two countries[1]. Thus, we have three countries with different adoption patterns. The UK had a high level of mobile telephone adoption and a high proportion of prepaid phones. France had a lower level of adoption and a relatively high proportion of contract services among mobile users. Meanwhile, Germany had a high level of adoption and the same proportion of contracts as in France.

[1]It is important to note that, unlike in other markets such as the US market, a mobile user in these countries is not charged for receiving calls (the calling party pays). This means that a prepaid user can spend virtually no money if she only uses the mobile phone to receive calls.

	"How is your mobile phone paid for?"			"How much do you spend per month?"	
	Prepaid	Contract	Paid by other	Prepaid	Contract
United Kingdom	68%	26%	6%	€14	€35
France	45%	48%	7%	€14	€30
Germany	44%	52%	4%	€12	€29
European Average	62%	32%	6%	€15	€31

Source: Forrester's Consumer Technographics Q2 2002 European Study

Table 1.2. Distribution of contract/prepaid consumers (June 2002)

There are a few interesting aspects that arise from the comparison between these three countries, as can be seen in Figure 1.1. In 1998, after the UK had been ahead of France and Germany in terms of penetration for some years, the three countries presented a similar level of adoption. The launching of prepaid plans changed this situation dramatically, increasing the gap between the UK and France, and leaving Germany in an intermediate situation. It is also interesting to note that, in 1999, France had a higher penetration rate than Germany. This situation changed one year later when the adoption rate increased considerably in Germany considerably increased its rate of adoption, leaving France behind in terms of mobile usage. It is difficult to consider demographic or cultural factors - that are relatively stable - as explaining these patterns of adoption. In the following section I discuss how pricing decisions taken by the MNOs in the different countries, and the impact of prepaid plans, can partly offer an explanation to understand the evolution of mobile telephony in these markets.

1.2.2. Adoption of Mobile Telephony

Adopting mobile telephony involves certain up-front costs: the cost of acquiring the handset and other payments, such as connection charges. Jain, et al. (1999) developed a game theoretic model to explain why handset prices declined over time in markets with more than one operator, while the price of phone calls remained constant. In their study, they show empirically that light users (measured in terms of call usage) of mobile services were more price sensitive to handset prices than heavy users, with the reverse being true for call rates.

In addition, they show, using a conjoint analysis, that consumers give greater importance to the price of the handset than to the price of phone calls. This suggests that handset prices were more important to the adoption decision than per minute call rates and, therefore, the incentive to reduce up-front costs through subsidizing handsets might be justified to encourage adoption.

Hence, it is important to consider up-front costs as being critical to adoption. This helps explain why, since the inception of mobile telephony, MNOs have marketed this service as usage-based with a two-part tariff price structure. A service marketed only with a two-part tariff will normally have a higher adoption usage threshold than the same service marketed with a pure usage-based payment plan (Oren, Smith and Wilson 1982). A contract of a pre-determined length and with periodic fixed fees can be less appealing to a potential adopter who is not certain about committing themselves to the service or is expecting to be a light user, than the freedom conferred by a linear pricing plan. Thus, launching a product with a two-part tariff contract only seems to go against the logic of mass adoption. On the other hand, however, customers signing telephony contracts assure future revenue for MNOs, thereby making handset subsidization less risky.

The business practice of subsidizing adoption costs to capitalize on future revenue streams is used widely in various industries. Telecommunication services provide a clear example (e.g., satellite radio), but the practice is also common in situations where adoption locks in customers with switching costs. Such situations arise in areas such as video-games where the vast bulk of revenue for console makers - e.g., Sony, Nintendo, Microsoft - comes from royalties from game sales (Hall et al. 2006). Inkjet printers offers another example, in that manufacturers' profits come mainly from ink cartridges (Tam 2004). In mobile telephony, MNOs have

used two-part tariff contracts to reduce the risks associated with handset subsidies, assuring a minimum amount of revenue per customer.

That policy changed when some MNOs started offering usage-based pricing schemes without monthly fees (i.e. prepaid plans). Customers welcomed this alternative to postpaid contracts of at least 12 months duration with monthly fees, even when the prepaid tariffs were often a more expensive option. With handsets becoming cheaper and MNOs heavily subsidizing adoption costs, prepaid plans became very attractive to consumer segments who could not enter into a contract plan because of lack of credit, or who were interested in avoiding unexpectedly large bills (e.g., parents wishing to control the expenditures of their children). Below, I present the evolution of prices for contracts and prepaid phones in France, Germany, and the UK.

1.2.3. Impact of Adoption Costs

Figure 1.2 shows the evolution of the cost of using a mobile phone for 30 minutes each month with a contract ($CCOST$) and the cost of buying a prepaid package ($PCOST$) for the three countries[2]. We find that the UK market was ahead of the French and German markets in lowering prices. We also see how this price differences were reduced from 1998 onwards. In June 2001, Germany offered the cheapest contract plans, and adoption costs for prepaid phones were almost the same in the three countries. Not surprisingly, the evolution of mobile telephony in the UK was faster than in the other two countries and this might be attributed to higher investments in customer acquisition. France and Germany later reduced the considerable gap between their up-front costs of adoption and those in the UK, and

[2]They are presented in natural logs. I include handset costs, connection charges, and calling costs using the cheapest option available in the market. More details are provided in the section description the data from the empirical analysis in section 1.6.

consequently the level of adoption became very similar before the launch of prepaid phones (see Figure 1.1 for adoption levels in 1998).

As concerns the cost of adopting a prepaid plan, between June 1998 and January 2000 in the UK and Germany prices were lower than in France. Light users regard adoption costs as comparatively more relevant, as for this consumer segment they represent a higher percentage of total expenditure for service usage. The effect of category expansion of prepaid phones in the UK and Germany, therefore, should be more important than in France, where we should observe a higher level of substitution between prepaid and contract phones. The rationale for this is that the lower mobile telephony pricing available in Germany and the UK is more appealing to light users and thus has expanded the market to a greater extent.

We see how - besides differences in cultural factors – MNO's have followed different pricing strategies in France, Germany, and the UK. In view of this situation, I will formally analyze how up-front costs and the availability of prepaid plans affected the diffusion of mobile telephony in the three countries. For example, it would be interesting to answer whether prepaid plans have had mainly a substitution or a category expansion effect in the three countries under study. If the patterns of substitution and category expansion are similar for the three countries, cultural factors might be indeed the ultimate reason for the lower penetration of mobile telephony in France relative to the UK. But if these patterns are not the same, we could think about the supply factors that have motivated these differences,enabling us to better understand the reasons behind the market evolution of those markets In the next section, I present the theoretical background for building a model capable of answering the question of how price changes and the launching of prepaid plans impacted the evolution of mobile telephony.

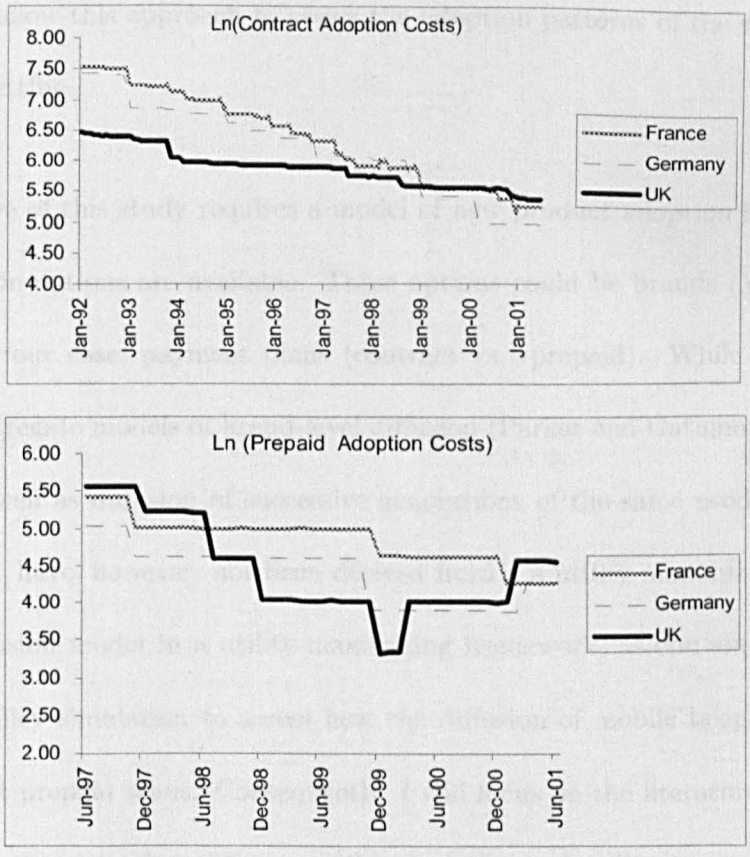

Figure 1.2. $\ln(CCOST)$ and $\ln(PCOST)$ for France Germany and the UK.

1.3. Model Background

The typical approach in cross-national diffusion studies tends to focus on understanding the evolution of the hazard rate function of the population under study by applying, for example, some version of the Bass model (1969) (see Mahajan et al.(2000) for a review). This approach usually models category sales, and remains agnostic about the underlying process of consumer choice. On the other hand, micro-models of new product adoption look at consumer choice to explain diffusion patterns (Roberts and Lattin 2000). These individual-level diffusion models derived from economic theory attempt to model changes in the utility of an innovation over time. This approach has the advantage that by looking at individual consumers one can ground the model in discrete-choice theory (Roberts and Urban 1988). In

this chapter, I follow this approach to assess the adoption patterns of the same product in a cross-national setting.

The objective of this study requires a model of new product adoption in contexts where different adoption options are available. These options could be brands (Vodafone vs. Orange), or, as in our case, payment plans (contract vs. prepaid). While there is existing literature on aggregate models of brand-level diffusion (Parker and Gatignon 1994; Krishnan el al. 2000) as well as diffusion of successive generations of the same product (Norton and Bass 1987), they have, however, not been derived from a a utility maximization framework. I develop a diffusion model in a utility-maximizing framework, as one aim of this study is to perform a policy simulation to assess how the diffusion of mobile telephony *would have occurred* without prepaid plans. Consequently, I will focus on the literature of new product adoption models that considers diffusion within an individual utility-maximizing framework.

1.3.1. Diffusion and Utility-Maximizing Behavior

Fourt and Woodlock (1960) propose a simple model of new product adoption that is capable of capturing the pattern of first purchases of many new groceries in the United States. The underlying behavioral assumption of their model was the existence of a constant set of homogenous consumers with an unconditional constant probability of adoption. If we translate this assumption into a random utility representation, we get a model that assumes a group of homogenous consumers with a constant non-random utility. (Left part of Figure 1.3).

In the right upper part of Figure 1.3, I present the pattern of the cumulative number of adopters as generated using a Bass model (1969). Suppose now that all the potential adopters are homogenous and will adopt the product if their utility exceeds a threshold. If the error of the utility is Gumbel-distributed (i.e., the unconditional probabilities of adoption

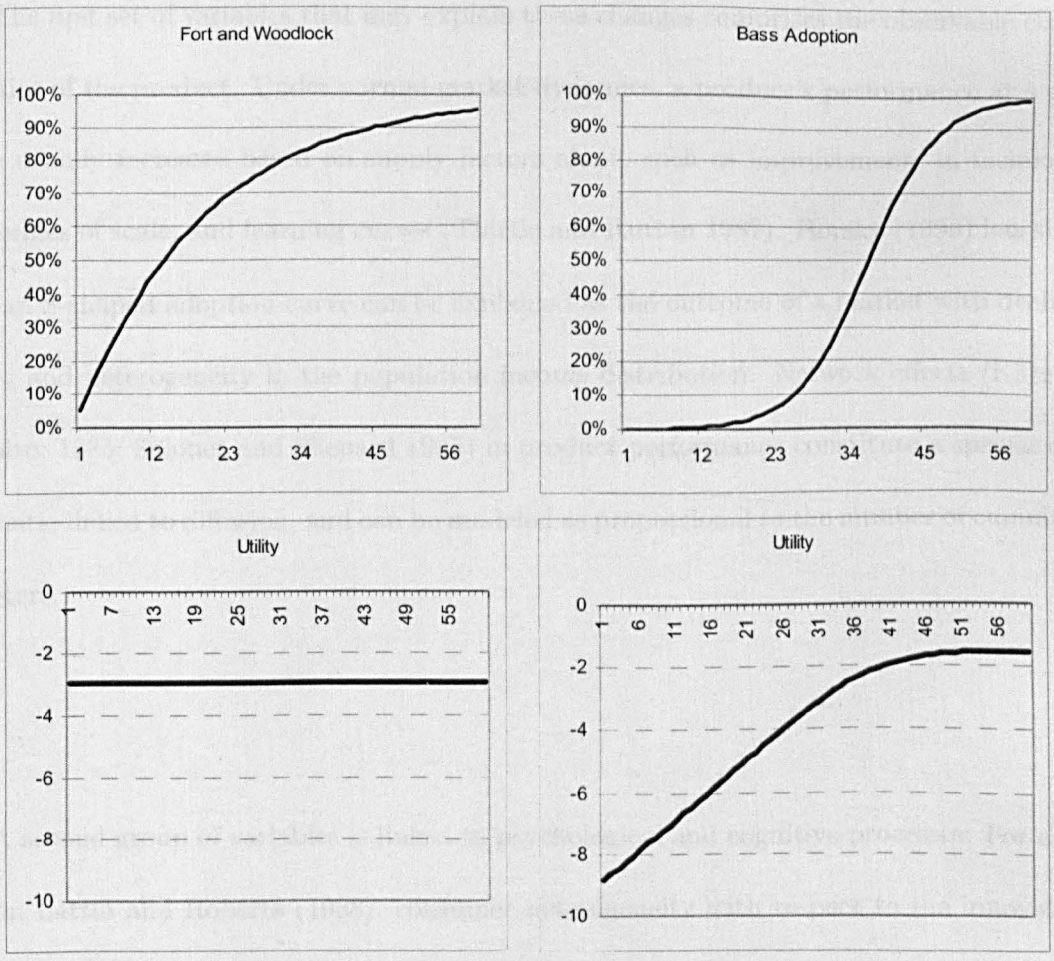

Figure 1.3. Latent utility associated to the Fort and Woodlock (1960) and Bass (1969) adoption models (Assuming logit probabilities)

follow a logit model), the evolution of the non-random part of the utility of adoption for these consumers takes the shape represented in the lower right part of Figure 1.3.

If we accept that the Bass model is a good representation of the diffusion process of a new product, we can see that, approaching it from the standpoint of random utility theory, the main characteristic of an S-shaped adoption curve is that the consumers' utility to adopt increases for a period of time. Previous research on diffusion models that are based on individual-level explanations of the adoption decision attributes these increases to various driving factors.

The first set of variables that may explain these changes comprises the observable characteristics of the product. Under normal market dynamics, a product's performance at a given price usually increases based on supply factors alone, such as improvements in technology, economies of scale, and learning curves (Thirtle and Ruttan 1987). Horsky (1990) has shown how an S-shaped adoption curve can be explained as the outcome of a market with declining prices and heterogeneity in the population income distribution. Network effects (Katz and Shapiro, 1985; Saloner and Shepard 1995) in product performance constitute a special characteristic linked to diffusion, and can be modeled as proportional to the number of cumulative adopters.

A second group of variables is linked to psychological and cognitive processes. For example, in Lattin and Roberts (1988), consumer heterogeneity with respect to the innovation's potential benefits drives the diffusion process. In Chaterjee and Eliashbergh (1990) diffusion is explained by assuming that there is consumer heterogeneity with respect to initial perceptions of the product, preference characteristics, and responsiveness to information. Roberts and Urban (1988) assume that "as consumers gain more information about the brand, beliefs about mean attribute levels and uncertainty change. Bayesian updating provides the framework used to incorporate the effect of new information on a potential consumer's prior beliefs and information uncertainty" (p. 169). Finally, Song and Chintagunta (2003) explain the adoption of a new brand in contexts where consumers are forward-looking and have heterogeneity in their tastes. Consumers make a trade-off between the utility of adopting now and the utility of adopting in future periods. This assumption introduces dynamics into the market that are dependent on the consumer's anticipation of future conditions. Markets where expectations are higher in view of future improvements will have higher disutility of

early adoption. Song and Chintagunta use their model to explain the evolution of sales in the digital camera category and assess the impact of entry of a new brand.

A third explanation of how consumer utility evolves over time has its theoretical foundations in sociology, and states that it is information about who has adopted, rather than about the innovation itself, that generates social bandwagon pressure on potential adopters to conform to other adopters (Abrahamson and Rosenkopf 1997). The behavioral interpretation behind the Bass model is related to this explanation: the model's coefficients are linked to "internal" and "external" influences in the decision to adopt. In this case, as in all bandwagon explanations of diffusion, the utility of adoption increases with the number of adopters.

Explanations that account for the dynamics of the utility to adopt a new product have different roots and suggest why the utility of adopting a new product can change over time. Hence, we have to consider carefully how to model these factors if we want to develop a random utility model to explain the adoption decision. In this study, I develop a utility-based model to analyze the adoption of categories where substitutes are available. I assume that there are unobserved variables with carry-over effects following an autoregressive process. It is an individual level model but it can be calculated with aggregate data, capturing consumer heterogeneity by means of simulation methods (Train 2003). This model combines the approach offered by Song and Chintagunta (2003), modeling adoption as a stopping problem, and the proposed methodology from Sriram et al.(2006) of using a Kalman filter estimation to measure an autoregressive term in a brand choice model.

1.4. Model

Let us denote:

- t subscript for time period t=1,2,3,...

- i subscript for consumer $i = 1, 2, 3...M$
- j subscript for option, j=0, contract, prepaid where 0 denotes the "no purchase" option or outside good.
- x_{jt}, variables observed by both the consumers and the researcher.
- y_{jt}, variables observed by the consumers but not by the researcher with carry-over effects
- β_i, individual level parameters

As in Song and Chintagunta (2003), I set up the adoption decision as a stopping problem. I assume that consumers have an individual utility of adoption for each option. If consumer's i utility for option j exceeds a certain threshold, she adopts option j and exits the market. There are no repeat purchases and the consumer who has exit the market cannot select another option in later periods. Given this, the individual probability of entering the market at time t with option j is:

$$h_{ijt} = p_{ijt} \prod_{\tau=1}^{t-1} p_{i0\tau} \ , \tag{1.1}$$

where p_{ijt}, is the probability of consumer i of adopting brand j at period t and $p_{i0\tau}$ is the probability of consumer i of non-adoption in a previous period τ. The probabilities p_{ijt} are determined by the utility that option j provides to consumer i in each period. Let us define this utility as:

$$U_{ijt} = x_{jt}\beta_i + \zeta_{ijt}(y_{jt}, \omega_{ijt}), \tag{1.2}$$

where x_{jt} are observable variables, β_i is the vector of parameters associated with these variables and ζ_{ijt} are variables observed by the consumer but unobserved by the econometrician. There are two sources of error in the set of unobservable variables: an idiosyncratic random

component (ω_{ijt}) and another component coming from unobserved common shocks that have carry-over effects (y_{jt}). In many cases, the observed variables will be non stationary due to a time-trend (e.g., decreasing prices, increasing levels of observed quality). If the unobserved variables are also non-stationary, the errors will be correlated with the observed variables inducing a potential bias in the estimation of the parameters.

1.4.1. Modeling Carry-over Effects

What is the nature of these "carry-over effects"? Let us assume, for example, that consumers value mobile service providers with better coverage and that this variable is unobserved by the econometrician. This unobserved factor will be included in the error of the utility model. It is evident that this part of the error will not be random. In general, network coverage will improve over time. Therefore, when modeling the adoption of a new product, we consider a situation were the errors are not independent and random: the product quality will usually improve, consumers will learn more about the product in further stages of the diffusion process, and social influence to adopt will increase or decrease but will probably follow an autocorrelated pattern. In other words, we expect that the changes that take place during one period will still be there to some extent during the following periods. Sriram et al. (2006) develop a similar reasoning to model the evolution of brand preferences as an autoregressive process in a choice setting.

Hence, we need to account for these carry-over effects to avoid misspecification. In some situations, it will not be possible to justify any specific structural form to account for the effect of these unobservable variables that remain from one period to the next. Therefore, I assume that the unobserved variables that have carry-over effects follow an autoregressive process. This approach, without analyzing the specific driving factor that leads the diffusion process, would capture the basic feature of those variables with carry-over effects: the best predictor

of the unobservable variable in this period is a function of that variable in the previous one. Thus, if we assume further that the unobserved error terms have an additive structure and that the part of the error related to the carry-over effects follows an autoregressive process, then,

$$\zeta_{ijt} = \theta_{jt}(y_{jt}) + \omega_{ijt} \tag{1.3a}$$

$$\theta_{jt} = \rho_{0j} + \rho_{1j}\theta_{jt-1} + \nu_{jt}, \tag{1.3b}$$

where ρ_{0j} and ρ_{1j} are the parameters of the autoregressive process and ν_{jt} are i.i.d errors. With this structure, we capture that the mean valuation of option j, common to all consumers, changes over time. We expect θ_{jt} to have a positive trend because it captures features such as changes in quality, reduction of uncertainty, and social imitation that facilitate adoption.

1.4.2. A Nested Logit Specification and Individual Heterogeneity

Having considered equation (1.3a), I assume that individual heterogeneity in tastes can be captured as a random coefficient on the intercept. If we follow the assumptions about the distribution of the errors of Berry, Levinshon and Pakes (1995), the utility for consumer i to adopt product j in period time t can be written as:

$$U_{ijt} = \mu_{0j} + \mu_{ij} + x_{jt}\beta + \theta_{jt} + \xi_{jt} + \lambda\varepsilon_{ijt}, \tag{1.4}$$

where μ_{0j} is the mean intercept of the population for option j, $\mu_{ij} \sim N(0, \Sigma_{\mu}^2)$ captures heterogeneity as a deviation from the population mean . As noted by Song and Chintagunta (2003), it is important to account for individual heterogeneity in consumer tastes given that the percentage of potential consumers changes over time because those who value the product more highly tend to adopt it earlier (Goldenberg et al. 2002). Consequently, heterogeneity

not only adds flexibility to the pattern of the market-level adoption curve but is useful for obtaining more accurate estimates.

The term ξ_{jt} represents the part of the error that is brand specific and it is observed by the consumer but not by the econometrician. This error is assumed to be distributed $N\left(0, \sigma_{\xi}^{2}\right)$. This error is uncorrelated with time and captures demand shocks that are specific to one option. The error $\lambda\varepsilon_{ijt}$ is assumed to be general extreme value distributed (Train 2003; Verboven and Brenkers 2006) This type of distribution gives rise to the nested logit model. I propose analyzing the problem by imposing a minimum nested structure in the buying process because the decision to buy a category precedes the decision as to which option to buy. With the error thus specified, integration of the stochastic part of the utility has a closed solution form. Now, if we define

$$\delta_{jt} = \mu_{0j} + x_{jt}\beta + \theta_{jt} + \xi_{jt}, \tag{1.5}$$

as the mean value of option j, the probability of consumer i of adopting product j in period t can be written as:

$$p_{ijt} = \frac{\lambda I_{it}}{1+\lambda I_{it}} \frac{\exp\left(\frac{\delta_{jt}+\mu_{ij}}{\lambda}\right)}{\sum_{k=1}^{J} \exp\left(\frac{\delta_{kt}+\mu_{ik}}{\lambda}\right)} \tag{1.6}$$

$$I_{it} = \ln\left(\sum_{k=1}^{J} \exp\left(\frac{\delta_{kt}+\mu_{ik}}{\lambda}\right)\right), \tag{1.7}$$

where we have normalized the utility of the outside good (i.e. non-adoption) to zero. The term I_{it} is known as the inclusive value. The first part of p_{ijt} is the category choice probability. Hence, the probability of not adopting any option in period t can be written as:

$$p_{i0t} = \frac{1}{1 + \lambda I_{it}} \tag{1.8}$$

The nested logit model formally acknowledges that non-adoption of the product is different from the other alternatives and presents a different pattern of substitution relative to the various inside options (Villas Boas and Zhao 2005). If $\lambda \rightarrow 0$, the various options are perfect substitutes. The value of λ has to be in the interval (0,1] and is an indicator of the correlation of the elements inside the nest. We recover a standard logit when $\lambda = 1$.

1.4.3. Modeling Time Varying Parameters

Some researchers have modeled time varying parameters in diffusion models to improve their forecasting ability. For example, Xie et al. (1997) use an augmented Kalman filter with continuous states and discrete observations with the Bass model. Van Everdingen et al. (2005) combine the previous methodology with the matching procedure proposed by Dekimpe, Parker and Sarvary (1998) to study the diffusion of Internet access and mobile telephony among households in 15 countries of the European Union. Van Herde et al. (2004) use a dynamic linear model (DLM) to calculate time varying parameters in situations where there is important cross-sectional heterogeneity and missing data. With this approach, they measure the impact of an innovation in the market structure of the frozen pizza category in the US.

In a choice model context, Sriram et al. (2006) use a Kalman filter estimation to control the evolution of brand preferences. They model brand preferences as time varying parameters to capture the influence of marketing actions such as brand-level advertising. I follow their approach, as the same considerations apply to the current setting.

From equation (1.5) we see that the mean utility values δ_{jt} depend on the time varying parameters θ_{jt} that follow an autoregressive process. There is a unique mapping between

observed shares and mean utilities given λ and σ_μ^2 (Berry 1994). Hence, the evolution $\delta_{jt}|\lambda, \sigma_\mu^2$ can be seen as the state-space representation of a dynamic system (Hamilton 1996):

$$\delta_{jt} = \mu_{0j} + x_{jt}\beta + \theta_{jt} + \xi_{jt} \tag{1.9}$$

$$\theta_{jt} = \rho_{0j} + \rho_{1j}\theta_{jt-1} + \nu_{jt}, \tag{1.10}$$

where (1.9) is known as the observation equation and (1.10) as the state equation. Assuming independence of θ_{jt} with any of the realizations of ξ_{jt} and ν_{jt}, this system can be solved recursively by using a Kalman filter estimation. Moreover, if ξ_{jt} and ν_{jt} are Gaussian, it can be shown (as it is described in Appendix A) that the distribution of δ_{jt} conditioned on the value of x_{jt} and the information set through date $t-1$ ($\Delta_{t-1} \equiv \delta_{jt-1}, \delta_{jt-2}..., \delta_{j1}, x_{jt-1}, x_{jt-2}..., x_{j1}$) can be written as:

$$\delta_{jt}|x_{jt}, \Delta_{t-1} \sim N\left(\mu_{0j} + x_{jt}\beta + \theta_{jt|t-1}, \Sigma_{t|t-1}\right) \equiv N\left(\overline{\delta}_{jt}, \Sigma_{t|t-1}\right), \tag{1.11}$$

where $\theta_{jt|t-1} = \rho_{0j} + \rho_{1j}\theta_{jt-1}$ is the best guess of the time varying parameter given Δ_{t-1}. The covariance $\Sigma_{t|t-1}$, defined also in Appendix A, captures the propagation of the error ν_{jt} through the dynamic system jointly with the error of the observation equation (ξ_{jt}).

1.4.4. Accounting for Individual Heterogeneity

I consider individual heterogeneity as a deviation from the population mean. I do not include heterogeneity in other parameters given to the fact that consumers only choose one option once. In this kind of setting it is not clear that we could distinguish heterogeneity in the intercept (μ_{ij}) from heterogeneity in another parameter. Hence, conditional on the individual level heterogeneity parameter (μ_{ij}), we could write the likelihood of an individual adopting product j in period t as follows. Let us denote:

$$A_{ijt} = \begin{cases} 1 \text{ if consumer } i \text{ adopted product } j \text{ during period } t \\ 0 \text{ otherwise} \end{cases} \tag{1.12}$$

After consumer i chooses a product, she exits the market. This implies that for an observation of T periods:

$$A_{ijt} = 1 \Rightarrow A_{ik\tau} = 0 \;\; \forall \; k = 1, ..., J, \;\; \tau = t+1, ..., T \tag{1.13}$$

Then, the log-likelihood for the A_{ijt} choices is:

$$\ln\left(A_{ijt}|\lambda, \mu_{ij}, \Omega(\mu_{0j}, \beta, \rho...), x_{jt}\right) = \sum_{i=1}^{M}\sum_{j=1}^{J}\sum_{t=1}^{T} A_{ijt} \ln(h_{ijt}) \tag{1.14}$$

where h_{ijt} is the probability defined in Equation (1.1). To derive the aggregate number of adopters we have to integrate the individual parameters over their distribution. I approximate this integral with a Monte-Carlo simulation averaging over the D realizations $(\overline{\mu}_d)$ of the heterogeneity distribution $N(0, \Sigma_\mu^2)$ where $\overline{\mu}_d$ is of dimension J :

$$\ln\left(n_{jt}|\lambda, \Sigma_\mu^2, \Omega(\mu_{0j}, \beta, \rho...), x_{jt}\right) = \int \sum_{i=1}^{M}\sum_{j=1}^{J}\sum_{t=1}^{T} A_{ijt} \ln(h_{ijt}(\delta_{jt}; \mu_{ij}))dP(\mu_{ij}) \tag{1.15}$$

$$\approx \frac{K}{D}\sum_{d=1}^{D}\sum_{j=1}^{J}\sum_{t=1}^{T} n_{jt} \ln(h_{djt}|\lambda, \overline{\mu}_d, \delta_{jt}), \tag{1.16}$$

where K is a constant combinatorial number associated with that multinomial process. Note that once we have integrated the heterogeneity distribution, the likelihood function is now defined over the aggregate number of adopters n_{jt}. Finally, note that the estimation should also include the consumers in the market who have not adopted by the end of the T periods. If we define $S_{jt} = \frac{1}{D}\sum_{d=1}^{D} \ln(h_{djt}|\lambda, \overline{\mu}_d, \delta_{jt})$,the log-likelihood of the data for T periods can be written as:

$$LL = \sum_{j=1}^{J}\sum_{t=1}^{T} n_{jt} \ln\left(S_{jt}\right) + \left(M - N\left(T\right)\right) \ln\left(1 - \sum_{j=1}^{J}\sum_{t=1}^{T} S_{jt}\right), \tag{1.17}$$

where M is the market potential and $N(T)$ is the cumulative number of adopters at time T. Hence, the value of the log-likelihood is conditional on the market potential. As in Song and Chintagunta (2003), I assume that this value is known and fixed. In the empirical application, I will use an estimate of the total population for each country for M.

1.5. Estimation

1.5.1. Assumption of Exogeneity

Sriram et al. (2006) use a generalized method of moments (GMM) approach in their estimation to account for price endogeneity. I do not consider endogeneity issues in my empirical application. In other words, I assume that there is no correlation between the observable variables (x_{jt}) and the random error (ξ_{jt}). More specifically, I assume that adoption costs are set independently of random demand shocks unobserved by the econometrician. There are several reasons for this. First, tariff changes involve significant administrative costs for MNOs and do not adapt as easily to random shocks as prices in other products or services, such as packaged goods. Therefore, mobile telephony can be considered as an industry where endogeneity problems might be less severe than other industries where price changes are easier to implement. The second reason is a practical one: it is not clear what kind of instruments we could use to correct any endogeneity problems. Marginal cost of a mobile telephone call is zero, and prices in other markets, as we have seen in Section 1.2, are not necessarily representative of the prices in a focal market. In the last section of this paper, I point out some relevant aspects about how to deal with endogeneity issues among other suggestions for further research.

Basket	100 calls/year	200 calls/year	400 calls/year	3100 calls/year
France	Cont* / Pre	Pre / Cont	Pre / Cont	Cont /Cont
Germany	Cont / Cont	Cont / Cont	Cont / Cont	Cont / Cont
UK	Pre / Pre	Pre / Pre	Pre/Cont	Cont / pre

* In France, the cheapest option for a basket of 100 calls/year was a contract and the second cheapest a prepaid package (Source: Ofcom 2001):

Table 1.3. Two cheapest options available in each country for different patterns of consumption (December 2001)

It is also important to point out that prepaid plans are not an inferior or cheaper option for mobile telephony. In this instance, one could argue that prepaid plans were used as an intertemporal price discrimination tool. In fact, prepaid plans were often a more expensive option for different patterns of usage in the three countries under study. The attractiveness of a prepaid plan as compared to a two-part tariff contract is determined by two elements: the monthly fee, and the difference in call rates associated with the two options.

In Table 1.3 we present the two cheapest options available in 2002 for various usage patterns in the three countries. For a UK customer, the cheapest options were always with prepaid mobiles, except when usage was high. In Germany, consumers always were better off with contract plans, while in France the two options were comparable, except when usage was high, in which case contract services were the better option (Ofcom 2001). Hence, we see how prepaid plans were positioned in different ways to attract light users, consumers unable to enter into a one-year contract, or those who not have a bank account (tourists, teens, etc.).

The assumption of exogeneity allow us to establish the estimation procedure over n_{jt} and exploit the normality conditions of an approach based on a maximum likelihood estimation.

1.5.2. Mapping of the Mean Utilities

It is important to note that there is no contraction mapping of n_{jt} on δ_{jt} for the proposed model. In other words, there is no autorecursive procedure, such as the one described in

Berry (1994) to recover $\delta_{jt}|\lambda, \sigma_\mu^2$. A possible approach to overcome this problem consists in doing the search manually from a starting point that is close to the mean valuations δ_{jt} and is easy to estimate. I propose taking as a starting point the mean valuation δ_{jt}^* for the static choice of the market consumers who have not adopted yet, and to proceed as follows:

(1) Define:

$$ms_{jt}^* = \frac{n_{jt}}{\left(M - \sum_{j=1}^{J} \sum_{\tau=1}^{t-1} n_{j\tau}\right)} \tag{1.18}$$

(2) Calculate the contraction mapping for the shares ms_{jt}^* to the integral of the probabilities described in equation(1.6). obtaining $\delta_{jt}^*|\lambda, \sigma_\mu^2$

(3) Look for the values e_t to recover the observed market shares $\left(ms_{jt} = \frac{n_{jt}}{M}\right)$.

(4) To complete the search routine, set up a tolerance error over the differences on the logarithms of observed data and predicted by the model in order to keep the relative errors below a threshold. In the empirical application of this study I set up $\epsilon = 0.01$. [3]

$$\left[\log\left(S_{jt}(\delta_{jt} = \delta_{jt}^* + e_t)\right) - \log(ms_{jt})\right] < \epsilon, \tag{1.19}$$

There are three factors that facilitate the mapping of δ_{jt} using δ_{jt}^* as a starting point. First, if σ_μ^2 =0, δ_{jt}^* is analytically δ_{jt} . Second, the values e_t are always positive and the search routine is trivial. Third, the values e_t are not option specific. In other words, e_t are common for all brands for a given period and the complexity of the search only depends on the number of periods but not in the number of brands.

[3]This error is small enough to provide accurate estimates of $\delta_{jt}|\lambda, \sigma_\mu^2$ (error in the 4th significant digit) and it is still computationally fast

1.5.3. Procedure

I built the estimation procedure around the likelihood of the observable data (n_{jt}). Given λ, σ_μ^2, I obtained the mean valuation δ_{jt} as described in the previous section. Through the recursive method described in Appendix A, the parameters of the dynamic system $\Omega(\mu_{0j}, \beta, \rho...)$ determine an estimate of the mean utility values $\overline{\delta}_{jt}$ as defined in equation(1.11). Therefore, conditional on the information set through date $t-1$ (Δ_{t-1}) the likelihood can be written as:

$$(n_{jt}|\lambda, \sigma_\mu^2, \Omega(\mu_{0j}, \beta, \rho...), x_{jt}) = (n_{jt}|\lambda, \sigma_\mu^2, \overline{\delta}_{jt}, \Delta_{t-1}, x_{jt}) \tag{1.20}$$

Finally, some adoption figures for this empirical application are higher than one million. This automatically implies a very high level of precision in the estimates of the model. To provide more conservative confidence intervals of the estimates I acknowledge that the reported data has some random measurement errors (rounding, misreporting). Hence, I assume that there is no perfect observation of n_{jt} and run the analysis with simulated data ($\widehat{n}_{jt}$) coming from the distribution $\widehat{n}_{jt} \sim N\left(n_{jt}, \sqrt{n_{jt}(1-ci)}\right)$ where n_{jt} is the reported data and ci is a confidence interval. For this empirical application, I performed 100 replications of the analysis assuming a $ci = 99\%$. In other words, I assume that there is a standard deviation of the measurement error of 1% and I report confidence intervals related to those simulations.

1.5.4. Simulation Studies

I generated datasets with known parameters to assess whether these parameters can be recovered with the suggested estimation procedure. I compared the performance of the proposed model with (1) a model that does not carry over effects and (2) a model that captures carryover effects with a time-varying functional form. Previous research has suggested capturing diffusion effects with a function of time. For example, Jun et al. (2001) use individual-level data to develop a forecast model to predict the pattern of substitution from analog mobile

phones to digital. In their paper, unobserved variables affecting diffusion are modeled as a time-linear function. In a different study, Kim et al. (2001) model network externalities, psychological utility, and other factors as a concave function related to the cumulative number of adopters.

I ran simulations of various sizes with the unobserved factors $(\sigma_\xi^2, \sigma_\nu^2)$. For datasets with a similar structure to the one in this empirical application, the estimation procedure recovered the parameters, and I observed the following:

(1) As expected, if the model does not include carry-over effects and these effects are present, there is an upward bias in the observed variables (i.e., the effect of the observed variables is overestimated).

(2) The estimates of modeling carry-over effects with a time-varying functional form are contingent to the chosen functional form. In other words, if the "true model" has carry-over effects that follow an autoregressive process, then a model with a quadratic form of a time counter (t, t^2) or the cumulative number of adopters (N, N^2) would not recover the true parameters..These models would be easier to estimate but the estimates would not necessary be consistent with the "true" ones.

(3) The variances of the errors $(\sigma_\xi^2, \sigma_\nu^2)$ are difficult to identify empirically. However, there is a relationship between the errors that can be estimated correctly and this is enough to identify the other parameters. See Appendix A for a discussion about this issue.

1.6. Empirical Analysis

As mentioned above, the main purpose of this analysis is to understand the comparative differences in mobile service adoption in France, Germany, and the UK. To this end, it is vital to assess the impact that adoption costs and the introduction of prepaid services had in each

country. It is interesting to note that the segment of the population that benefits most from a prepaid phone is that comprising light or occasional users - who regard the fixed fee of a monthly contract as too high in relation to their level of usage - and customers without bank accounts, such as teenagers, etc... Therefore, the proportion of category expansion relative to the substitution effect is an interesting magnitude reflecting the comparative appeal of each of the two payment options, especially among light users. For example, a situation with a high level of expansion in the prepaid category and little substitution would imply that prepaid phones were targeted by consumers who otherwise would have not entered into a contractual relationship. The comparison of the three countries under study allows us to draw some conclusions about these aspects.

1.6.1. Data

I apply the model to a data set of active monthly subscribers for mobile telephony in France, Germany, and the UK between 1992 and June 2001. At the beginning of the observation period, the rate of adoption was lower than 2% in the three countries. Hence, the unobserved period –from 1985 to 1992– is marginal in terms of total adoption.

I consider the consumer decision to buy a service from an MNO given the option of two payment modalities: a monthly contract or prepaid. I account for the fact that contract phones were the only option available until prepaid plans were launched during 1996 and 1997.

I assume that customers who switched mobile operators did not change payment plan type. This seems a reasonable assumption, given that when prepaid plans were launched mobile phone penetration was less than 12% in the countries under consideration. That means that the number of prepaid users who had a mobile contract before getting a prepaid

phone is very low in comparison with the total number of new prepaid adopters[4]. On the other hand, I would not recommend using this model to analyze the mobile telephony market at the MNO firm level: "churn" between companies was high, and should be taken into account in the modeling approach. I collected information on the number of monthly active subscribers, monthly contract fees, call rates, connection charges, and prices for prepaid packages from the EMC World Cellular Database. In compiling price data, I looked for the cheapest option available in the market during each period. Additional information for handset costs was collected from public sources such as the Office of Communication (Ofcom) in the UK.

With this data, I define the non-random part of the utility for the equation's two options in the following way (I drop the time subscript):

$$U_{ic} = V_{ik} + V_c \tag{1.21}$$

$$U_{ip} = V_{ik} + V_p \tag{1.22}$$

$$V_{ik} = \mu_i + \beta_1 XTMASS \tag{1.23}$$

$$V_c = \mu_c + \beta_{2c} CCOST + \theta_c \tag{1.24}$$

$$V_p = \mu_p + \beta_{2p} PCOST + \theta_p \,, \tag{1.25}$$

where U_{ic} is the utility for a contract plan and U_{ip} is the utility for a prepaid plan. V_{ik} is the part of the utility that is common to both options while V_c and V_p designate the part of the utilities relating specifically to the alternatives. Heterogeneity is included in the intercept (μ_i) as a random draw from a normal distribution[5]. Note that I introduce heterogeneity at the category level and there are not IIA problems inside the members of the nest. With more than

[4]An exception to this pattern can be found in Italy. There, the inrush of prepaid plans seriously affected the migration of active contract mobile phone subscribers to prepaid plans. This pattern is not observed in any of the three countries analyzed.

[5]In the estimations, I use 200 random Halton draws. Replications of the model with different random draws justifies this number as being sufficient to cover the heterogeneity distribution

two options, I recommend using the Cholesky decomposition of the heterogeneity variance-covariance matrix as is the usual procedure in random coefficient logit models (Chintagunta 2002). Therefore, the mean valuation of the utility for the contract and prepaid option can be written as:

$$\delta_c = \mu_c + \beta_1 XTMASS + \beta_{2c} CCOST + \theta_c \quad (1.26)$$

$$\delta_p = \mu_p + \beta_1 XTMASS + \beta_{2p} PCOST + \theta_p \quad (1.27)$$

where θ_c and θ_p are the time varying parameters that capture the carry-over effects of equation (1.3). $XTMASS$ is a dummy variable for the Christmas period (December) when mobile operators heavily promote their offers. $CCOST$ is calculated as the natural log of the yearly cost of a contract mobile phone. I include handset costs[6], connection charges, and the cost of calling 30 minutes peak time/month, in each instance using the cheapest option available in the market. I do not split the different elements of the pricing structure since they had correlations above 0.8. The reason for including a twelve-month cost is that the price of the handset is to some extent included in the fixed fee of the contract. $PCOST$ is the log of the entry cost of a prepaid package including a SIM card and the handset. Both magnitudes were prices adjusted by inflation in US$ holding a constant exchange (Base year: 1992, the beginning of the observation period).

Prepaid phones were introduced between October 1996 (UK) and March 1997 (Germany). In 1999, helped by heavy investment in handset subsidies, prepaid plans took off, and by the end of June 2001, half of all customers in Germany and France were prepaid subscribers, while in the UK the percentage was higher than 70%.

[6]Handsets were subsidized by MNOs. I use as handset cost the amount of money that the final user had to pay in each period for an entry level handset. For contract services and for the three countries this amount is close to zero since 1996.

	FRANCE		GERMANY		UK	
	Mean*	95% P.Interval	Mean	95% P.Interval	Mean	95% P.Interval
XTMASS(β_1)	**0.69**	[0.68, 0.70]	**0.43**	[0.42, 0.44]	**0.39**	[0.38, 0.40]
Intercept Contract(μ_c)	**-4.69**	[-5.61, -4.27]	**-2.64**	[-2.98, -2.41]	**7.97**	[6.06, 8.22]
CCOST(β_{2c})	**-0.70**	[-0.71, -0.59]	**-0.74**	[-0.77, -0.70]	**-2.62**	[-2.72, -2.38]
Intercept Pre-paid(μ_p)	**0.32**	[0.23, 0.48]	**-5.51**	[-5.74, -5.28]	**-5.19**	[-5.42, -4.91]
PCOST(β_{2p})	**-1.37**	[-1.41, -1.35]	**-0.45**	[-0.50, -0.43]	**-0.54**	[-0.61, -0.50]
θ_{ct}: Intercept (ρ_{0c})	**0.16**	[0.15, 0.17]	**0.02**	[0.01, 0.02]	**0.74**	[0.66, 1.00]
θ_{ct-1} (ρ_{1c})	**0.97**	[0.96, 0.97]	**1.01**	[1.01, 1.01]	**0.44**	[0.41, 0.45]
St.dev ($\sigma_{\nu c}$)	**0.45**	[0.38, 0.49]	0.01	[0.00, 0.02]	**0.41**	[0.12, 0.83]
θ_{pt}: Intercept (ρ_{0p})	**0.09**	[0.08, 0.1]	**0.27**	[0.24, 0.28]	**0.47**	[0.45, 0.50]
θ_{pt-1} (ρ_{1p})	**0.97**	[0.96, 0.98]	**0.94**	[0.93, 0.95]	**0.90**	[0.89, 0.90]
St.dev ($\sigma_{\nu p}$)	**0.66**	[0.62, 0.71]	**1.14**	[1.03, 1.68]	**0.47**	[0.35, 0.83]
Inclusive value(λ)	**0.60**	[0.57, 0.62]	**0.77**	[0.75, 0.78]	**0.79**	[0.78, 0.83]
St.dev Heterogeneity(σ_μ)	**1.04**	[1.03, 1.12]	**0.27**	[0.21, 0.54]	**0.19**	[0.10, 0.21]
Log-likelihood	18810.6		30179.1		22838.0	

*In bold, p>0.05

Table 1.4. Results of the Model

1.6.2. Cross-Country Analysis

I ran the proposed model for the three countries. Table 1.4 provides the results of the estimation. The model recovers the pattern of the cumulative number of adopters accurately (see Figure 1.4 the actual and predicted data from the model for Germany). Adoption prices seem to be especially important in two cases: contract phones in the UK ($\beta_{2c}^{UK} = -2.62$) and prepaid phones in France ($\beta_{2p}^{F} = -1.37$). The unobserved factors captured by the time varying parameters are important for understanding the evolution of mobile telephony in the three countries. These unobserved factors are depicted in Figure 1.5 As expected, these factors generally increase with time: the intercept of the autoregressive process $\rho_0 > 0$ and the autoregressive parameter ρ_1 is close to one. The exception to this pattern is contract phones in the UK, where adoption costs capture the observed sales pattern better than in the other two countries.

December promotional campaigns were significant in boosting adoption in the category. The range for $\beta_1$is from 0.39 in the UK to 0.69 in France. The parameter (λ) (inclusive value)

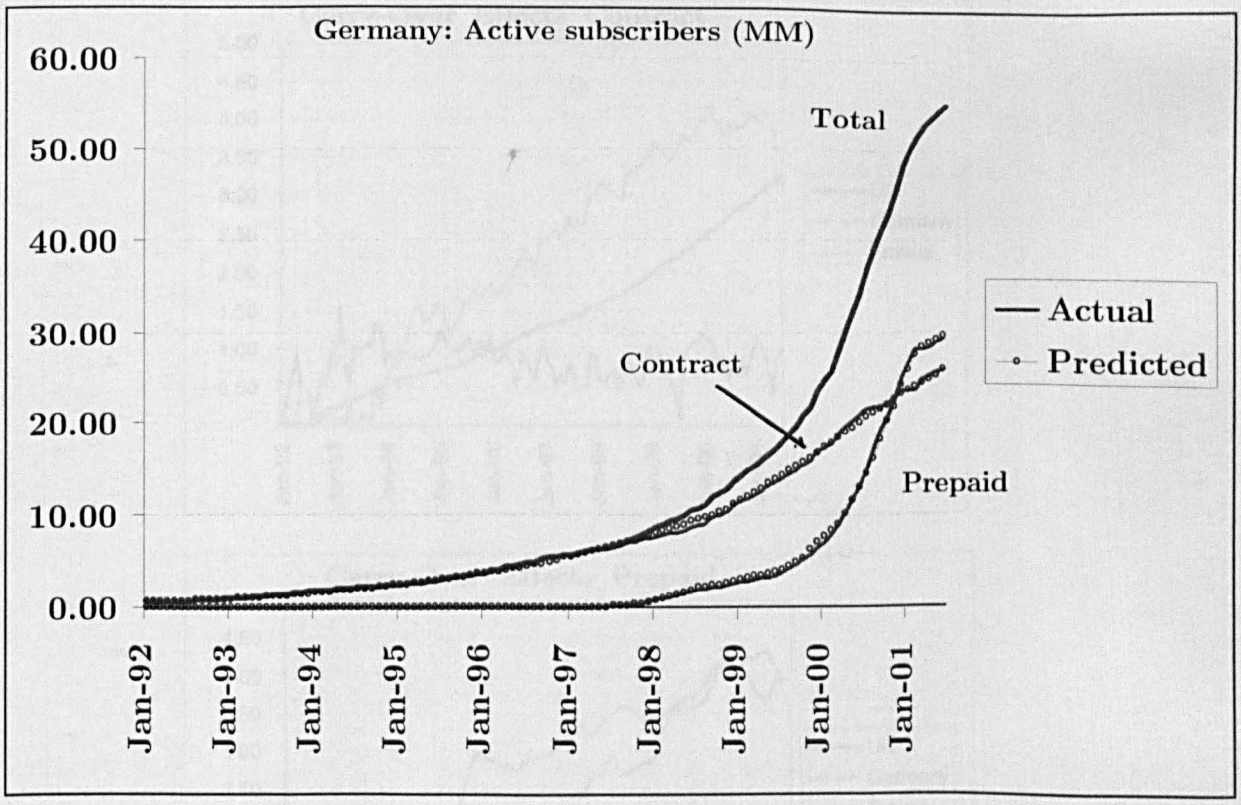

Figure 1.4. Adoption of Mobile Telephony in Germany: Actual and Predicted by the Model

is higher for the UK (0.79) and lower for France (0.60). From these estimates, we can expect that the level of category expansion will be higher in the UK. An inclusive value closer to zero indicates a higher level of substitution among the members of the nest. In all three cases, λ differed significantly from zero. This justifies the use of a nested instead of a simple logit.

In summary, the model captures the evolution of the category in all three markets. Even though an important part of the utility is related to unobserved factors, up-front costs were important in driving product adoption. Thus, to better understand the evolution of mobile telephony in the different markets, I will analyze the impact of the launch of prepaid phones and disentangle the effects of category expansion and substitution of mobile phones with contract plans.

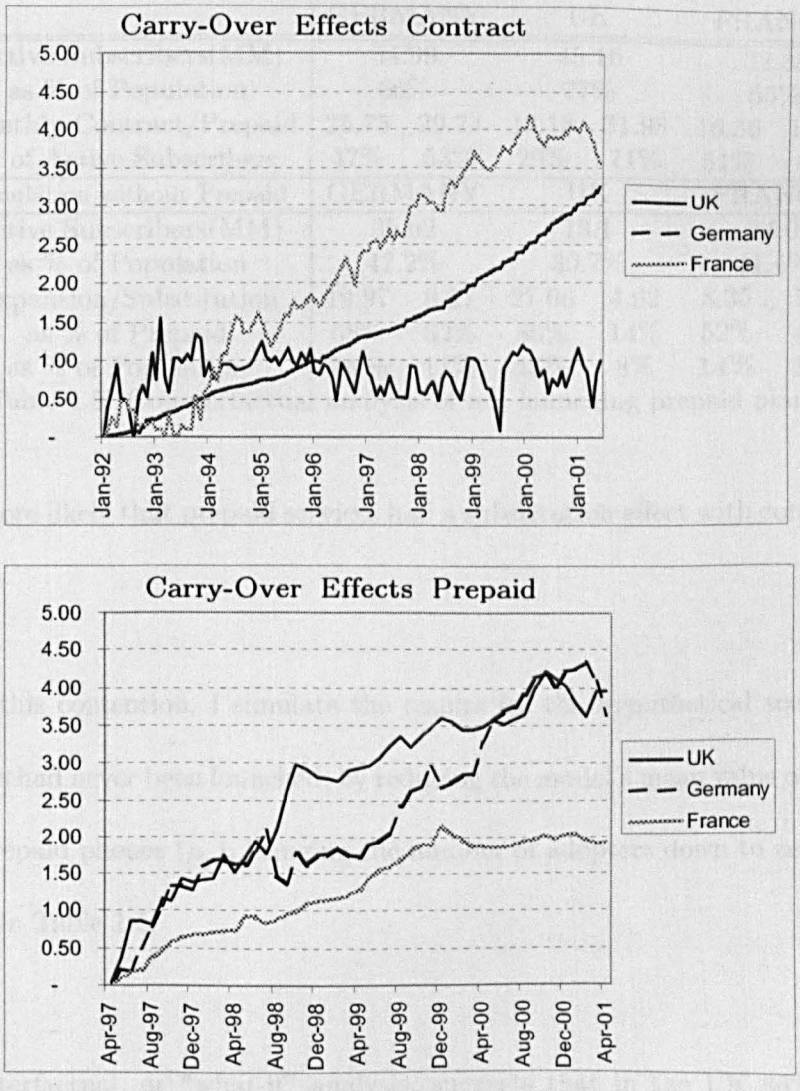

Figure 1.5. Carry-Over Effects $(\theta_{ct}, \theta_{pt})$

1.6.2.1. What- if Analysis. Calculating the Impact of Prepaid Phones on the Adoption of Mobile Telephony: The split between contract and prepaid services was 47%-53% in France, 51%-49% in Germany and 29%-71 in the UK. It seems that there is some correlation between the market share of prepaid prepaid services and total penetration: France had the lower penetration of mobile services on the overall population (56%), Germany had a penetration of 66% and UK had a 77%. There are reasons for this pattern. The more the appeal of a prepaid service, the higher the category expansion effect among light users,

	GERMANY		UK		FRANCE	
Active Subscribers(MM)	54.99		45.16		32.38	
as % of Population	66%		77%		56%	
Monthly Contract/Prepaid	25.75	29.24	13.18	31.98	16.36	16.02
% of Active Subscribers	47%	53%	29%	71%	51%	49%
Simulation without Prepaid	GERMANY		UK		FRANCE	
Active Subscribers(MM)	35.02		18.1		24.0	
as % of Population	42.2%		30.7%		41.4%	
Expansion/Substitution	19.97	9.27	27.06	4.92	8.35	7.66
as % of Prepaid	68%	32%	86%	14%	52%	48%
as % of Population	**24%**	11%	**45%**	8%	**14%**	13%

Table 1.5. Counterfactual analysis of not launching prepaid plans

but also the more likely that prepaid services had a substitution effect with contract servcices.

To assess this contention, I simulate the results for the hypothetical scenario in which prepaid phones had never been launched, by reducing the model's mean value of the individual intercept of prepaid phones (μ_p), bringing the number of adopters down to zero. The results are presented in Table 1.5.

This counterfactual, or "what-if" analysis, suggests that in the UK 86% of customers adopting prepaid plans would not have entered into a contract had the prepaid option not been available. This figure is around 52% in France and 68% in Germany. Therefore, the model suggests that the main impact of launching prepaid plans was category expansion. These results also imply that a market without prepaid plans would have had a final penetration of approximately 42-45% in Germany and France and approximately 31% in the UK.

What conclusions can we draw from these results? First, the prevalence of category expansion resulting from the launch of prepaid plans is reasonable if we are to believe the expectations prior to 1998. For example, in 1997, when prepaid plans where still in their first months of introduction, business analysts were predicting that by 2000 the number of

subscribers would reach 10.7 million in the UK (Cane 1997; the number of active subscribers in January 2000 was around 25 million, half of which used prepaid phones). Second, a penetration rate of approximately 40% would be aligned with the penetration rates in countries where prepaid plans were not very popular before 2001. Such an example could be the US: at that stage the US had an adoption rate of 42.6%[7] . The most controversial figure in this analysis is probably the conjecture that the penetration rate for the UK without prepaid plans would have been far lower than for their neighbors, which might sound counterintuitive, as historically the UK has been one of the leaders in mobile telephony adoption.

There is an interesting aspect worth noting: the counterfactual experiment proposed is a "ceteris paribus" analysis. This means that we are assuming that all the other variables would remain constant. Figure 1.6 shows the price evolution of the cheapest monthly contract phone in the three countries with a usage of 30 minutes peak-time/month. As mentioned above, this shows how the UK had cheaper prices than France and Germany until 1998. Then, both Germany and France started offering monthly contract services with cheaper rates than in the UK. It is not surprising that a market with higher prices would have fallen behind in terms of penetration. Furthermore, it is also likely that UK operators would have brought down threshold adoption prices for monthly contract services, had they not covered the low-usage segment with prepaid offers. In other words, what my analysis suggests is that if prices had remained constant and prepaid plans had not been so heavily promoted, eventual levels of mobile adoption in the UK might well be lower than in France or Germany.

Hence, this "what-if analysis" suggests that the UK cellular market has grown faster due to supply factors (e.g., prices, affordable prepaid offers). Even with higher prices, total market growth in 1997 and 1998 was higher in France and Germany than in the UK. The

[7]Data from the EMC database. June 2001

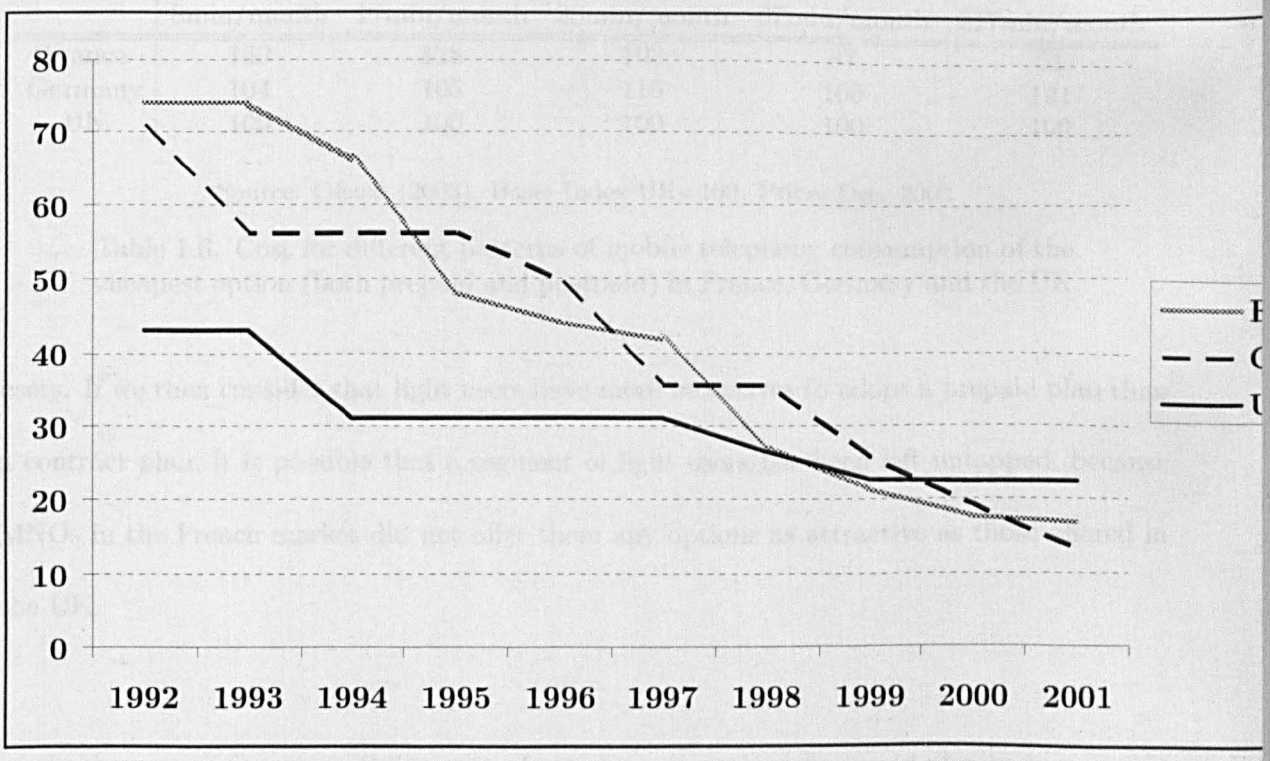

Figure 1.6. Evolution of the cheapest monthly cost of 30 minutes peak time calls for a contract service in France, Germany and the UK (US $)

main driving forces for the faster development of the mobile telephony market in the UK were the heavy investments of MNOs in 1999 and 2000 to reduce adoption costs and offer cheaper call rates for prepaid customers.

Meanwhile, the higher percentage of substitution in France supports the idea that both prepaid and contract plans were suitable for the same segment of consumers, and therefore were more substitutable. As we have seen, adoption prices were higher in France for the period analyzed. These differences remain even in later years. An example can be seen in Table 1.6 which compares call costs for various levels of usage using price data for the two cheapest options in June 2001 (Ofcom 2003). Total cost in the UK is set as the reference (100) for each column. The interpretation is as follows. For use of eight minutes per month, the cost in France is 50% higher than in the UK. This comparison shows that the French market was the most expensive for light users, while offering the cheapest options for heavy

	8min/month	17min/month	30min/month	67min/month	217min/month
France	150	128	103	87	91
Germany	104	105	116	105	121
UK	100	100	100	100	100

Source: Ofcom (2003). Base: Index UK=100. Prices Dec. 2002

Table 1.6. Cost for different patterns of mobile telephony consumption of the cheapest option (both prepaid and postpaid) in France, Germany and the UK

users. If we then consider that light users have more incentives to adopt a prepaid plan than a contract plan, it is possible that a segment of light users has been left untapped, because MNOs in the French market did not offer them any options as attractive as those offered in the UK.

In the case of Germany, the impact of category expansion of prepaid phones was greater than in France (68% vs. 52%), while the ratio of contract to prepaid phones was somewhat similar. This may have been the outcome of lowering the costs of both contracts and prepaid phones. As mentioned previously, of the three countries, Germany is the one in which the consumer was always better off with a contract, regardless of the level of consumption. It seems, therefore, that German MNOs have followed an aggressive policy of consumer acquisition while focusing primarily on developing a wide base of contract customers, even when the level of usage was small.

1.6.2.2. Trend Analysis of the Attractiveness of Prepaid Plans: The results shown so far offer a snapshot of the situation in the three markets as of June 2001. It is also interesting to analyze the temporal evolution of the attractiveness of prepaid plans. This can be achieved by adapting a compensating variation welfare analysis to this setting. The compensating variation (CV) is an indicator of how consumers would have had to be compensated to maintain the same level of utility if the product had had different characteristics (MacFadden 1999). It is defined as:

$$E(CV) = \frac{1}{\alpha} \int_{u_0}^{u_1} S_{jmt}(u) du \tag{1.28}$$

In the case of the nested logit model, Equation (1.28) has a closed form solution and can be written as:

$$E(CV) = \frac{1}{\alpha} \ln \left[\sum_g \sum_{k \in g} \left(\exp \left(\frac{u_k}{\lambda} \right) \right)^{\lambda} \right]_{u_0}^{u_1}, \tag{1.29}$$

where α is the marginal utility of income. Assuming that all three countries have the same parameter α we can compare how the introduction of prepaid plans increased the expected utility of consumers in the three markets. The compensating variation will be higher in countries with (1) a higher rate of adoption of prepaid plans and (2) a lower degree of substitution between prepaid and contract phones. Figure 1.6 provides the average compensating variation for the three countries after the launch of prepaid phones.

We see from Figure 1.7 that, consistent with the result of a higher total category expansion and a lower degree of substitution between prepaid and contract phones, the $E(CV)$ in the UK is greater than in France and Germany. This means that prepaid phones have provided consumers in the UK with higher utility than in the other two countries. This is shown by the higher number of total adopters of prepaid phones and the inference that most of them would not have adopted a mobile phone if prepaid phones had not been available.

This analysis also allows us to assess the evolution of the relative attractiveness of prepaid plans in the different countries. For example, the decline of $E(CV)$ in Germany and UK after the end of 2000 indicates that the appeal of prepaid plans waned in these countries. The slow-down in the diffusion of prepaid plans in these two countries is due therefore not only to market saturation, but also to the fact that the relative attractiveness of prepaid phones

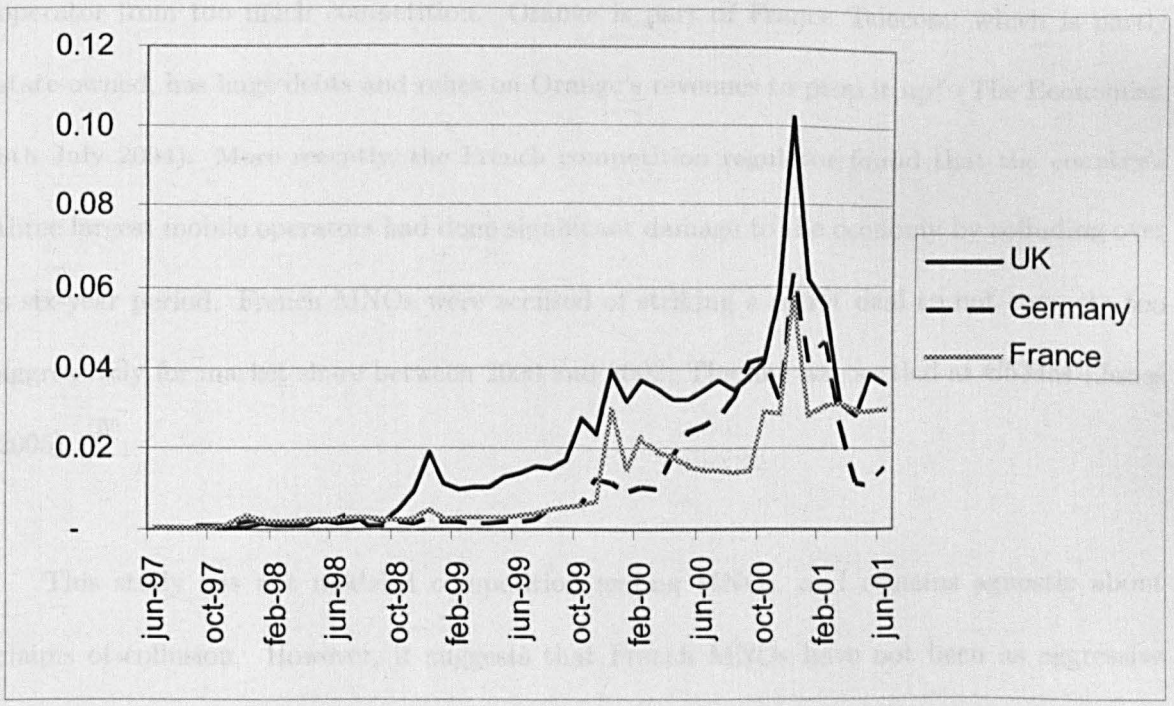

Figure 1.7. Compensating variation of the introduction of prepaid plans

declined in the first months of 2001. This is consistent with the following assumption: prices for prepaid packages increased slightly after an intense promotional campaign in 2000, and the focus for marketing efforts evolved from customer acquisition to increasing revenue per user and migrating customers from prepaid plans to contract plans.

1.6.2.3. Discussion: From the analysis of the data, we see that prices for mobile telephony have been higher in France than in Germany and the UK. After the "what-if analysis" done in this study, we can infer that these higher prices may have restricted the appeal of prepaid phones for the segment of light users, as reflected in the effect of smaller category expansion of prepaid phones in France. Thus, these findings suggest that the lower rate of penetration of mobile telephony in France could be explained by the acquisition policy of French MNOs, which was more conservative than the policies observed in Germany and the UK. This would be consistent with business press claims that the mobile market is less developed in France than in other EU countries because of "the desire to protect Orange, the dominant mobile

operator from too much competition. Orange is part of France Telecom, which is partly state-owned, has huge debts and relies on Orange's revenues to prop it up" (The Economist, 8th July 2004). More recently, the French competition regulator found that the country's three largest mobile operators had done significant damage to the economy by colluding over a six-year period. French MNOs were accused of striking a secret deal to not compete too aggressively for market share between 2000 and 2002. The fine was settled at €534M (Jones 2005).

This study has not modeled competition among MNOs, and remains agnostic about claims of collusion. However, it suggests that French MNOs have not been as aggressive as in other countries in terms of customer acquisition. These differences are still present in 2007. The UK and German markets have mobile penetrations above 100% (i.e. there are more wireless subscribers than total population), while the French market has a penetration of 79% But from a profitability standpoint, French MNOs generated in 2006 an EBITDA margin in absolute terms higher than their counterparts in the UK and Germany (Merrill Lynch 2006)[8] It seems then that MNOs in France have been more focused on increasing mobile usage per subscriber than achieving a higher number of subscribers and that the output of this strategy has been profitable for shareholders.

The insights obtained here are also useful for understanding recent developments in other markets. In the United States, for example, prepaid phones still account for a small proportion of total users and developed later than in Europe. However, the launch of mobile virtual network operators (MVNOs) such as Virgin Mobile and Boost, which exclusively target prepaid users, has pushed the adoption of mobile telephony in the United States beyond

[8]Total revenues and EBITDA generated by MNOs in the three countries (in bn $) during 2006 is as follows: France: 28,9/11,6; Germany: 27,9/11,5; UK: 32,6/9,1

expectations (Golvin 2005)[9] . Adoption does not automatically mean profitability, but Virgin Mobile's successful US$1 billion IPO in the UK in July 2004[10] indicates that a pay-as-you-go strategy that targets customers unlikely to enter into a contractual relationship with an MNO (youths, travelers on short stays, people without credit history) might create value for customers and shareholders in the United States as well. Several MVNO have been launched in the three countries under study focusing normally on prepaid strategies and "low cost" positioning.

Finally, the analyses in this study might also offer some insights for analyzing how the adoption of 3G mobile services will evolve in the future[11]. For example, at the end of 2005, Italy and the UK were the European leaders in mobile services adoption with UMTS technology (Van Veen, et al. 2005). It is possible that in Italy and the UK there is a greater intrinsic preference for wireless web-browsing, video calls and music downloads. On the other hand, however, this faster development could also be the outcome of the marketing efforts of "3", a 3G pure player owned by the Hong-Kong conglomerate Hutchinson Whampoa, that pioneered the launch of 3G mobile services in March 2003 in countries such as Italy and the UK. Incumbent MNOs started promoting 3G services in Europe much later[12].

It is also interesting to note that prepaid plans are unusual in the traditional fix-line internet access market where contracts with a flat fee are very popular. Hence, it seems that a market with a higher proportion of customers with contracts could be more suitable for

[9]A mobile virtual network operator is a mobile service provider that does not own the radio infrastructure over which its services are provided. An example is Virgin Mobile, which in the United States operates over the Sprint mobile network. Forrester Research reports that the proportion of prepaid consumers in the United States has risen from 5% in 2002 to 10% as of the end of 2004.

[10]Virgin Mobile UK was launched at the end of 1999 as a joint venture between T-Mobile and Virgin. The number of Virgin subscribers in 2004 was approximately four million

[11]The third-generation (3G) mobile telephony is based on mobile technologies such UMTS (Universal Mobile Telecommunications System). One of the differences of technologies such as UMTS is that they support up to 1920 kbit/s data transfer rates, making them more suitable than their predecessors (GSM, GPRS) for data access (i.e., internet browsing, video streaming) through wireless devices.

[12]For example, Vodafone was the second MNO that launched 3G services for mobile phones in the UK in November 2004 (http://news.bbc.co.uk/1/hi/business/3996971.stm)

the diffusion of 3G mobile telephony since the upgrade decision in such a market would be more straightforward. Therefore, I suggest that conjectures about the future evolution of the 3G market should incorporate considerations about how the existing pricing formats would affect the migration of the customer base from GSM to UMTS. Given that Italy and the UK historically have had a high proportion of prepaid as compared to contract customers, I suggest that an important consideration in these countries will be as to how MNOs should adapt their pricing schemes so as to attract prepaid customers to 3G services.

1.7. Conclusion

In this chapter, I have developed a cross-national diffusion study of mobile telephony adoption. Taking a consumer-level approach, we have seen how pricing decisions of MNOs and the launching of prepaid plans have been crucial in understanding the development of mobile telephony in different markets. We have seen, for example, that the principal impact of prepaid phones on the number of active mobile telephony subscribers was category expansion, and the diffusion of mobile telephony would have been much slower in the three countries under study had only two-part tariff contract phones been offered. The cross-country analysis also suggests that the differences in adoption exhibited in France, Germany, and the UK might be motivated not only by intrinsic factors (e.g., demographics), but also by the marketing strategies of MNOs with respect to customer acquisition. This is shown by the example of the French market, where the relative impact of category expansion versus prepaid phone substitution was less than in the other two countries.

Disentangling the effects of category expansion and substitution is a general problem that may be relevant for other scenarios. To quote an example, consider Kodak's infringement of the Polaroid instant camera patent (Dubbin 1998). The fine that Kodak had to pay was calculated in relation to the impact Kodak's actions had on Polaroid's sales. Hence, it was

important to acknowledge that it involved not only substitution between brands, but also the effect of boosting total sales for instant cameras. In general terms, companies tend to be interested in assessing whether a competitor is mainly stealing sales from them, or is actually helping to increase sales at the category level.

Another interesting context where this analysis might be relevant is in the case of cannibalization within a given product line of a company selling durables. In order to assess the financial evaluation of the launch of a new product it is important to disentangle expansion from substitution effects, especially if the new product has smaller margins.

From a modeling perspective, we have seen that the decision to adopt a new product might be influenced by several factors. How to model unobserved variables with carry-over effects is an important issue in the development of a random utility model with observable variables that have a time trend. The assumption that these variables follow an autoregressive process allows us to solve the dynamic system using a Kalman filter.

There are some interesting avenues of further research related to this study. First, it is the question of how to adapt the present model to apply to situations in which price endogeneity has greater importance. For example, I think that it would be interesting to compare the performance of a GMM procedure (Berry, Levinshon and Pakes 1995, Nevo 2001) with a procedure that jointly estimates sales and prices in a likelihood framework. It is not clear whether it would be appropriate to compare moments from errors that have a different nested logit scale parameter (λ) because the impact of the error ξ_{jt} on the observable sales (n_{jt}) depends on the value of the scale parameter λ. Differences become dramatic when $\lambda \rightarrow 0$. In other words, it is possible that a model M1 with parameters Φ_1, λ_1 would have a better

GMM function than another model M2 with parameters Φ_2, λ_2 and at the same time, that M2 had a better fit with the observable data.

Second, it would be interesting to adapt this model to a setting where consumers have a choice not only of horizontally differentiated products but also of different generations of the same brand, as is the case for videogame consoles. In such a context, two issues should be taken into account:

- How to model vertically differentiated products: the launch of a new model, and even just announcing it, will have a special impact on the sales of the previous generation. The choice model used in this context would have to incorporate a more flexible pattern of substitution to acknowledge the superiority of one specific option over another (i.e., for the same price, nobody would purchase a Sony Playstation2 instead of a Playstation3).
- How to model the upgrade decision: The number of customers upgrading the product could be important. Therefore, the assumption that a consumer who buys one option in a given period will exit the market for the remaining periods may not be applicable. This issue would make it necessary to have access to information about household purchase behavior.

Finally, an interesting avenue to explore could be modeling usage, particularly in relation to the adoption of different options of mobile telephony. It has been shown that pricing plan choices are determined by expectations about future consumption (Miravete 2002). Such features would have to be incorporated, allowing us to develop a model which allows for both adoption and migration from one payment plan to another.

CHAPTER 2

Market Effects of Generic Entry: The Role of Physicians and of Non-Bioequivalent Competitors

2.1. Introduction

Rising health care costs have become a major public health concern in recent years. Because prescription drugs represent a significant component of such costs, with shares ranging from four percent in the United States (US) to nearly 18 percent in France and Italy (Kyle 2003), one of the avenues pursued by public policy officials to contain costs has been to seek greater substitution of branded molecules with lower priced generic versions (Gleckman 2002). The benefits from such substitution can be substantial. For example, Fischer and Avorn (2003) analyze state-by-state Medicaid prescription drug spending in the US for the year 2000. The authors find that states would have saved US$229 million with a greater use of generic drugs, and total savings would have reached US$450 million if the best available prices from each state had been used nationally. Hence, public policy officials are especially interested in having a deeper understanding of the different factors that influence the adoption of generics in the marketplace

But public policy officials concerned with health care cost containment are not the only market agents interested in better understanding generic versus branded drug substitution patterns. With a significant number of major blockbuster molecules no longer protected by patents, or nearing patent expiry, drug companies have demonstrated an increased interest in studying generic drug competition and its market penetration (over the next five to ten

years about US$40 billion of prescription revenue is expected to be affected by patent expiry and consequent generic entry; Van Arnum 2004).

The interest of both drug companies and health officials has spurred significant research efforts in the area of generic drug competition and adoption. A significant portion of this recent literature has focused on the institutional factors and supply side issues that affect generic demand (e.g., Caves et al. 1992; Scott-Morton 1999, 2000 and 2002; Danzon and Chao 2000), and on the aggregate effects of generic entry on the branded drug losing patent protection (e.g., Frank and Salkever 1992 and 1997; Magazzini et al. 2004; Lexchin 2004). The role of physicians on the demand for generics and on generic competition has received far less attention (e.g., Hellerstein 1998), though a critical feature of prescription pharmaceuticals is that the end consumer, the patient, does not select the drug she will consume. Instead, the physician decides the drug therapy and, as it is the case in most US states and European countries, whether the patient will receive a branded drug or its generic alternative. The objective of this study is to show how marketing decisions influence the evolution of a generic drug by analyzing the impact of these marketing decisions on the prescription behavior of physicians.

Using a unique panel data set on physician prescribing and competitive marketing activity, I study how physician characteristics (observable and unobservable) and their prescribing decisions impact the competition among molecules of a therapeutic class, once generic versions of one of these molecules enter the market. Specifically, I study the evolution of the Selective Serotonine Reuptake Inhibitors (SSRIs), a subcategory of antidepressants, after the introduction of generic versions of fluoxetine (brand name Prozac) in the United Kingdom (UK).

Unlike previous research, I analyze simultaneously the competition between the entering generics and the brand that faces patent expiration (within-molecule competition), and also the competition among all of the molecules in the given therapeutic class (i.e. between-molecule competition). In the analysis I control for the marketing activity targeted at physicians and for drug similarity due to bioequivalence, as in the case of branded molecules and their generic counterparts. These are factors ignored by previous research. Finally, I take advantage of the natural experiment created by the generic entry to compare the behavior of physicians before and after patent expiry. This allows us to study how physician characteristics like drug preference, sensitivity to marketing activity, and sensitivity to prices impact the market evolution of the generic, the brand facing the patent expiration, and the remaining brands in the therapeutic class.

The results show that, to fully understand the market impact of generic drug entry and its subsequent adoption, it is essential to (1) study the full competitive market dynamics (both the within- and the between-molecule competition), (2) account for the marketing activity of pharmaceutical companies, and (3) determine how physicians respond to the marketing actions and drug prices at the individual level. In this empirical application, for example, the total market share of the molecule losing patent protection (also called multi-source molecule) decreased after patent expiration (a pattern not uncommon for many drugs losing patent protection, see for example Caves et al. 1992). This share reduction occurred despite the availability of generics at significant price discounts, and despite the more favorable price differential for the multi-source molecule after patent expiry, when compared to the remaining drugs in the therapeutic class. I argue that this reduction occurred because a segment of physicians sensitive to promotional activities of the brand losing patent protection switch from the multi-source molecule to other drugs in the category after generic entry. After generic

entry, the brand losing patent protection significantly reduces marketing support, possibly because of free-riding from the generic drugs (after patent expiry, the original manufacturer cannot be certain that its marketing efforts are going to generate branded prescriptions; this uncertainty reduces the incentives for the manufacturer to engage in marketing activities that are "molecule specific").

In addition, I identify a price-sensitive segment of physicians that increases prescribing of the multi-source drug to the detriment of the remaining drugs in the category, as it would be expected due to the average cost advantage of the molecule losing patent protection. However, this smaller segment is unable to fully compensate the behavior of promotion-sensitive physicians and other changes in the market such as the increased use of a newer drug.

The results also show that the substitution between the branded drug that loses patent protection and the entering generics (within-molecule competition) depends critically on how physicians prescribed the drug before patent expiration. Before patent expiry only the branded version on the multi-source molecule is available and dispensed to patients, regardless of how physicians prescribe the molecule (i.e., whether using the generic or the brand name). After patent expiration, pharmacies in most countries will be able to dispense generics only if the generic name is used (unless the physician specifically allows for substitution). Because physicians tend to maintain their prescribing habits from before patent expiry, the take-off of generic drugs will depend critically on the proportion of physicians prescribing the generic name (molecule) even before generics enter the market.

These findings are of interest to both policy makers and managers. First, governments and drug companies interested in assessing the diffusion of potential generic drugs might

want to monitor, before patents expire, how physicians prescribe the molecules due to lose patent protection (i.e., whether prescriptions are generally written using the generic or brand name). Even if information is not available for the vast majority of physicians, governments and companies could also determine which physicians to target using observable physician characteristics. In this data set, for example, women prescribe generics more often than men after patent expiry, and physicians who are partners in larger practices prescribe more generics than those in smaller practices.

In addition, both governments and companies might want to assess physician responsiveness to marketing activity and prices since the final adoption and diffusion of the cheaper alternatives will depend greatly on these two factors. Governments might then want to think of policies to increase price sensitivity of physicians or to take advantage of the sensitivity to marketing activity. For example, as reported in Mizik and Jacobson (2004), several US states are now engaging in "counter-detailing" activities to promote generic drug prescribing. Finally, from the results of this study, it is also clear that the full set of competitive interactions—not only the within but also the between-molecule competition effects—must be considered, in order to understand and predict the diffusion and adoption of generic drugs.

This chapter is organized as follows. Next, I present the literature review and the findings relevant to this work. Then I describe the adopted methodology, present the data used, and provide more information on the empirical application setting and estimation issues. Finally, I present the results, elaborate on the implications for policy makers and drug companies, and conclude with the limitations and areas for future research.

2.2. Literature Review

The level of consumption of generic drugs in a market is the outcome of both supply (e.g., generic entry, generic and brand pricing) and demand factors (e.g., patient requests, prescription by physicians, and substitution at pharmacies). Because health is an essential dimension of the welfare of a country, governments usually play a proactive role in providing and subsidizing health care to citizens, and in regulating both the supply and demand sides of prescription drug consumption. Hence, the institutional features of the market, and the way they affect the actions of drug companies, physicians and pharmacies, also play an important role in shaping generic drug consumption.

2.2.1. Aggregate Level Studies

The importance of generic consumption has created a fertile ground for research on generic drug competition and adoption. A significant portion of the recent literature on generics has focused on the effect of institutional factors or on supply side issues. Such work comprises the analysis of topics such as: the effect of regulation on competition (Danzon and Chao 2000; Arosson et al. 2001; Kyle 2003), the role of buying system characteristics such as insurance and Medicaid coverage (Jayachandran et al. 2003), advertising and licensing as entry deterrents (Grabowski and Vernon 1992; Scott-Morton 2000), the decision to integrate the production of generics and branded drugs (Ferrandiz 1999; Scott-Morton 2002), and the factors influencing generic entry (Bae 1997; Scott-Morton 1999 and 2000).

Another significant stream of research investigates the dynamics of market shares, quantity sold, and prices after generic entry in the US and other developed countries like Canada, UK, and France (e.g., Hurwitz and Caves 1988; Caves et al. 1992; Frank and Salkever 1992 and 1997; Aronsson et al. 2001; Regan 2002; Reiffen and Ward 2003; Lexchin 2004; Magazzini

et al. 2004). Results from those studies have not always been in agreement, depending often on data and methodology employed, though several important conclusions can be made. For example, most studies report a significant decrease in market share of the original brand after patent expiry, with major brand names typically losing half of their market share within one year of patent expiration (e.g., Grabowski and Vernon 1996). In contrast, prices of original brands increased (e.g., Grabowski and Vernon 1992; Frank and Salkever 1997) or remain mostly unchanged (e.g., Caves et al. 1992; Lexchin 2004) after the entry of generics, even though generics enter the market at significant price discounts and continue to decrease their prices with each new entrant (e.g., Reiffen and Ward 2003). The net effect is still a reduction of average price of a prescription for an off-patent drug (Frank and Salkever 1997). Results also show that the original brand market share is directly proportional to its age, and negatively related to the number of generic entrants (e.g., Hurwitz and Caves 1988), but despite these commonalities, there is significant heterogeneity in price and share dynamics across countries (Magazzini et al. 2004) which can be explained, in part, by the different regulatory environments.

2.2.2. Physician Role

The volume of studies and findings on generic competition and adoption in the medical, economics, and management literature is impressive. However, with few exceptions, the role of physicians' characteristics and physician decision-making is often ignored and seldom studied. This is despite the central role that physicians play in prescription drug markets. Patients lack the information regarding the most effective treatment and depend on physicians to diagnose and prescribe a drug, though physicians neither directly benefit from treatment nor pay for it. In most Western countries, physicians will also decide whether the patient will receive the generic or the branded version of a drug, if both versions are available.

Consequently, we should expect physicians to exert a direct and significant influence on the extent of competition between different providers of a certain molecule, and between the providers of alternative treatments.

The lack of research in this area is probably due to the reliance on aggregated data that do not allow the study of individual physician influence. Recently, however, few studies that analyze physician-level prescribing data have shed some light on the influence of physicians on generic adoption. Hellerstein (1998), for example, uses US physician prescription data to examine physician choice of drug version (branded versus generic) for molecules whose patents had recently expired. She concludes that some physicians are significantly more likely to prescribe generics, whereas others are more likely to prescribe branded versions (though almost all physicians prescribe both versions), and that physicians are indeed important agents in shaping the fate of generics. Hellerstein (1998) also concludes that little of the prescription decision between the two versions could be explained by observable characteristics of physicians or patients.

Two other studies on physician role in generic prescribing draw similar conclusions. Coscelli (1998) analyzes prescription data in a market where price competition was absent and where physicians and patients had been tracked over the course of a three-year period. The author examines the role of physician habit and patient taste in prescribing behavior and finds that both are very important. Lundin (2000) finds similar effects. Using individual-level data of physician prescribing, this author investigates whether the choice made by physicians concerning what drug version to prescribe —trade name or generic—is subject to moral hazard. The study concludes that even though physicians prescribe across versions, their prescribing habits are important in explaining the choice of drug version.

These recent studies provide important insights regarding the role of physician in shaping within-molecule competition. Mainly, these studies conclude that physicians and physician habit have significant influence on generic versus brand-name choice. However, several questions remain unanswered. First, competition in pharmaceuticals exists both within a molecule (branded versus generic, prescription versus over-the-counter) and between different molecules that treat the same condition. Previous studies demonstrate the importance of intermolecular competition. For example, Stern (1996) estimates a demand system for pharmaceuticals and finds low cross-price elasticities between branded and generic versions of the same drug and high cross-price elasticities between therapeutic substitutes. In addition, Lichtenberg and Philipson (2000) find that the loss in sales due to the entry of new drugs to the same therapeutic class reduces the value of a drug considerably more than the entry of bio-equivalent generics. Despite this evidence, Hellerstein (1998), Coscelli (1998), and Lundin (2000) do not incorporate nor study the competition among non-bioequivalent drugs in the same therapeutic class (between-molecule competition).

Second, marketing actions (e.g., sales calls to physicians also referred to as detailing) represent substantial investments in the pharmaceutical industry where it constitutes a major competitive force by which firms strive to differentiate their products and soften price competition. Pharmaceutical firms spend as much on marketing as they do on research and development (Hurwitz and Caves 1988) and promotion-to-sales ratios are among the highest of all manufactured goods. In addition, a long stream of literature has demonstrated that marketing actions, including detailing and sampling, have a significant impact on physicians' choices and monthly prescribing behavior (e.g., Gönül et al. 2001; Wittink 2002; Manchanda and Chintagunta 2004; Manchanda et al. 2004; Mizik and Jacobson 2004). However, prior studies of the role of physicians in generic adoption and competition have mostly ignored

pharmaceutical marketing. This is despite the importance of marketing actions in this industry and the significant changes in their levels after generic entry (e.g., the brand losing patent protection tends to significantly reduce its marketing, and generic versions do not invest in goodwill building activities; Caves et al. 1992).

Finally, physician differences in their drug preferences and responsiveness to marketing actions and price can also influence market dynamics after generic entry. If governments and companies wish to implement any type of incentive to influence market evolution, it will be essential to know who and how to target. However, heterogeneity in preferences and responsiveness is ignored in Hellerstein (1998), Coscelli (1998), and Lundin (2000), though significant heterogeneity across physicians in prescription levels and in the response to marketing activity is reported by several pharmaceutical studies (Manchanda and Chintagunta 2004; Manchanda et al. 2004; Narayanan and Manchanda 2006).

In this study I will investigate how physician characteristics (observable and unobservable) and physician prescribing decisions impact the competition among molecules of a therapeutic class (SSRIs, a subcategory of antidepressants), once generic versions of one of these molecules (fluoxetine) enter the market. Using a unique panel data set on physician prescribing and competitive marketing activity I will (1) control for the marketing activity to which physicians have been exposed, (2) account for drug price changes, and (3) analyze both the within- and the between-molecule competition. This analysis will also control for drug similarity due to bioequivalence and for the heterogeneity in physician drug preference and responsiveness to marketing activity and prices.

Next I will present the modeling approach, describe the setting of the empirical application, and present the model results.

2.3. Modeling Approach

I adopt a two-step approach to investigate how physician characteristics and physician prescribing decisions impact the competition among molecules of a therapeutic class, once generic versions of one of these molecules enter the market. In a first stage, I study physician prescribing behavior to characterize physicians in terms of unobservable characteristics like brand and drug preference, responsiveness to marketing activity, and price sensitivity. In a second stage, I study drug prescribing after the initial market settling period, and model the prescribing rate of the molecule losing patent expiry versus (1) all other drugs in the therapeutic category (between-molecule competition) and (2) the generic competitors (within-molecule competition). For the second phase, I use as covariates the estimates calculated in the first phase. In this way, I test whether the level of detailing sensitivity and other unobservable physician characteristics can help us to better understand how physicians prescribe (i.e. which molecule and if it is a generic or a branded prescription) and how they change their behaviour after patent expiry

2.3.1. Stage 1: Random Effects Multinomial Nested Logit Model

In the first stage, I model the physician decision of drug choice for each patient visit given a drug prescription in the focal therapeutic category using the well-known multinomial nested logit model (for model details and derivation please see Appendix B.1). Hence, I model the prescribing as a two-level process: physicians select which molecule to prescribe given a prescription in the category (e.g., fluoxetine versus citalopram given an SSRI prescription) and then which version (e.g., branded versus generic). This modeling approach creates a nested structure that can be represented by a two-level tree, with molecule choice in the first level and version choice in the second, as depicted in Figure 2.1. In addition, I estimate individual level parameters via a random effects formulation. These individual-level parameters (e.g.,

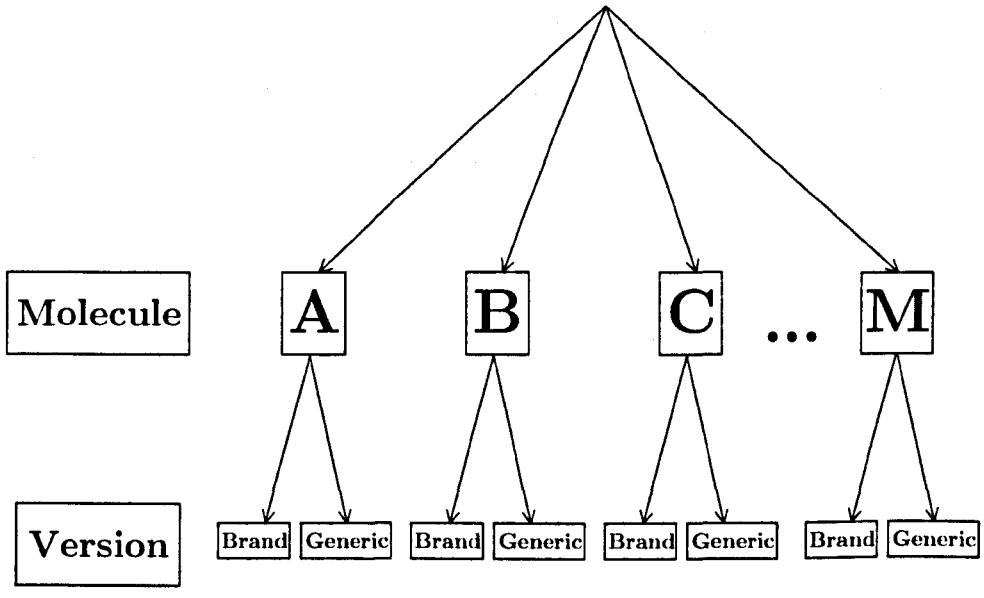

Figure 2.1. Choice tree of multi-source drugs

the underlying preferences, the responsiveness to marketing activity and the responsiveness to prices) are used to characterize physicians based on their low or high level of responsiveness and preference, and will enter the second modeling phase. The resulting random effects multinomial nested logit formulation is estimated using Bayesian simulation methods (for estimation details please see Appendix C).

In order to reliably measure physician characteristics and their preference for drug version we need to observe physicians' prescription behavior not only for a significant period before patent expiry (to get reliable individual-level parameters estimates), but also for a period in which physicians have the opportunity to select among different versions of the same molecule. This is because low cost generics do not benefit from previous investments in goodwill (e.g., advertising) and from years of market presence and experience as do branded versions. As a result, physicians can see generics as a trade off between cost and (perceived) quality (see Caves et al. 1992). Therefore, during this first modeling stage we will observe physicians for a significant period before patent expiration, and during the initial stages of generic entry while the market settles (I will call this time period as "Period 1").

I believe that the proposed random effects multinomial nested logit approach is the most adequate to study the demand for pharmaceuticals when different versions of the same molecule are available. First, multinomial logit models are well known, robust, and widely used to study choice behavior when full competitive information is available. Previous applications include the analysis of pharmaceuticals (e.g., Narayanan and Manchanda 2006; Gönül et al. 2001), transportation mode (e.g., Ben-Akiva and Lerman 1985), and packaged goods (e.g., Bucklin and Gupta 1992).

Prior studies of drug performance (Jayachandran et al. 2003) also suggest that the entry of generic pharmaceuticals does not lead to appreciable market expansion (the data used for this study also supports this contention). As a result, we can account for the full competitive actions when modeling drug choice conditional on a prescription using a multinomial choice model. In addition, previous studies on pharmaceuticals have shown that physicians are persistent in their prescribing behavior, that is, at a given patient visit physicians tend to be influenced by their own previous prescription choices (Richard and Van Horn 2004; Janakiraman et al. 2005). As a result, by modeling the prescription decision for each individual patient we can account for carryover effects from one patient to the next at the physician level.

Finally, the nested structure adopted avoids the Independence of Irrelevant Alternatives (IIA) that is present in standard multinomial logit models. Governments evaluate and approve the bioequivalence of generic drugs, and though controversy persists about the bioequivalence of a handful of medications, nearly all other generic drugs provide identical therapeutic benefits (Fischer and Avorn 2003). In contrast, different branded molecules in a therapeutic class can be used to treat the same illness, but are not therapeutically equivalent, and patients can differ in their susceptibility towards them. Standard models cannot account for

this higher similarity of two or more alternatives[1] because of the IIA property (see Ben-Akiva and Lerman 1985). Using the tree structure described previously I avoid IIA and allow for complex patterns of substitution across alternatives.

2.3.2. Phase 2: Binomial Models

In the second phase of the analysis, I study drug prescribing after the initial market settling period. I will denote this time period as Period 2 (the same physicians are tracked in Period 1 and 2). Using the data in Period 2, I model (1) the rate of prescribing of the molecule losing patent protection versus all other drugs in the therapeutic category (between-molecule competition) and (2) the rate of prescribing of the brand losing patent protection versus its generic competitors (within-molecule competition). In these between- and within-molecule competition analyses I will use the physician characteristics obtained in the first phase to determine how such unobservable characteristics predict the market evolution after generic entry. I will also study whether observable physician characteristics (e.g., gender and practice size) can predict the observed market evolution.

To study the prescriptions of the molecule losing patent protection versus all other drugs in the therapeutic category (between-molecule competition), I estimate a binomial model (model details presented in Appendix B.2). I assume that physician i probability of prescribing the multi-source molecule irrespective of its form (p_{B_i}), across all n_i prescriptions in the category after patent expiry, is a function of (1) physician-specific variables that summarize the unobservable characteristics obtained in the first phase, (2) physician-specific observable

[1]Though generics and branded drugs are bioequivalent with respect to their active ingredients, they do not necessarily contain the same inactive ingredients, nor are sold under the same dosages or formats. That is why the two versions are "more similar" and not "exactly the same." As explained before, the structure of the nested multinomial logit will also allow us to test the level of substitution within and between molecules by looking at the inclusive value parameter.

characteristics, and (3) a prescription baseline. Hence, the prescription probability is then given by:

$$p_{B_i} = \frac{\exp(s_i^B + \alpha^B + Z_i\theta^B)}{1 + \exp(s_i^B + \alpha^B + Z_i\theta^B)}, \tag{2.1}$$

where, Z_i is a $(1 \times q)$ vector of physician specific characteristics (observable and unobservable), θ_B is the corresponding $(q \times 1)$ vector of parameters, α_B represents the model intercept, and represents the prescription baseline. I estimate two alternative binomial model formulations that correspond to two alternative baseline formulations: one that will allow us to study the prescribing changes from Period 1 to Period 2, and another one that will allow us to study Period 2 prescribing levels.

If we are interested in understanding how the prescription decisions changed after generic entry from the period before generic entry, we set as prescription baseline the logit transformation of each physician's share of the multisource drug from Period 1, that is $s_i^B = \ln\left(\frac{SHARE_i^B}{1+SHARE_i^B}\right)$ where $SHARE_i^B$ is the prescription share for the multisource molecule (the molecule with generic entry vs. all molecules of the category) during Period 1 (I will call this Model I; see Table B.1 in Appendix B). The interpretation is straightforward (assume for simplicity that $\alpha^B = 0$): if physicians change their prescribing following patent expiry, in a way predicted by their characteristics (e.g., demographic information, practice size, responsiveness to marketing activity and prices), then the parameters θ_B will be significantly different from zero; in contrast, if the observable and unobservable physician characteristics are not predictive of prescribing changes from Period 1 to Period 2, then the parameters θ_B will not be significantly different from zero and the best model will be one in which $p_{B_i} = SHARE_i^B$.

If instead of modeling changes, we are interested in determining how different types of physicians prescribe the drug after patent expiration, then we set to zero the prescribing

baseline ($s_i^B = 0$; I will call this Model II). The interpretation of the parameters is again straightforward: if after patent expiry physicians prescribe the multisource drug in a way predicted by their characteristics, then the parameters θ_B will be significantly different from zero; in contrast, if the observable and unobservable physician characteristics are not predictive of the prescribing levels for the multisource drug vis-à-vis other molecules in Period 2, then the parameters θ_B will not be significantly different from zero and the best model will be one in which $p_{B_i} = \alpha^B$ (a simple constant).

I adopt similar model formulations to study within-molecule competition using data from Period 2. In this case the variables of the binomial likelihood will correspond to branded prescriptions versus total multi-source prescriptions from Period 2 (see Appendix B.2 for more details). Both baseline formulations are also possible for the within-molecule binomial model: when studying prescribing levels we set to zero the prescribing baseline ($s_i^W = 0$) and have named it Model III; when studying prescribing changes (Model IV as described in Appendix B.2) I set $s_i^W = \ln\left(\frac{SHARE_i^W}{1+SHARE_i^W}\right)$ where $SHARE_i^W$ is the prescription share for the branded molecule (vs. all prescriptions of the multisource drug) during Period 1.[2]

The results from these binomial models will help us determine whether physicians play an important role in shaping both within- and between-molecule competition after generic entry. We can then better understand the dynamics of drug competition, in terms of prescription changes and prescription levels, and whether physician preferences, their responsiveness to marketing activity, and their responsiveness to prices provide an explanation for some of the changes observed in the market.

[2]Prescription of drugs under their generic denomination is commonplace before patent expiration. But patients can only be given the branded version of the molecule until generic versions are available after patent expiry.

2.4. Data

The goal of this chapter is to study how physician observable and unobservable characteristics, and their prescribing decisions, impact the competition among molecules of a therapeutic class once generic versions of one of these molecules enter the market. Such analysis, as described previously, requires the use of individual level physician data covering a significant period of time and comprising information on (1) drug choice for each patient visit, and (2) marketing activity targeted to each individual physician. However, datasets with such detail were not available for a multitude of categories and countries. As a result, I am unable to engage in an extensive study across multiple molecules and countries. Instead, I will use a unique panel data of general practitioners (GP) from the UK to study the evolution of the Selective Serotonine Reuptake Inhibitors (SSRI), a subcategory of antidepressants, before and after the introduction of generic versions of fluoxetine (brand name Prozac).

2.4.1. The Selective Serotonine Reuptake Inhibitors Category in the UK

Fluoxetine Hydrochloride was the first SSRI, marketed worldwide under the name of Prozac. It was launched in 1988 and was an unprecedented success. Proclaimed as a "wonder drug," it benefited from the unprecedented media attention, the marketing efforts of Eli-Lilly (its manufacturer), milder side effects, and the novel feature of non-lethal overdoses. This success led to introductions of more SSRIs during the 1990s: Seroxat (Glaxo-Smithkline-Beecham) and Lustral (Pfizer) both introduced in 1991, and Cipramil (Lundbeck) introduced in 1995.[3] In January 2000, the last patent held by Eli-Lilly in the UK on its blockbuster drug ended, and 14 companies launched generic versions of fluoxetine. At the end of 2000, the combined sales of generic versions of fluoxetine had overtaken Prozac in unit sales, and the amount of money paid by the UK National Health System for Prozac 20mg (the most common format)

[3]The commercial names in the US are Paxil (Seroxat), Zoloft (Lustral) and Celexa (Cipramil)

plunged from £88.1 million in 1999 to £61 million in 2000. In 2000, the average prescription price for Prozac was £26.12 whereas generic versions were priced at £15.29 (Department of Health 2002).

The UK market developments after the entry of fluoxetine in generic form are similar to those in other markets and pharmaceutical categories: the original brand tends to lose market share rapidly because generics are offered at deep discounts from the branded versions; however, the molecule as a whole does not necessarily grow. This makes the example of Prozac/fluoxetine in the UK as a representative case for many other similar situations.

2.4.1.1. Institutional Characteristics of the Pharmaceutical Market in the UK. The specific conditions of the UK market make this case especially appealing to study the impact of physician characteristics on the effects of generic entry. First, patients tend to exert a weak influence on physician prescribing (unlike other situations such as the US market). This is due to weak cost-related incentives and lack of information. Direct to consumer advertising of prescription drugs is not allowed in the UK and drugs can only be advertised in medical journals. As a result, patients have, in general, little information on the alternatives available. Also the ubiquity of the National Health Service (NHS) means that patients pay a flat rate for prescription drugs, regardless of the cost of the drug. For example, in 2004 UK patients paid £5.25 per prescription, which covered about 40% of the average prescription cost. There were few exceptional situations in which a different rate has been applied, and these relate to specific therapeutic categories, patients with certain chronic diseases, the elderly, and those with very low income.

Furthermore, in the UK, prices of drugs under patent are the outcome of negotiations between pharmaceutical companies and the NHS, translating into small price variations across drugs and for each drug across time. For example, in this sample there were only two

significant price changes across all brands during the two-year period under analysis, and these changes were motivated by exogenous and not strategic reasons (Department of Health 2002).[4] Hence, patients not only know little about the available alternatives, there is little incentive for patients to keep track of prices and price changes in the market.

In addition, physicians in the UK play an important role in deciding under which format, generic or branded, patients will receive the multisource drug. There are prescribing incentive schemes in which general practices receive feedback on the costs of their prescribing, and on their performance against a pre-set prescribing budget. Based on this performance, general practices can receive funds to purchase materials or equipment, and this mechanism provides an incentive for physicians to be price sensitive and care about the format (brand vs.generic name) under which a molecule is being dispensed. It should also be noted that pharmacists have no right to substitute branded versions of a molecule with its generic equivalent. If a prescription is written for the molecule form the pharmacist can dispense any product that is bio-equivalent to that formulation but if a brand name is prescribed, the pharmacist has to dispense the brand. Because pharmacists have strong incentives to dispense generics if they want to remain competitive[5] , the format choice of a specific molecule will be mostly at the hands of the physician.

Lastly, prescription of generics is commonplace in the UK. Even when drugs are still under patent protection, molecules tend to be prescribed under generic denomination in a significant number of cases (e.g. even though Cipramil is the only marketed drug composed

[4]The Pharmaceutical Price Regulation Scheme (PPRS) regulates the prices that drugs protected by patents receive from the NHS. Under the PPRS, companies are obliged to reduce prices of a drug if the financial returns for that drug exceed certain threshold. One of the price reductions observed in the data was indeed imposed by PPRS; the other significant change was due to the entry of generics.

[5]Legislation in the UK fosters competition at the retail level. Generally speaking, the NHS calculates an average price for each drug in the UK and reimburses the pharmacist according to this price. Therefore, drugstores feel the pressure to be efficient in buying, and the cheapest alternatives tend to be generics. A complete description of how this system works is beyond this dissertation. For details, shortcomings and suggested ways of improving the system, read "Fundamental Review of the Generic Drugs Market". A Report prepared by OXERA on behalf of the Department of Health. July 2001.

of the molecule citalopram, about 70% of the physicians in the UK will prescribe the name of the molecule instead of the actual brand). This means that there are low learning costs associated with generic prescribing and that companies of branded drugs have an incentive to stop detailing quickly after patent expiry due to possible free-riding effects. For example, in the case of Prozac in the UK, there was no detailing visit of Prozac after March 2000, just a few months after its patent expiry (January 2000). This allows us to study simultaneously the impact of detailing cuts for the molecule as a whole (common after patent expiration), and to contrast its effects to the effects of average price reductions for the molecule, after generic entry.

In conclusion, in the UK factors such as direct to consumer advertising (Donohue and Berndt, 2004; Currie and Park, 2002), patient pressure, price wars, medical insurance, and the actions of Health Management Organizations (Gönül et al. 2001) do not play a significant role. As a result, these features make the UK an ideal setting to study within- and between-molecule competition and physician role in the diffusion and adoption of generics.

2.4.2. Detailed Data Description

I use a unique dataset on physician prescribing and competitive marketing activity from a continuous panel of General Practitioners (GP) in the UK, tracked from September 1998 to September 2000. The category of prescriptions tracked are those of SSRIs and the time-period under analysis covers the patent expiration of Prozac (January 2000). For each physician I have information on (1) new SSRI prescriptions and changes of SSRI medication to each patient, (2) frequency and timing of sales representatives' visits to physicians from all competing drugs in the market, and (3) physician specific information like gender and practice size.

I retain all the records in which Prozac (fluoxetine), Seroxat (paroxetine), Lustral (sertraline), and Cipramil (citalopram) had been prescribed. These are the four key players for this category during the two years covered by the data, representing over 98% of all SSRI prescriptions. I do not analyze the remaining smaller players because of their reduced impact in the market, though the analysis performed here could be easily extended to include also these other players.

I keep the prescription choices from 170 physicians who, in the two-year period under analysis, wrote at least ten new SSRI prescriptions and received at least one sales call from any of the four key players. To analyze only those physicians who are actually active in a category is common practice in the industry and it allows for the estimation of more reliable individual-level parameters. In addition, this subset of physicians provide a good indicator for the whole population as they accounted for more than 80% of all SSRI prescriptions in the time period under analysis.

Table 2.1 provides the summary statistics of prescriptions and detailing visits per molecule for the final dataset. Period 1 includes the 19 months from September 1998 till March 2000, and Period 2 includes the 6 months from April 2000 till September 2000. The final dataset comprises the records of 170 physicians, for a total of 10,079 patient visits (7,579 during Period 1 and 2,500 during Period 2).

On average each physician prescribed SSRIs about 60 times (45 in Period 1 and 15 in Period 2) and each physician received on average 15 detailing visits (an average of 12 in Period 1 and 3 in Period 2). There was significant heterogeneity both in the number of prescriptions and the number of detailing visits. The minimum number of prescriptions for Period 1 and 2

Molecule* (Brand Name)	Prescriptions				Detailing			
	Total Number		Percentage		Total Number		Percentage	
	Period 1	Period 2	Period 1	Period 2	Period 1	Period 2	Period 1	Period 2
Citalopram (Cipramil)	1488	638	20%	26%	474	173	23%	39%
Sertraline (Lustral)	733	241	10%	10%	556	140	27%	31%
Fluoxetine** (Prozac)	2753	854	36%	34%	540	17	26%	4%
Paroxetine (Seroxat)	2605	767	34%	31%	481	115	23%	26%
Total	7579	2500	100%	100%	2051	445	100%	100%

* Cipramil is the brand name of citalopram produced by Lundbeck; Lustral is the brand name of sertraline produced by Pfizer; Prozac is the brand name of fluoxetine produced by Eli-Lily; and Seroxat is the brand name of paroxetine produced by GSB. ** For Period 2, prescription values include the prescriptions of branded and generic alternatives.

Table 2.1. Summary Statistics of Prescriptions and Detailing Visits of the Sample

combined was 11, and the maximum was 236; for the number of detailing visits, the minimum was two and the maximum 66.

Fluoxetine (Prozac) and paroxetine (Seroxat) were the two market leaders with 36% and 34% prescription share in Period 1, and with 34% and 31% prescription share in Period 2, respectively. Citalopram (Cipramil) follows with 20 and 26% of prescription share in Period 1 and 2, respectively, and sertraline (Lustral) is the smaller brand with about 10% prescription share in both periods. An important change in prescription share is the 2,2% share reduction of fluoxetine as a whole (generic plus brand name) after generic entry. Aggregate data from the NHS also confirms this declining trend and details are available from the author upon request.

This is a surprising result considering significant reduction of fluoxetine average prices after generic entry (average prices of fluoxetine were down 37% immediately after generics entered the market) though not novel in the literature (e.g., Caves et al. 1992). The only SSRI molecule that did not lose market share was citalopram (Cipramil), which instead gained popularity among GPs. (Figure 2.2 provides also an aggregate level snapshot of the

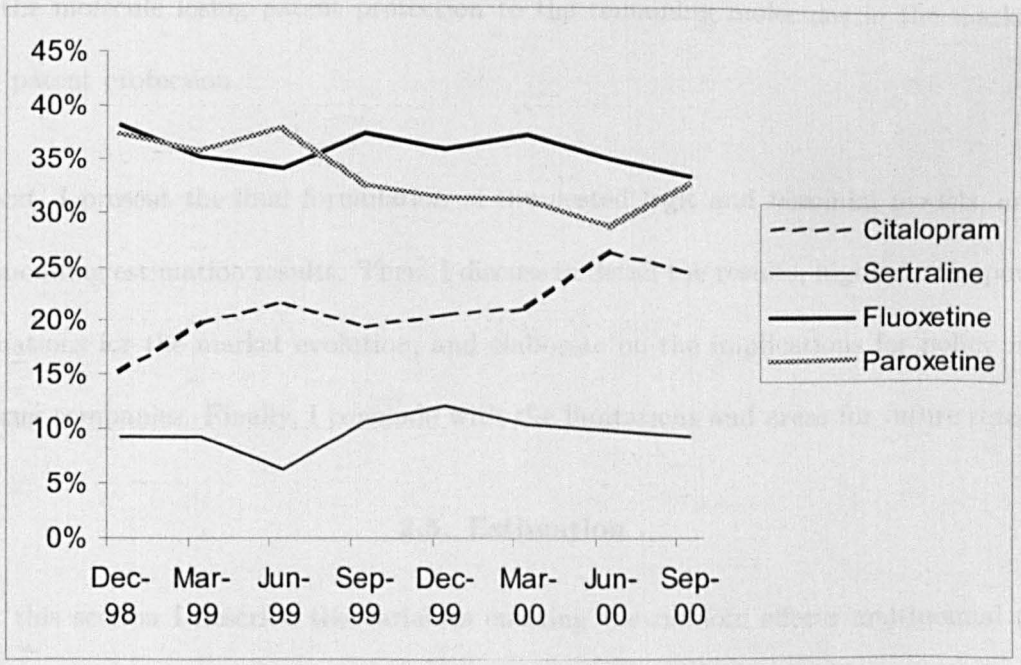

Figure 2.2. Evolution of the aggregate market share of SSRI among the panel Physicians

market evolution in which these trends are depicted.) A possible explanation for the market evolution could be changes in promotional activity. Though there are significant differences in prescription shares across molecules, the same does not occur with detailing in Period 1. In this period all drugs have similar detailing levels with a share of voice ranging from 23 to 27%. In contrast, detailing shares shift dramatically in Period 2: Lundbeck increased the detailing of citalopram reaching a share of voice of 39%. Prozac practically stops its detailing, and generic versions of fluoxetine do not engage in detailing activities. As a result, the detailing share of fluoxetine drops to 4%.

This is also a very significant result that demonstrates the importance of looking beyond within-molecule competition. If governments and pharmaceutical companies do not fully understand both within- and between-molecule competitive dynamics, it will be difficult to understand market evolution and the fate of brands and generics. It will also be difficult to take advantage of generic entry to reduce government costs if, for example, physicians switch

from the molecule losing patent protection to the remaining molecules in the market still under patent protection.

Next, I present the final formulation of the nested logit and binomial models, and the corresponding estimation results. Then, I discuss in detail the results, highlight the potential explanations for the market evolution, and elaborate on the implications for policy makers and drug companies. Finally, I conclude with the limitations and areas for future research.

2.5. Estimation

In this section I describe the variables entering the random effects multinomial nested logit model and the binomial models of between- and within-molecule competition. For each of the models I also provide a rationale for the use of such variables.

2.5.1. Random Effects Multinomial Nested Logit Model

Previous research has documented several factors influencing drug prescribing. The most significant ones include marketing activity directly targeted to physicians (e.g., detailing), drug prices, and prescription habit and persistence. In the model estimation I will account for all these.

2.5.1.1. Detailing Effects. Prescription drugs are the most heavily promoted of all manufactured goods with promotion-to-sales ratios that range from 10 to 20 percent (Leffler 1981). A long stream of literature in marketing and economics has also demonstrated that such marketing spending has a real impact on physicians choices and monthly prescribing (e.g., Gönül et al. 2001; Wittink 2002; Manchanda and Chintagunta 2004; Manchanda et al. 2004; Mizik and Jacobson 2004). Following previous research (e.g., Gönül et al. 2001, Janakiraman et al. 2005), I will account for the effect of detailing in the model of physician drug choice using a parsimonious and flexible exponential smoothing formulation. This formulation will allow

detailing meetings to have an impact on prescriptions even if they did not occur immediately before a prescription occasion, though it will give more weight to recent detailing visits. Hence, I define the stock of detailing at prescribing occasion t as:

$$\begin{aligned} SD_{ijt} &= SDD_{ij\omega(t)} \\ SDD_{ij\kappa} &= \sum_{\tau=1}^{\kappa} \delta_D^{\kappa-\tau} D_{ij\tau} \end{aligned} \tag{2.2}$$

for $i = 1, \ldots, N$, $j = 1, \ldots, J$, and $t = 1, \ldots, T_i$, where J is the number of alternative molecules, N is the number of physicians observed, T_i is the number of new prescriptions[6] written by physician i, $\omega(t)$ is a function that maps the prescribing occasion t to its corresponding calendar day t, δ_D is the parameter of daily decay[7] $(0 < \delta_D < 1)$, and D_{ijt} is a dummy variable that takes the value of one if molecule j is detailed to physician i in calendar day t, the value zero otherwise. With this formulation, the mean of the stock of detailing variables was between 0.18 (Cipramil) and 0.27 (Lustral)

2.5.1.2. Price Effects: Previous research has reached conflicting conclusions regarding physicians' sensitivity to drug prices. For example, Arosson et al. (2001) finds that the price of the original brand relative to the average price of the generic substitutes significantly affects the market share of the original drug. Lundin (2000) finds also that patients paying a large out-of-pocket sum are less likely to have the trade-name versions prescribed than patients getting most of their costs reimbursed. This would mean that physicians are indeed

[6] In this dataset, we only have data on the new prescriptions written by the doctor. That is, we do not observe (1) situations where a patient does not receive any prescription (2) situations where a patient is given a prescription for the same drug she was already using

[7] In this empirical application the daily decay parameter of detailing is fixed so that a detailing visit has a halftime life of 1 month, which means that if detailing is one on the day of the visit, it will be about one half, 30 days after ($\delta_D = 0.997$). We tested for alternative values of the decay parameter and concluded that for halftime lives between 15 and 45 days final results do not change significantly. These are values consistent with previous research on detailing effects.

considering the prices patients effectively pay for the drugs when deciding which drug to prescribe. In contrast, Newhouse (1993) performs a controlled health insurance experiment and finds no conclusive evidence that the average cost of prescriptions written by physicians varies according to the patients' insurance coverage. Gönül et al. (2001) present results that are even more extreme: positive and significant price coefficients for two of the three segments of physicians, and insignificant price coefficient for the third segment, though correctly signed.

Because it is yet unclear whether physicians are or not price sensitive, I will account for the price changes that occurred during the period under analysis and measure physician sensitivity to price. During the time-period under analysis there was one significant price change, unrelated to the entry of generic fluoxetine in the market, a price reduction of 38% of Lustral in June 1999 imposed by the government. To determine price sensitivity of physicians I account for this price cut by incorporating a dummy variable, PD_{jt}, that takes the value of one if j=Lustral and if a prescription occasion takes place after Lustral's price reduction; PD_{jt} will then be zero otherwise all other times. (I do not add a second price dummy for the price reduction of fluoxetine after generic entry because this is part of the overall market impact of generic entry and cannot be modelled independently; the nested structure of the model will account for such changes.)

2.5.1.3. Past Prescriptions Effects: Recent research has shown the importance of accounting for state-dependence in physician prescription behavior to correctly determine their responsiveness to marketing activity and prices (Janakiraman et al. 2005; Coscelli 1998). I incorporate information about physicians' past prescriptions by including a dummy variable, SX_{ijt}, that takes the value of one if physician i selects drug j in prescribing occasion $t-1$,

and that takes the value of zero otherwise (I have tested alternative state dependence specifications and found that the lagged dummy provides the best fit; details available from the authors upon request)

The final model formulation can then be written as:

$$V_{ijt} = \beta_{0ij} + \beta_{1ij} SD_{ijt} + \beta_{2ij} SX_{ijt} + \beta_{3ij} PD_{jt} + G_{ij} GA_{jt} + \varepsilon_{ijt} \quad (2.3)$$

where V_{ijt} is the valuation of molecule j for physician i at prescription occasion t, ε_{ijt} is a general extreme value distributed error term (Train 2003), and β_{1ij}, β_{2ij} and β_{3ij} represent the responsiveness to detailing, the effect of past prescriptions, and the responsiveness to price, respectively. The variable GA_{jt} is a dummy variable equal to one if the molecule j is available in generic form in the prescription ocassion t or zero otherwise. G_{ij} is the parameter associated to this dummy variable . It represents the change in valuation due to the trade-off between the significant price discounts of generic versions and their perceived quality. Note that GA_{jt} is only different from zero in this empirical application for the valuation of fluoxetine from January 2000 to March 2000. Finally, β_{0ij} is a constant that represents the baseline level of prescription of molecule j by physician i. This level of prescription is the outcome of several factors: long term experience with the different drugs in the category, type of patients that she visits etc. There are several factors that remain unobserved and influence the doctor to be more inclined to prescribe one molecule than the others.

All of the parameters are physician and drug specific. However, some constraints are necessary in the nested multinomial logit model for identification purposes: physician specific intercepts for Seroxat (Paroxetine) are set to zero for each physician. Because I am doing an individual level analysis, with physician specific parameters, I am also interested in reducing the number of parameters to a minimum, without losing goodness of fit. After conducting

several tests, I have further constrained past prescription parameters to be equal across all drugs ($\beta_{2ij} = \beta_{2i}$, for all j). This final specification requires the estimation of 11 parameters for each one of the 170 physicians and is very similar to the unconstrained version in terms of fit (details available from the authors upon request). These parameters are estimated using traditional Markov Chain Monte Carlo (MCMC) methods with a Gibbs-Sampler to draw from the closed-form conditional distributions, and a Metropolis-Hastings step to explore the posterior distribution of the parameters without closed form conditionals (Appendix C presents the detailed description of priors and estimation procedure).

2.5.1.4. Binomial Models of Within- and Between-Molecule Competition: I model the within- and between-molecule competition as a function of observable and unobservable physician characteristics. For the observable characteristics I use as covariates physician gender and practice size: gender is defined as a dummy variable that takes the value of one if the physician is male and zero if female; practice size is defined as the number of physicians working in the physician's practice. For the unobservable characteristics I include as explanatory variables the values of the individual-level parameters estimated using the multinomial nested logit. To reduce noise, I build 90% probability intervals for each physician-parameter combination based on 2000 draws from the posterior distribution, and kept only the values significantly different from zero. All others were set to zero. The parameters that were included are: the intrinsic attractiveness of Prozac ($\beta_{0iPROZAC}$), the responsiveness to Prozac detailing ($\beta_{1iPROZAC}$), the responsiveness to Lustral's price cut (β_{3i}), and the inclusive value parameter (λ_i).The other individual level parameters provided little information and will not be discussed.

Finally, to prevent confounding the responsiveness to detailing and the intrinsic preference with the level of detailing activity and the prescribing levels, I have also included several

	Posterior Mean	95% Prob. Intervals*
Intercepts (β_0)		
Prozac+Fluoxetine	0.02	[-0.19, 0.23]
Lustral	**-1.91**	[-2.23, -1.66]
Cipramil	**-1.09**	[-1.35, -0.85]
Detailing (β_1)		
Prozac	0.15	[-0.22, 0.53]
Lustral	**0.58**	[0.36, 0.86]
Cipramil	**0.83**	[0.59, 1.05]
Seroxat	**0.47**	[0.29, 0.64]
Past Prescription (β_2)	**0.31**	[0.23, 0.39]
Price Dummy Lustral (β_3)	**0.29**	[0.03, 0.54]
Inclusive Value (λ)	**0.02**	[0.01, 0.05]
Generic Fluoxetine (G)	**2.15**	[1.64, 2.69]

*Values in bold mean the 95% probability interval for the parameter does not include zero

Table 2.2. Random Effects Multinomial Nested Logit

control variables. These include the number of detailing visits from Prozac and from its competitors during Period 1 and Period 2, and the level of competitor prescribing during Period 1.

2.6. Results

Next, I present the estimation results and discuss their implications for government officials and company executives. Table 2.2 presents the posterior means and 95% probability intervals for the population level estimates of the random effects multinomial nested logit. Table 2.3 presents the results of the binomial regression of within-molecule competition estimated after generics have been introduced (what I called "Period 2"). Finally, Table 2.4 presents the results of the binomial regression of between-molecule competition estimated also after generics have been introduced (Period 2). All variables in the binomial models deemed non-significant at a 5% significance level were dropped from further analysis. I only present the parameters estimated for the retained variables.

2.6.1. Multinomial Nested Logit Model

Consistent with previous research (Janakiraman et al. 2005; Coscelli 1998) we find significant state-dependence across physicians' drug choices (the posterior mean of the population-level parameter of past prescriptions, β_2, is 0.31 with a probability interval of [0.23, 0.39]). The parameter associated with the price cut of Lustral, β_3, is also positive , with a posterior mean of 0.29 and a probability interval of [0.03, 0.54]. This positive but weak effect might explain why in some studies prices sensitivity is measured as significant and in others as non-significant. Regarding the intercepts, we find an overall preference for Prozac (fluoxetine) and Seroxat (paroxetine), consistent with their market shares (36% and 33% respectively).

These results also suggest that the average impact of Prozac detailing across all physicians is significantly lower than the impact of detailing for the remaining drugs. The parameter associated with Prozac detailing has a posterior mean of 0.15, with a wide 95% probability interval that includes zero. The parameters associated with the detailing of the remaining molecules are all significant (i.e., have 95% probability intervals that do not include zero) and highly positive with posterior means of 0.58, 0.83, 0.47 for Lustral, Cipramil, and Seroxat, respectively. This result does not mean that all physicians are not responsive to Prozac detailing and that all of them are highly responsive to the detailing of the remaining drugs. Because we allow for heterogeneity across physicians, some will be responsive and some will not. For example, 12% of the physicians have positive and significant individual parameters for Prozac detailing, with posterior mean values that range from 0.57 to 2.93. The population level results reveal only that on average Prozac detailing has little or no impact (consistent with the high level of brand awareness of Prozac and its market dominance) and that detailing from the remaining, newer and less popular drugs has a positive and significant impact on physician prescribing.

Regarding the parameters associated with the nested structure of the model, we find the posterior mean of the factor associated with generic versions of fluoxetine (G) to be 2.15, with the 95% probability interval of [1.64, 2.69]. This means that fluoxetine generics are being prescribed more often than Prozac, on those occasions that the molecule fluoxetine is prescribed. This is also consistent with previous findings in the literature that describe a very fast share erosion of brand name molecules once generics become available (typically, in recent years, major brand names have lost half of their market share within one year of patent expiry; see Grabowski and Vernon 1996). It is also consistent with the presence of "inertial physicians" (Janakiraman et al. 2005; Coscelli 2000) if we consider that even before patent expiration physicians were often prescribing Prozac using the generic denomination fluoxetine instead of the brand name.

I find also that the posterior mean of the inclusive value parameter (λ) is 0.02, a value very close to zero (the 95% probability interval is [0.01, 0.05]). The inclusive value parameter is related to the degree of within-molecule competition. When λ equals unity, the model tree collapses to a multinomial logit without a nested structure (consistent with generic versions of a multi-source molecule being viewed as completely different drugs from the branded alternative). If, in the limit, λ equals zero ($\lambda \rightarrow 0$), a molecule (irrespective of format) does not increase its choice probability regardless the introduction of generic versions. That is, the introduction of a generic version does not increase the degree of competition between molecules. Finally, if λ is positive, but less than one, physicians are indeed influenced by the low price of the generic alternative once generic versions of a given molecule enter the market. Physicians will then change the valuation of the molecule nest and prescribe more of

the molecule losing patent protection[8]. This means that the magnitude of the λ parameter provides us with a measure of how generics are perceived in the market and of their impact once they have entered the market[9].

In this empirical study, the parameter λ is very close to zero suggesting that there is great substitution within the nest and that the model tree with two levels (molecule and format) does not collapse into a simple multinomial logit model. The nested structure is then important to account for the higher similarity of generics and branded alternatives of a single molecule. This result also indicates that the introduction of fluoxetine generics, with the corresponding price reduction for the molecule had little or no impact on most physician choices during the first months after patent expiration.

Hence, most physicians perceive generic and branded alternatives of a molecule as very similar in terms of price-quality trade-offs (they are almost indifferent in prescribing one or the other), and generic entry does not change significantly the overall perception of the molecule as a whole, that is, did not lead to an expansion in molecule prescribing due to its lower price after patent expiry. In addition, even for those physicians in which an impact is most visible, this is still quite small. Though differences exist across physicians, the posterior means for the inclusive value parameters for each physician range from a minimum of 0.01 to a maximum of 0.08.

These results suggest that there is not much price sensitivity among the physicians in our study: even though fluoxetine was available at deep price discounts after generic entry,

[8]Note that in this type of application in which there is little price variation (e.g., due to regulation) and in which generics tend to enter the market at deep price discounts, it will be impossible to separate the effects due to price sensitivity for the molecule and due to perceived quality differences between a generic version and the corresponding brand name alternative.

[9]Using the terminology introduced in Chapter 1, when $\lambda \to 0$, we have a situation where all the impact of the launching of new product is in terms of substitution with the branded alternative. For $\lambda > 0$, we have that the introduction of generics is generating expansion at the molecule level and hence, increasing the level of between molecule competition.

it seems that only a few of them increased the level of prescription of that molecule. They also showed that only a few of them were sensitive to detailing activities and that there is an important amount of heterogeneity in their levels of response. In the next section, I will analyze how these individual unobservable characteristics are useful to understand the evolution of the market of SSRIs after the entry of generic versions of Prozac.

Finally, to test for the validity of the nested structure, and for the absence of serious structural breaks in the data, I also estimated the multinomial logit model with only the data before generic entry. The model parameters and the remaining results for the binomial models remain largely unchanged from the results we present in the paper. I also estimated a multinomial logit (without nested structure) for the choice of molecule (irrespective of format) with a dummy variable for prescriptions after generic entry (as an alternative model formulation). The posterior mean estimates of the inclusive value parameters and the generic entry dummies are highly correlated, which indicates that a nested logit model is able to capture the changes at the molecule level after patent expiration. The nested logit has the added advantage of modelling also the prescription of the version (branded vs. generic) of the multi-source that is prescribed. This suggests that the multinomial nested logit is a valid model to capture the introduction of a generic in a category as I do in this analysis.

2.6.2. Binomial Models Post Generic Entry

Tables 2.3 and 2.4 present the results of the binomial regressions of between- and within-molecule competition, respectively, estimated after generics have been introduced (what we called Period 2). All variables in the binomial models deemed non-significant at a 5% significance level were dropped from further analysis, and we only present the parameters estimated for the retained variables.

	Model I: With Baseline (Analyze Change) $s_i^B = \ln\left(\frac{SHARE_i^B}{1+SHARE_i^B}\right)$			Model II: No Baseline (Analyze Levels) $s_i^B = 0$		
	Estimate	St. Error	t-statistic*	Estimate	St.Error	t-statistic*
Intercept	-0.745	0.198	[-4.45, -2.92]	-0.733	0.185	[-4.64, -2.94]
Obs. Characteristics						
Gender	n.s.	n.s.		n.s.	n.s.	
Practice Size	-0.061	0.026	[-2.62, -2.04]	-0.085	0.024	[-3.8, -3.17]
Unobs.Characteristics						
Prozac ($\theta_{1\,Prozac}$)	-0.22	0.075	[-3.89, -1.98]	n.s.	n.s.	
Price Dummy (θ_2)	0.272	0.12	[1.5, 2.74](87)**	n.s.	n.s.	
Inclusive Value (λ)	18.731	4.595	[3.04, 5.37]	18.967	4.407	[2.88, 5.56]
Int. Prozac ($\theta_{0\,Prozac}$)	n.s.	n.s.		0.763	0.053	[13.67, 14.73]
Control Var. Competitors						
#Prescriptions Period 1	0.018	0.007	[4.2, 4.96]	n.s.	n.s.	
#Details Period1	0.007	0.002	[2.13, 2.66]	n.s.	n.s.	
#Details Period2	n.s.	n.s.		-0.064	0.022	[-3.18 -2.75]
Model BIC	873.94			NA		
Null Model BIC	911.52			NA		

*Range of the t-statistic for the 100 replications of the posterior mean of the Unobservable Characteristics. **In parenthesis, number of times that |t-stat|>1.96 (i.e. 95% significance cut-off point)
Table 2.3. Summary of Results for the Binomial Models of Between-Molecule Competition

In these binomial models, we use as covariates the estimates of unobservable characteristics obtained from the nested logit (these include the sensitivity to detailing and prices). Because such estimates have significant measurement error (e.g., the individual-level parameters obtained from the first stage of the analysis have wide confidence intervals) we need to assess the robustness of our estimates. To do so we use a bootstrap procedure. We re-estimate the binomial models 100 times including as covariates the posterior means of the parameters from the nested logit computed using 100 different random samples of physician-specific draws (we retained 2000 draws during estimation of the nested logit for each physician and each sub-sample has 200 draws; re-sampling was performed with replacement). We report the parameters of the binomial models (posterior means used as covariates are computed across

	Model III: No Baseline (Analyze Levels) $s_i^B = 0$			Model IV: With Baseline (Analyze Change) $s_i^W = \ln\left(\frac{SHARE_i^W}{1+SHARE_i^W}\right)$		
	Estimate	St.Error	t-statistic*	Estimate	St. Error	t-statistic*
Intercept	-0.614	0.439	[-2.28, -0.08](5)**	2.382	0.697	3.42
Obs. Characteristics						
Gender	-1.074	0.27	[-4.41, -3.48]	-2.337	0.629	-3.72
Practice Size	0.178	0.048	[3.35, 4.27]	0.219	0.111	1.97
Unobs.Characteristics						
Prozac ($\theta_{1\,Prozac}$)	-0.821	0.125	[-7.21, -5.15]	n.s.	n.s.	
Price Dummy (θ_2)	0.93	0.356	[2.00, 3.99]	n.s.	n.s.	
Inclusive Value (λ)	42.784	10.306	[2.25, 5.64]	n.s.	n.s.	
Int. Prozac ($\theta_{0\,Prozac}$)	n.s.	n.s.		n.s.	n.s.	
Control Var. Competitors						
#Prescriptions Period 1	0.031	0.006	[4.91, 5.8]	n.s.	n.s.	
#Details Period1	0.037	0.016	[1.65, 2.71](62)	n.s.	n.s.	
#Details Period2	n.s.	n.s.		n.s.	n.s.	
Model BIC	NA			347.39		
Null Model BIC	NA			375.64		

*Range of the t-statistic for the 100 replications of the posterior mean of the Unobservable Characteristics **In parenthesis, number of times that |t-stat|>1.96 (i.e. 95% significance cut-off point)

Table 2.4. Summary of Results for the Binomial Models of Within-Molecule Competition

the 2000 draws) and the range of the empirical distribution of the t-statistic for the different replications.

Physicians Sensitive to Prozac Detailing Decrease Fluoxetine Prescribing

A first significant result from the binomial models is the reduction of fluoxetine prescribing (Prozac plus generics) in Period 2 by those physicians sensitive to Prozac detailing in Period 1. The first and second columns of Table 2.3 present the results of Model I (model of between-molecule competition that uses the share of fluoxetine prescribing from Period 1 as baseline). This model is adequate to explain the changes in prescribing of fluoxetine (Prozac plus generics) versus other SSRIs from Period 1 to Period 2. The binomial parameter associated with Prozac detailing is -0.22 and significant across all replications. This means that those physicians who are more sensitive to Prozac detailing are the ones who 'move away from' fluoxetine the most (Prozac plus generics) in Period 2 compared to Period 1.

This prescription reduction is quite significant. Based on physician's individual probability intervals for the parameter of Prozac detailing, we have classified physicians into those sensitive to Prozac detailing (HIGH Group) and those not sensitive (LOW Group) with p>0.9. About 12% of the physicians were classified as being sensitive (HIGH) and on average these physicians prescribe 8.08% less fluoxetine (Prozac plus generic versions) in Period 2 than what would have been expected considering their prescribing levels from Period 1. Using a Chi-square test we conclude this is a significant change at a 5% significance level. The remaining physicians (the 88% classified as LOW, that is, not responsive to Prozac detailing) did not exhibit any significant change in their prescription behavior in Period 2 from what would have been expected given their prescribing behavior in Period 1 (the change in fluoxetine prescriptions was1.30% and not significant).

The reaction of detailing sensitive physicians is perhaps due to the sudden reduction, and subsequent elimination, of Prozac detailing (generics do not engage in marketing activities in this market). Physicians who were greatly influenced by marketing activities end up reducing their fluoxetine prescribing once the marketing actions of Prozac stop and switching to the other SSRIs that maintain (or even increase) their promotional effort. This a very important result as it reveals that to predict the impact of generic entry we should consider the marketing actions of pharmaceutical companies, and the full competitive setting in the relevant therapeutic class, not just the direct effects of generics on the brand losing patent protection.

With respect to the cross-sectional variation of prescribing in Period 2, we note that the responsiveness to Prozac detailing does not explain the physician prescribing split into fluoxetine and other drugs across all physicians (the variable is not significant in Model II; see Table 2.3) though it explains the prescribing of Prozac versus generic versions of fluoxetine,

once fluoxetine is the prescribed molecule. Physicians responsive to Prozac detailing in Period 1 prescribe generics fewer times, given that the fluoxetine molecule is chosen (the variable has a negative impact, $\theta_{PROZACDetail} = -0.82$ and is significant in Model III, the within-molecule model without baseline; see Table 2.4). This is an interesting result from a public policy point of view. Though physicians sensitive to Prozac detailing (all else constant) do not prescribe the molecule fluoxetine differently from those not responsive (only the changes from Period 1 to Period 2 at the individual-level are affected), once the molecule is chosen physicians prescribe fewer generics if they were sensitive to Prozac detailing. In this case, detailing has a long lasting effect on the market even after it is no longer used by the company: it created loyalty to the brand. This result would have not been discovered had we used traditional regression based techniques using aggregate level data.

Price Sensitive Physicians Increase Fluoxetine Prescribing

Physicians with an estimated higher inclusive value (λ) switch from other SSRI molecules to fluoxetine in Period 2 ($\theta_{\lambda} = 18.73$ in Model I; recall that this parameter measures also the responsiveness of physicians to price, i.e., the farther away from zero, the more physicians increase the use of fluoxetine because of the presence of low cost generics). The same pattern is present for physicians sensitive to Lustral's price cut ($\theta_{RPcut} = 0.27$ in Model I), even though the effect is less pronounced (this parameter was not significant in 13 replications, out of 100, and we should consider the result cautiously). Such behavioral pattern is simple to explain: price sensitive physicians see a greater advantage in using fluoxetine, versus all other drugs in the category, because of its reduced price after generic entry. These physicians will then prescribe more fluoxetine than before, and reduce the use of the remaining molecules (switch from other SSRIs to fluoxetine).

Again, the prescription changes are significant. For example, physicians classified as LOW with respect to the inclusive value parameter (about 80% of the sample) reduce their fluoxetine prescriptions by 3.83%; those classified as HIGH (about 20%) increase the use of fluoxetine by 5.07% more than what would have been expected given their prescriptions in Period 1. Both changes are statistically significant. However, the increase in fluoxetine prescribing (a result most public policy officials hope for after generic entry) was not able to compensate the reduction of fluoxetine prescription from other physicians that are not especially price conscious and might be sensitive to other marketing actions such detailing. In addition, the move towards fluoxetine is fuelled by generic prescribing and not Prozac prescribing (as most public officials would hope for and as it would be expected). This can be seen from the results of Model IV (Table 2.4): physicians with higher inclusive values and higher response to the price cut prescribe more generics than those with lower values for these parameters ($\theta_{RPcut} = 0.93$ and $\theta_{\lambda} = 42.74$ in Model IV).

Observable Physician Characteristics can help to predict Generic Use

Consistent with previous research (e.g., Hellerstein 1998), we find that observable physician characteristics can explain part of the variance of format choice decisions. The results in Table 2.4 (models of within-molecule competition) provide clear evidence that though there is a total increase in prescription under generic format, male doctors and those working in smaller practices are less proactive in increasing these levels ($\theta_{Gender} = -2.34$ and $\theta_{PRACTSIZE} = 0.22$ in Model III). In addition, all else constant, we find that physicians in smaller practices and male physicians prescribe fewer generics than the remaining physicians In Period 2, when fluoxetine is the chosen molecule ($\theta_{Gender} = -1.07$ and $\theta_{PRACTSIZE} = 0.18$ in Model IV). However, it is not clear why we obtain such result. One possible explanation, for example, is that smaller practices are not as well informed about the potential cost benefits

of generic prescribing. Another possible explanation for the practice size result is that current incentives are designed to benefit mostly bigger practices. It is difficult to find explanations for why male physicians prescribe fewer generics. It is possible that gender is working as a proxy for some other factor we are not accounting for and that further research is required to fully understand this result. Such understanding will be important if the UK government is to increase generic prescribing.

In summary, these are important results. First, they demonstrate that to fully understand and predict the market dynamics post generic entry it is essential to look beyond within-molecule competition, which has been the focus of most empirical research to time. In addition, these results provide, for the first time, clear individual level evidence of the important detailing and price related mechanisms that determine the fate of generics and branded drugs. This in turn further highlights the importance of analyzing simultaneously between- and within-molecule competition.

2.6.3. Discussion

Overall aggregate-level changes in the SSRI category were small in the months following the entry of generic fluoxetine. Figure 2.2 depicts a small decrease of fluoxetine (Prozac plus generics), but nothing in the time series reveals the presence of a significant change in the market structure. In contrast, this individual-level analysis reveals a very different picture. Though on average changes are small, there are significant variations between physician groups that respond differently to promotional efforts and prices, two factors that influence the market in opposite directions.

On the one hand, I detect the presence of a small group of physicians who seems to be price sensitive. These physicians increase their level of fluoxetine prescribing after patent expiry

due to the lower average cost of the drug. On the other hand, this increase is compensated for by the reduction of fluoxetine prescribing by a bigger number of doctors. Part of this reduction is related to the decrease, and then suppression, of detailing visits by Prozac. This is because a segment of physicians, sensitive to the detailing activity of Prozac before patent expiration, reacts negatively and reduces fluoxetine prescribing.

These results suggest that shifts between the generic and branded versions of fluoxetine are not the only important changes to be monitored in the market. It is also important for governments and for pharmaceutical companies to follow the fluctuations of fluoxetine prescribing versus all other SSRI drugs, even if not bio-equivalent. Though Prozac market share declines rapidly once generics enter the market, depending on the number of physicians who switch to other branded alternatives, potentially even more expensive than the original Prozac, the reduction in health care costs might be much smaller than expected. Such market changes could have not been detected if only within-molecule competition had been studied and an individual level analysis of the physician role had not been conducted.

2.7. Conclusion

In this article I try to shed some light about the factors that must be considered when analyzing the effects of generic entry in the market. We find that between-molecule dynamics play a significant role in determining the fate of generic and branded molecules, and that the mechanism and final outcomes will depend greatly on physician prescribing behavior and on the different segments of physicians present in the market. This means that beyond the competition between a branded molecule and its generic versions, it is also essential to consider the competition among non-bioequivalent brands in a given product category and how physicians respond to the changes in prices and detailing. I note that, with few exceptions,

previous research has focused mostly on institutional factors and on within-molecule competition. Rarely are physicians and their characteristics considered (one exception is the work of Hellerstein 1998), and rarely is between-molecule competition considered (one exception is the work of Ellison et al. 1997). To the best of my knowledge no previous work has simultaneously analyzed such factors.

Consequently, from a public policy perspective this study also reveals that cost-reduction strategies promoting the increase of generic prescribing should be considered using a framework of within- and between-molecule dynamics, along with physician characteristics and their segmentation. Analyses that consider only within-molecule dynamics would be myopic and could lead to the development of ineffective incentive schemes. For example, to impose the substitution of branded versions by their generic alternatives at pharmacies might not produce the expected and desired cost reductions if physicians switch to other branded molecules of the same category that are still under patent protection.

In addition, the importance of between-molecule competition is perhaps what explains the counter-detailing activities of some U.S. states (Mizik and Jacobson 2004), that is, detailing visits promoting the generic versions of molecules. Unless between-molecule considerations are made, it would be very difficult to justify such actions by the local governments. Attempts to establish empirical generalizations on drug characteristics that predict a higher level of between-molecule competition, and individual-level studies that characterize the physician population with respect to unobservable features like responsiveness to price and detailing, would then be extremely useful for public policy officials (and pharmaceutical companies) facing future generic entry.

It is important to note however, that newer and more expensive drugs are constantly being presented in the market and promoted heavily by pharmaceutical companies. These new product introductions might make physician incentives not aligned with those of governments. In such situations, trying to induce greater price sensitivity of physicians to encourage the use of lower cost generics, and trying to induce a lower detailing sensitivity or limit promotional activities from pharmaceutical companies, might work as a double-edged sword. Strong incentives for doctors to be cost-conscious might introduce moral hazards in their decision process affecting negatively the welfare of some patients who might require the new and better drugs. Hence, public officials should consider very carefully the implications of using the knowledge of physicians' unobservable characteristics in their policy design.

The conclusions of this study might be also insightful for pharmaceutical companies. For example, when the U.S. appeals court in Washington D.C. set a sooner-than-expected end to the Prozac patent protection in the US, analysts warned that the sales of one of the most important competitors to Prozac, Cipramil also known in the U.S. as Celexa, could be damaged by competition form generic versions of Prozac (McCarthy 2000). The results demonstrate that two factors with opposite effects, price cuts due to generic entry and the reduction in promotional activity by the drug losing patent protection, play an important role. This article shows that it is necessary to study physicians' choice behavior and their responsiveness to price and detailing to fully understand the market events and better predict the fate of generics and brands.

The analyses in this chapter were done solely on U.K. SRRI data. Previous research indicates that the institutional features of each market have a great influence on prescribing behavior and on the effects of generic entry, and that each pharmaceutical category might reveal different market evolutions and dynamics (e.g., Danzon and Chao 2000, Magazzini et

al. 2004). As a result, it might be difficult to extrapolate these results to other countries and drugs. However, given the importance of side effects in the use of SSRI's, I believe this empirical example is conservative regarding the impact of price and detailing changes. It is likely that such impacts are bigger in contexts where drugs have fewer and less severe side effects. I also believe that the impact of detailing in this empirical application is particularly small because of the many years of experience of the panel physicians and because of the age of the drugs. I would expect that physicians starting their professional career, and physicians considering the adoption of new drugs, will be more influenced by the informative role of detailing (Narayanan and Manchanda 2006). In addition, I would also expect price effects to be more important in those countries or situations in which final consumers are more price sensitive (e.g., countries in which final consumers bear a greater share of the cost).

An area for future research could be the application of similar studies in different countries and across multiple categories. It would then be possible to understand how institutional features of each market interact with the physician segmentation and the competitive dynamics. In addition, it would be important to further understand why in the U.K. male and smaller practice physicians are less interested in prescribing generics (all else constant). Further analysis of what drives these physicians away from generic prescribing is warranted.

CHAPTER 3

Assessment of Retailer-Brand Interactions in the Theatrical Movie Industry.

3.1. Introduction

In the past decades, branding has been the center of significant streams of research in consumer behavior, psychology, marketing, and economics (Aaker and Keller 1990, Keller 1993, Yoo et al. 2000, Berry 2000, Erdem and Swait 1998). This literature has had a predominantly consumer-based focus in its empirical and theoretical dimensions. More recently, some scholars have suggested that brands might also play an important role in the management of inter-organizational relationships. For example, it has been suggested that manufacturer brands are a source of trade-leverage by adding to the bargaining strength of suppliers (Aaker 1991), whereas other authors suggest that brands can be seen as pledges of long-term continuity in channel relationships (Anderson and Weitz 1992, Brown et al. 1995). Despite these theoretical speculations, to the best of our knowledge, there is limited research that addresses these issues empirically.

With this paper we contribute to the literature on the inter-organizational role of branding by empirically studying the value of manufacturer brands in channel management. Following previous research, we argue that strong manufacturer brands are less dependent on retailers for their performance, which can in turn contribute to their bargaining advantage. We test this proposition by measuring the effect of the retail channel on brand performance using data on consumer purchases across competing retailers, and testing whether the effect of retailers differs between strong and weak brands. The proposed approach, which is applied

to theater-level data of movie audiences, accounts for the impact of distribution decisions, brand competition and assortment effects. Specifically, we focus our analysis on a local movie exhibition market and measure the impact of theaters (retailers) on movie (brand) performance, and test how such impact differs with audience appeal (brand strength).

Consistent with previous research (e.g., Reibstein and Farris 1995) our findings reveal that theaters have a significant effect on brand performance and that exhibitors expectations of movie performance influence which movies are shown in any given week (i.e., we find evidence of the two-way relationship between performance and distribution). In the market under analysis we also find that one of the theater chains performs, on average, consistently better than the other. As a result, a movie that is shown in this best performing chain is more likely to perform well, all else constant. However, brand strength plays a moderating role: differences in performance across the two chains are larger for weaker movies than for stronger movies. These results suggest that weaker brands (i.e., movies with limited audience appeal) rely more on the quality of the venue chosen for their performance.

These results are of great significance for brand managers. First, they provide evidence that strong brands can indeed enhance the bargaining power of manufacturers when facing increasingly powerful retailers (see Corstjens et al. 2004 for a review on retail power issues) because strong brands are less dependent on retailers for their performance. Second, our findings document an additional double jeopardy of weaker brands (Ehrenberg 1988): not only weaker brands will be bought less often by consumers and carried less often by retailers, weaker brands will also have less bargaining power with channel members because their performance depends more on the retailer ability in attracting sales. Finally, our approach provides a way to measure the effect of retailers on brand performance that complements existing methods in the literature (e.g., Bronnenberg and Sismeiro 2001). The proposed

approach can be used by manufacturers in assessing the best venue for offering their products, even when retailers' assortments differ.

The rest of this paper is organized as follows. Next we will present the relevant background literature that informs on the role of branding on channel management. These include studies on the complementary role of manufacturer and retailer brands, on the differential marketing effects of strong versus weak brands, and on the effects of branding on channel relationships. We will then describe the market we will be analyzing and we will present the details on the data used. Finally, we present our model and our results, and we conclude with the implications of our findings and future research directions.

3.2. Background

There have been many studies in the marketing and economics literature addressing retailer-manufacturer interactions and channel management issues. For example, previous research has studied the two way relationship between distribution and product performance (e.g., Reibstein and Farris 1995, Bronnenberg et al. 2000, Elberse and Eliashberg 2003), how channel members adopt new products (e.g., Montgomery 1975, McLaughlin and Rao 1991, Bronnenberg and Mela 2004), the retailer-manufacturer power-split (e.g., Hoch and Banerjee 1993, Messinger and Narasimhan 1995, Ailawadi and Farris 1999, Kadiyali et al. 2000) and its impact on retailer and manufacturer performance (e.g., Farris and Ailawadi. 1992, Messinger and Narasimhan 1995, Kadiyali et al. 2000, Corstjens et al. 2004, Dukes et al. 2006).

Previous research has also proposed alternative ways of incorporating distribution effects in predictive and descriptive models of brand diffusion and performance (e.g., Jones and Ritz 1991, Bronnenberg and Sismeiro 2002), has modeled simultaneously the supply and demand sides of a single market (e.g., Villas-Boas and Zhao 2005), and has studied multiple tools used

by manufacturers and retailers to manage their relationship, including slotting allowances, direct to consumer advertising, trade promotions and the introduction of private labels (e.g., Lal and Narasimhan 1996, Bloom et al. 2000, Wilkie et al. 2002).

3.2.1. Branding and Channel Management

In addition to this vast work, several researchers have also recognized that brands are of great relevance not only to manufacturers and consumers but also to resellers and other stakeholders (e.g., Duncan and Moriarty 1998, Anderson and Narus 1999). For example, it has been suggested that strong brands provide a bargaining advantage to manufacturers in their negotiations with resellers (Aaker 1991), and that managers could maximize channel influence by highlighting to resellers the value of brand resources such as funding for trade promotions, pricing collaboration, and service (Davis 2000).

Not only such views reflect the potential importance of branding in the management of channel relationships, they have also become more relevant with the recent transformations in reseller practices. These transformations have taken place in the past two decades and include an increased emphasis on private label, consolidation into larger organizations, expansion beyond traditional national boundaries, and implementation of category management (Shocker et al. 1994). These changes have also contributed to the trend of increased retailer power, which is well documented in academic and practitioner journals (e.g., Corstjens et al. 2004, Ailawadi and Farris 1999, Hoch and Banerjee 1993), as well as the popular press.

The increased in retailer power is often used to justify manufacturers' investment in building strong brands (Hoeffler and Keller 2003). Creating an maintaining strong brands has, as a result, become a marketing priority for many organizations. The presumption is that building strong brands yields a number of marketing advantages, including a stronger

position for manufacturers in channel management (Hoeffler and Keller 2003). In the face of such arguments, and despite the richness and breadth of existing branding studies, it is striking the lack of empirical work studying how branding influences channel relationships (Webster 2000).

3.2.2. Complementary of Manufacturer and Retailer Brands

Channel relationships are often seen as adversarial with an emphasis on inter-firm power and control (Gaski 1984). Though manufacturer influence strategies can lead to channel conflict, they can also improve manufacturers' relationships with resellers (Frazier and Antia 1995). As a result, there is now more consideration in the channels literature of relational outcomes including relational norms, inter-organizational governance satisfaction, trust and commitment (Weitz and Jap 1995, Heide 1994, Geyskens et al. 1998). It is in this context that brands can be seen as pledges of long term channel relationship continuity (Anderson and Weitz 1992, Brown et al. 1995).

This view is based on the complementary of manufacturer and retailer brands. For example, Porter and Claycomb (1997) find that store assortment is a critical element of store choice.and demonstrate that the perception of a retailer depends on the national brands it sells. They also find that the retailer's image is enhanced by the quality of the assorted brands it carries. Finally, Ghosh and John (1999) argue that major brands are more able to use market governance because strong brand equity adds value to the reseller's offering.

3.2.3. Differential Marketing Effects

Beyond the complementary role of manufacturer and retailer brands, recent research further substantiates the importance of manufacturer brands, and their strength, in generating

differential returns to marketing actions (such differential returns can in turn create differential responses from the part of retailers). For example, Macé and Neslin (2004) and Bell et al. (1999) show that product- or brand-specific characteristics can explain significant variation in promotion elasticities. Besanko et al. (2005) find that brands with larger market shares receive higher trade-promotion pass-through than smaller brands. Some of the reasons they gave is that "manufacturer reputation" positively influences retailer support of trade promotions or that larger-share brands are more likely to expand the category rather than cannibalize other brands in the category. In addition, Slotegraaf et al. (2003) demonstrate that brands with higher equity are able to generate higher immediate returns from their marketing mix efforts, whereas Slotegraaf and Pauwels (2006) find that brands' resources play an important role in the long-term effects of marketing actions. Finally, Lemon and Nowlis (2002), using scanner data analysis and experiments, find that high-tier brands benefit more than low-tier brands from price promotions, displays, or feature advertising, when these promotional tools are used by themselves.

Overall, this research reinforces our expectation that stronger brands can be less dependent on retailers for their performance and, as a result, manufacturer brand strength can counterbalance the power of retailers (Hunt and Nevin 1974). Despite this contention, to the best of our knowledge, no empirical study provides a clear test of the role of brand strength as a moderator of retailers' impact on brand performance. However, several studies do present evidence that is consistent with such moderating role. For example, Pauwels and Srinivasan (2004) demonstrated performance effects of store brand entry that benefit consumers, the retailer, and the premium-brand manufacturers, but harm second-tier brand manufacturers. They also showed that consumers do not obtain lower prices on all national brands, but only on some second-tier brands. Finally, Bloom and Perry (2001) find that manufacturers with

large market shares enjoy increased profitability from their relationship with Wal-Mart, even though, over time and on average, manufacturers are becoming worse-off.

Some analytical work also stresses that brands that invest more in "pull" marketing tools, such as advertising, can better leverage their power against retailers. For instance, Lal and Narasimhan (1996) showed that manufacturer's advertising can lower the retail margin while simultaneously increasing the wholesale margin. Similarly, Dukes et al. (2006) study channel bargaining with retailer asymmetry and show that manufacturers that advertise before consumers' retailer choices, can improve their bargaining position with retailers.

3.2.4. This Paper

With this paper we contribute to the literature on the inter-organizational role of branding by empirically studying the value of manufacturer brands in channel management. We first measure the effect of the retail channel on brand performance using data on consumer purchases across competing retailers. We then test whether strong manufacturer brands are less dependent on retailers for their performance, which can in turn justify a bargaining advantage. Next we will describe the empirical setting of our study, the model, and the measures used to test the moderating role of brand strength on retailer effects.

3.3. The Empirical Setting: Movie Exhibition Duopoly

We have selected to use movie audience data to empirically study the moderating role of brand strength on retailer effect on brand performance. The data used in this empirical application was provided by two independent exhibitor groups through EDI-Nielsen, which collects weekly revenue and admissions figures for every movie released. The data comes from a middle-sized European city. The two exhibitor groups (henceforth, Chain 1 and Chain 2) cover the whole market and run 12 screens each. The market under study can be defined a

duopoly as the closest theater to the city is 83 Km away (approximately 52 miles). In addition, there is no price competition for movie tickets in this market: admission prices were equal for the two chains (around €4.50) and flat during the observed time period (between October 2001 and October 2002).

We believe this is an excellent setting to answer our research questions for several reasons. First, not only movie brands are subject to the typical forms of brand management, including the use of signaling, brand extension, and development through advertising and other forms of market communication (Sood and Drèze 2006, Basuroy et al. 2006), it is also straightforward to measure movie brand equity. Indeed, one of the problems of studying the moderating role of brand strength (or brand equity) is its measurement. Previous research has used a multitude of measures to tap at the concept of brand equity. Some of these measures are based on financial performance and stock-market returns (e.g., Simon and Sullivan 1993); some are based on consumer based concepts like brand associations, esteem, recognition, awareness, and differential response to marketing variables (e.g., Keller 1993); and other methods are based on historical or replacement costs (see Aaker 1993 and Kapferer 1992 for a review).

One of the great advantages of our data set is that there is a clear and straight forwarded method to measure brand strength: strong movie brands are those with strong audiences. Movie audiences provide immediate profits for distributors, who take in a significant share of the box office revenue, and are directly related to the full revenue stream of a movie, which might include rentals, movie sales, and merchandising (Ravid and Basuroy 2003; Lehmann and Weinberg 2000). In addition, conversations with Hollywood movie executives have confirmed that brand strength is indeed associated to audience appeal and revealed that maximizing box office revenue is often the executives' main goal. Finally, we note the absence of price competition in this market, which is also typical of most exhibition markets (Orbach

2004). This means that, in general, there is no reason to make a trade-off between price and quality when deciding which movie to watch. It also means that strong audience does indeed correspond to a strong brand.[1] Hence, using total box-office revenue as a measure of brand strength is the same as measuring brand equity using the revenue premium method that has been frequently applied in previous branding research (e.g., Slotegraaf and Pauwels 2006; Ailawadi et al. 2003).

In addition, "theater quality" could have an impact on brand performance. Movies shown at the best theaters (in terms of location, convenience, ambience, and additional services) might observe an addition boost in audience that otherwise would not be there just because the best theaters might attract more audience. Hence, an additional advantage of our dataset is that it will allows us to measure the impact of theater quality on movie performance, and control for factors such as movie assortment. One final advantage of our study is that we are able to model the full life-cycle of all products and test whether the life-cycle stage plays a significant role in terms of performance and retailer effects. In addition, because movies life-cycles tend to be short, we can ensure that no significant changes have occurred during the period under analysis in terms of market structure and with respect to the exhibition chains. This increases the internal validity of the study by limiting the number of alternative explanations for the effects we find.

For all these reasons we suggest that the movie exhibition market is a good setting for studying the role of branding in channel management. Table 1 provides the summary statistics for the movies released in both chains, and Table 2 presents the performance difference (per movie and in total) between Chain1 and Chain2.

[1] In other contexs the presence of price competiton poses additional challenges. For example, premium products might have stronger brands and have fewer sales simply because they are sold at higher prices. Under these conditions we cannot equate brand strength to the sales of a product. Alternative methods will have to be used

	Box Office ('000€) Chain1		Number of Movies	Box Office ('000€) Chain2		Number of Movies
	Total	Per Movie	Chain1	Total	Per Movie	Chain2
Common	1573.9	31.5	50	1436.1	28.7	50
Unique	1134.3	12.2	93	833.0	8.2	102
TOTAL	2708.2	18.9	143	2269.1	14.9	152

Table 3.1. Box office Revenue (000' euros) and number of releases for Chain 1 and Chain 2

	Chain2 compared to Chain1(%)	
	Total Box Office	Box Office per Movie
Common Releases	-8.8	-8.8
Unique Releases	-26.6	-33.0
TOTAL	-16.2	-21.2

Table 3.2. Percentage difference in box-office revenue of Chain 2 versus Chain 1

All the movies considered in this dataset (a total of 245) ran for at least two weeks in a given theater and through consecutive time periods (we removed movies that run for only one week, including movie reruns, which were fairly uncommon).[2] "The Fellowship of the Ring" was the main blockbuster of the year, and Ron Howard won the Best Director and Best Picture Oscar awards for "A Beautiful Mind", inspired by the life of John Nash. Of the movies considered, 50 were released by both theaters ("common releases") and *195* released by a unique theater (93 in Chain 1 and 102 in Chain 2). We note that Chain 1 released fewer movies than Chain 2 (143 vs.152) although both chains have the same number of screens (12) and a similar number of total seats.

From Table 3.1 and 3.2 we can see that Chain 1 is a better place to release a movie than Chain 2 if we are trying to maximize sales. Chain2 has 16% less total box-office revenue than Chain1, and 21% less box-office revenue per movie. Further analysis supports this contention. For example, if we only consider common releases Chain 2 generates an 8,8% less revenue than Chain 1. In addition, for the unique releases of each chain in the city under study, we

[2]The movies retained represent the vast majority of movies in the original sample. In addition, the cases discarded account for a marginal contribution in terms of box-office performance and mostly introduce noise into the analysis. We also performed the full analysis including these cases and obtain the same results though the estimates are more noisy. Results are available from the authors upon request.

	Audience in the MB Market (000')*	
	Total	Per Movie
Unique Release Chain1	108,352	1,165.1
Unique Release Chain2	108,832	1,067.0

* Correspond to the audiences measured in the MB market across the movies released only by one chain in the focal market

Table 3.3. Box-office revenue in the MB market of the movies released by Chain 1 or Chain 2 in the focal market

collected aggregate box-office performance data from a separate region. This other market (which we will call market MB) covers a wide region of the country but does not include the city under analysis. In Table 3.3 we report the total box-office revenue in the MB market for the movies released only by Chain 1 or only by Chain 2. As it can be seen in Table 3, audience differences in the MB market for the unique releases are negligible (audiences of 108.4 vs. 108.8 million). Hence, it seems that movies released in Chain1 perform significantly better in the focal city because of the preference consumers have for that theater, and not simply because movies released in Chain 1 were intrinsically better.

As a preliminary analysis on whether the effect of a retailier on movie performance is the same for movies with different brand strength, we compare vis-à-vis the set of common releases. To do so we sort the movies exhibited by both theaters in ascending order in terms of total revenue. These 50 movies represent the 60% of total box-office revenue. We then compare the revenue generated per quartile and present the differences between the two chains in absolute terms and percentages in Figure 3.1. Figure 3.1 reveals a sort of U-shape relationship between the relative advantages of one theater over the other, on the basis of the total revenue generated by both theaters. In general terms, very successful movies tend to perform more closely in the competing theaters than less popular movies. Also very unpopular movies perform similarly in both chains.

These preliminary analyses seems to indicate that a movie will perform better if released in Chain 1 because of the quality of Chain1 in terms of location and facilities, and because

of its ability to attract more audiences. In addition, it seems that the strongest (but also the weakest) brands might be less dependent on retailers for their performance. We note, however, that this analysis does not provide conclusive answers. First, in these analyses we do not account for within- and across-chain competition from other movies. During a movie tenure there is a varying portfolio of competing movies, each of which might attract audiences differently. In this preliminary analysis we also do not consider any life-cycle effects. Because the two chains do not keep movies running for the same number of weeks, the difference in chain performance could be related with movie tenure decisions and with the movie life-cycle stage at the time it is cut from further showings. Finally, the previous analyses do not take into account the possible endogeneity of movie cutting decisions: exhibitors form expectations regarding the future revenue stream of each movie and might have good knowledge regarding which movies to stop showing. Movie cutting decisions are specially relevant with theater-level data as these produce truncated box-office revenue data: once a movie is eliminated from a single theater, we stop observing movie audiences for that theater, even though some moviegoers might have chosen to see the movie had that movie been available.

All these are factors pose specific modeling challenges. To answer our research question, we develop a box-office revenue model that will allow performance comparison of movies in different theaters of the same market and will account for all such factors. In developing our model, we follow the extant literature on box-office revenue modeling and prediction, and we adapt current models to the type of data at hand, specifically, to the disaggregate nature of the revenue data we have available. Next we will describe the modeling approach and present the empirical results.

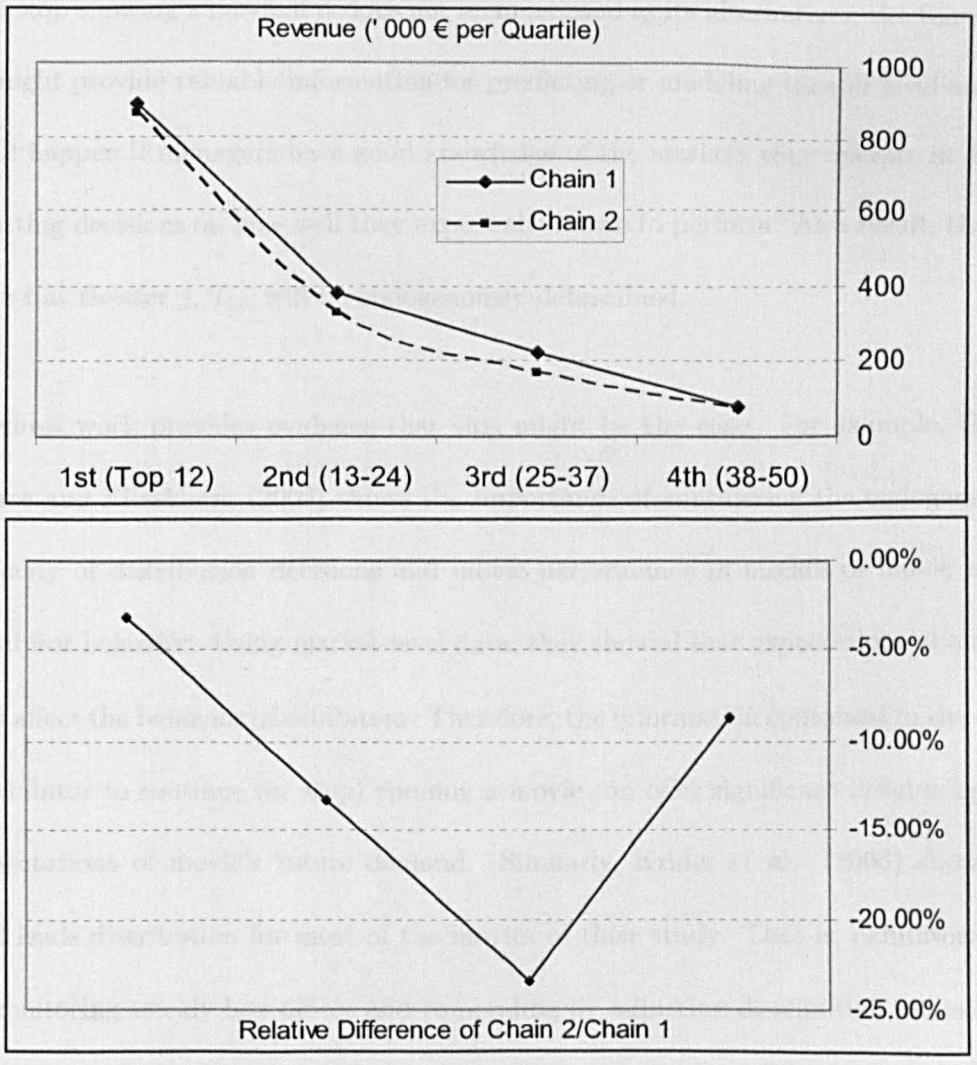

Figure 3.1. Revenue (000'€) and Relative Difference (Chain2/Chain1) of movies in ascending order for Chain 1 and Chain 2

3.4. Modeling Approach

Consider n_{ijt}, the true audience of movie i in exhibition at theater j during week t (for $j = 1, ...S$; $i = 1, ..., M_j$ and $t = 1, ..., T$ where S is the total number of theaters in the market, M_j is the total number of movies presented at theater j, and T is the total number of weeks observed[3]). The true audience of a movie is only observed while the movie is being shown in a given theater, that is, for $t \leqslant T_{ij}$, where T_{ij} is the movie tenure. Because theaters are

[3]Note that t does not represent a calendar week, but for each movie and theater it will correspond to the running week ($t = 1, 2, 3 \ldots$). In addition, in the way we set up the indices, the i^{th} observation corresponds to a unique number for each movie presented in a theater (i.e. across theaters the same number could correspond to different movies). The unit of analysis is therefore, movie i exhibited in theater j during T_{ij} weeks

likely to stop showing a movie if it does not seem as good as its alternatives, the tenure of the movie might provide valuable information for predicting or modeling theater level audiences. This will happen if managers have good knowledge of the markets they operate in and base their cutting decisions on how well they expect the movie to perform. As a result, the tenure of movie i at theater j, T_{ij}, will be endogenously determined.

Previous work provides evidence that this might be the case. For example, the work of Elberse and Eliashberg (2003) shows the importance of considering the endogeneity and simultaneity of distribution decisions and movie performance in models of movie audience and exhibitor behavior. Using market-level data, they showed that expectations about future demand affect the behavior of exhibitors. Therefore, the information contained in the decision of an exhibitor to continue (or stop) running a movie can offer significant insights regarding the expectations of movie's future demand. Similarly, Krider et al. (2005) showed that demand leads distribution for most of the movies of their study. That is, exhibitors appear to be monitoring weekly box offices and responding by adjusting distribution intensity.

If the tenure of a movie is set endogenously, and if we do not take into consideration the theater's decision to cancel a movie, we will likely obtain biased estimators and incorrect predictions of movie audience (see for example DeSarbo and Choi 1999 and Braun et al. 2006 for additional discussions on adequately modeling truncated data). Though this bias might be negligible when a movie has been shown for many weeks in a theater, for movies with shorter runs will might be greatly affected. Hence, we propose to jointly model the exhibitor's tenure decision for each movie and the theater-level movie audience.

Following previous research (Bucklin and Sismeiro 2003; DeSarbo and Choi 1999), we adopt a discrete time approach to model the tenure of movie i in theater j, T_{ij}. A discrete

time model of movie tenure is especially appropriate in our setting because theater managers make their tenure decisions weekly, rather than in days or minutes (Eliashberg et al. 2001, Gil 2005). To model movie audience we also follow previous research and adopt a flexible Gamma distribution, similar to the work of Ainslie et al. (2005). Next we will describe in more detail both the tenure and the audience model components.

3.4.1. Modeling Movie Tenure (T_{ij})

We assume that, at the beginning of each time period, every theater must decide whether to keep on showing (or replace) the movies shown the previous period. That is, on the premise that a movie is being shown in week t, the theater owner will decide at the beginning of week $t+1$ whether or not to show it again. We also assume that there is no time-lag between placing an order for a new movie and its arrival. That is, considering that a movie is not performing as expected, the exhibitor has access to other options for that week, which is something typical in this industry (Swami et el. 1999).

We define C_{ijt} as a dummy variable to represent the decision by theater j of whether movie i is going to be shown, or not, during week t, such that:

$$C_{ijt} = \begin{cases} 1 & \text{if movie } i \text{ is on at theater } j \text{ during week } t \\ 0 & \text{if movie } i \text{ is off at theater } j \text{ during week } t \end{cases}. \tag{3.1}$$

As we model only movies with unique and consecutive runs (see previous discussion in the empirical section), the following holds:

$$C_{ijt} = 1 \Rightarrow C_{ijt-1} = 1, \text{ and} \tag{3.2}$$

$$C_{ijt} = 0 \Rightarrow C_{ijt+1} = 0. \tag{3.3}$$

In addition, we model movies from the moment they are shown at a theater, which means that they must run for at least the first week, therefore:

$$C_{ij1} = 1. \tag{3.4}$$

Let us define now a latent variable y_{ijt} representing the attractiveness for theater j of showing movie i during week t. We assume that:

$$y_{ijt} = W_{ijt}\mu_j + \nu_{ijt}, \text{ and} \tag{3.5}$$

$$\nu_{ijt} \sim N(0,1), \tag{3.6}$$

where W_{ijt} is a $(1 \times k)$ vector of covariates and μ_j is a $(k \times 1)$ vector of theater specific parameters (the product $W_{ijt}\mu_j$ represents the deterministic component of the attractiveness of continuing to run a movie). The term ν_{ijt} is a normal error term with zero mean and unit variance, for identification. We also assume that:

$$C_{ijt} = \begin{cases} 1 \; if \quad y_{ijt} \geqslant 0 \\ 0 \; if \quad y_{ijt} < 0 \end{cases} \text{ for } j = 1,...S;\ i = 1,...,M_j \text{ and } t = 2,...,T_{ij}+1, \tag{3.7}$$

and obtain a standard binary probit model. Note that the subscript time goes from $t = 2,...,T_{ij}+1$ given that we do not model the release of the movie (i.e. we take $C_{ij1} = 1$ as given) and we observe the behavior of the theater manager that decides to show the movie for T_{ij} weeks, and to cut the movie in week $T_{ij}+1$. Since we do not consider the possibility of a re-release (Eq. (3.3)), as discussed previously, we also take as given $C_{ijt} = 0$ for $t = T_{ij}+2, T_{ij}+3....$

3.4.2. Modeling Audiences (n_{ijt})

The literature on movie box-office modeling is vast both in marketing and economics (e.g., Litman 1983, Litman and Kohl 1989, Sawhney and Eliashberg 1996, Zufryden 1996, Eliashberg et al. 2006). Previous work had often forecasting purposes, with models that assessed

the temporal evolution of audiences during the running period of a movie. For example, Sawnhey and Eliashberg (1996) used a Generalized Gamma to evaluate the temporal evolution of movie attendance. The authors show that even with only a three-week calibration period, the model provided a good forecast of overall movie performance. Neelamegham and Chintagunta (1999) developed a Bayesian prediction procedure that provided revenue forecasts at different stages within the movie release process. More recently, Ainslie et al. (2005) developed a market share model that incorporates competition between movies, by combining a sliding-window logit model and a Gamma diffusion pattern in a hierarchical Bayes framework. These authors show that taking into account competition from other movies available in a given week increases both model fit and its forecasting performance.

Following this literature, we use similar functional forms to model movie performance over its life-cycle. These allow us to capture different sales patterns (i.e. the sales pattern of a blockbuster vs. that of a sleeper; see also Sawnhey and Eliashberg 1996) and to incorporate the changing competitive environment, within- and across-chains. As the movies being offered or introduced change week by week (both within the same chain a movie is being shown, or in other chains), so does the competitive environment for a single movie. Because these changes might explain differences in movie performance, we measure the impact of exhibitors on movie performance while controlling for such effects.

Consider n^*_{ijt}, the observed truncated audience, which is defined as:

$$n^*_{ijt} = \begin{cases} n_{ijt} \; if & t \leqslant T_{ij} \\ 0 \; if & t > T_{ij} \end{cases} \quad \text{for } j = 1, ...S;\; i = 1, ..., M_j \text{ and } t = 1, ..., T. \tag{3.8}$$

Even though a movie could potentially have a positive audience during any week after its release, in a given theater, we only observe the true audience (n_{ijt}) when the movie is being shown in that theater ($t \leqslant T_{ij}$). Given Equation (3.7), the truncated audience variable can

also be defined defined as:

$$n^*_{ijt} = \begin{cases} n_{ijt} \; if \quad y_{ijt} \geqslant 0 \\ 0 \; if \quad y_{ijt} < 0 \end{cases} \quad for \; j = 1, ...S; i = 1, ..., M_j \text{ and } t = 1, ..., T. \tag{3.9}$$

We model movie audiences using a Gamma distribution. Ainslie et al. (2005) showed that their adapted Gamma model outperformed other existing models in terms of weekly estimates and out of sample, one-week-ahead forecasts of box-office revenue.[4] Let us define n_{ijt} as the audience for movie i in theater j on week t (for $t \leq T_{ij}$):

$$n_{ijt} = N_{ij} \frac{1}{\beta_{ij}^{\alpha_{ij}} \Gamma(\alpha_{ij})} t^{\alpha_{ij}-1} \exp(-\frac{t}{\beta_{ij}}) \exp(Z_{ijt}\delta_j + \varepsilon_{ijt}). \tag{3.10}$$

where N_{ij} represents the total demand for movie i at theater j, which is then distributed over different weeks and follows a Gamma distribution. The term β_{ij} is the positive speed parameter of the Gamma distribution (it represents the speed at which an audience can grow and decline), α_{ij} is the positive shape parameter, and $\Gamma(.)$ represents the Gamma function. Finally, $Z_{ijt}\delta_j + \varepsilon_{ijt}$ represents a demand shock that might contain an observable component ($Z_{ijt}\delta_j$). The $(1 \times p)$ vector Z_{ijt} represents time specific covariates for movie i and theater j, and δ_j is the corresponding $(p \times 1)$ vector of theater specific parameters. Note that the Z_{ijt} covariates depend on the calendar week associated with running week t and that these observable demand shocks will include measures of the launching of new movies and holiday periods (more details on the variable specification will be provided in Section 3.4.2).

Finally, we assume that the random shocks, ε_{ijt}, are normally distributed. To reduce heteroschedasticity problems we model the logarithm of movie audience, rather than audience

[4]Ainslie et al (2005) provide also an improved version of the Gamma distribution model that accounts for competition among movies. This is shown to improve slighltly demand predictions. However, this version model requires the estimation of seasonality patterns, using long time series, to evaluate the attractiveness of the outside good. Due to data limitations, we are unable to use such extended model (in our empirical application we only have 52 weeks of data). However, we do incorporate measures of movie competition in the final model formulation.

directly. Hence, we have that:

$$\ln(n_{ijt}) \sim N(\ln(\widehat{n}_{ijt}), \sigma_n^2) \tag{3.11}$$

where $\widehat{n}_{ijt}$ are the expected audiences given the the data and the model parameters $(N_{ij}, \alpha_{ij}, \beta_{ij}, \delta_j)$, and σ_n^2 is the variance of the random shocks.

3.4.3. Error Correlation Structure

We allow the error terms of movie tenure and movie audience, $(\upsilon_{ijt}, \varepsilon_{ijt})$, to be correlated. We assume that these error terms follow a joint multivariate normal distribution such that:

$$(\upsilon_{ijt}, \varepsilon_{ijt}) \sim MVN\left((0\ 0), \Delta = \begin{pmatrix} 1 & \sigma_{\upsilon n}^2 \\ \sigma_{\upsilon n}^2 & \sigma_n^2 \end{pmatrix}\right) \tag{3.12}$$

where $\sigma_{\upsilon n}^2$ is the covariance of υ_{ijt} and ε_{ijt}. Because it is more likely for a theater manager to keep showing a movie after an unexpected good week of performance, we expect a significant and positive correlation between error terms. With such an error specification, Equation 3.9 represents a Type II Tobit model (Amemiya 1984). This type of model allow us to account for the .kind of truncation process we find in our data and it has been widely used both in marketing and economics literature to tackle similar problems. For recent applications in marketing please see Bucklin and Sismeiro (2003) and DeSarbo and Choi (1999).

3.4.4. Accounting for Assortment, Retailer, and Brand Strength Effects

We assume that total sales and the temporal evolution of movie audiences (as defined by the Gamma parameters N_{ij}, α_{ij}, and β_{ij}), can be decomposed into three factors: one that is movie specific $(\Phi_{1\tau(i)})$, one that is theater specific (Φ_{2j}), and one that is the outcome of a movie-theater interaction (Φ_{3ij}). The theater specific factor will allow us to measure the effect of retailers on brand performance, both in terms of total audience that could be expected for the movie and temporal evolution of that same audience. This movie specific factor will

provide the performance benchmark for the movie, based on the movie's own characteristics, and irrespective of the venue in which it is being presented. Finally, the interaction term will allow us to test whether brand strength plays a moderating role on the effect of venue on movie performance.

Following the work of Ainslie et al. (2005), we re-parametrize the Gamma distribution used to model audiences by setting:

$$\gamma_{ij} = (\alpha_{ij} - 1)\beta_{ij}. \tag{3.13}$$

where γ_{ij} represents the location of the peak of the gamma distribution.

We then adopt a hierarchical Bayes framework to account for movie heterogeneity on $\log(N_{ij})$, γ_{ij}, and $\log(\beta_{ij})$, such that:

$$\begin{bmatrix} \ln(N_{ij}) \\ \gamma_{ij} \\ \ln(\beta_{ij}) \end{bmatrix} = \Phi_{1i} + \Phi_{2j} + \Phi_{3ij} + \omega_{ij}, \tag{3.14}$$

where Φ_{1i} is a (3×1) movie specific effect, Φ_{2j} is a (3×1) theater-specific effect, Φ_{3ij} is a (3×1) interaction term, and ω_{ij} is a (3×1) normal error term with zero mean and Σ variance-covariance matrix.

Movie-specific effects are defined as:

$$\Phi_{1i} = A \times X_{\tau(i)}, \tag{3.15}$$

where $X_{\tau(i)}$ is a $(q_1 \times 1)$ vector of movie specific covariates ($\tau(i)$ represents a function that converts the movie index into a unique movie identifier), A is the corresponding $(3 \times q_1)$ matrix of coefficients. The terms contained in Φ_{1i} provide the baseline parameters for movie i and establish the benchmark of the expected audience of movie i, irrespective of theater venue.

Theater-specific effects, Φ_{2j}, are defined as follows:

$$\Phi_{2j} = B \times Q_j \tag{3.16}$$

where Q_j is a $(3 \times (S-1))$ matrix of dummy variables that identify each theater (taking the first theater as the based case), and B is a $(3 \times (S-1))$ matrix of parameters. If there are theater differences, the parameters $B = (B_N, B_\gamma, B_\beta)$ will be different from zero which will mean that movie venue has a significant impact on its performance.

The movie-theater interaction effects are defined as follows:

$$\Phi_{3ij} = C \times Q_j \times BSTR_i \tag{3.17}$$

where C is a $(3 \times (S-1))$ matrix of parameters, and $BSTR_i$ is a measure of movie's i brand strength.

With this model we can study whether brand strength plays a moderating role on the effect of retailers on movie performance. Next, we will present the details on the model variables and estimation. We will then describe and discuss the results.

3.5. Variable Definition and Model Estimation

In this section we will first present in detail the model variables used. There are three different sets of variables that deserve special attention: the variables that enter the movie tenure decision model (W_{ijt}), the variables that enter the deterministic component of the audience model (Z_{ijt}), and the variables that enter the hierarchical structure of the audience model ($X_{\tau(i)}$, Q_j, and $BSTR_i$). These latter variables are central to our research question.

3.5.1. Movie Tenure Decision Variables (W_{ijt})

Previous research suggests that theater managers continuously monitor the expected movie profitability in making their screen allocation decisions (e.g., Eliashberg et al. 2001). Therefore, the decision to run a movie for one additional week will be a function of the demand expectations formed by theater managers. However, theater managers need not only consider the total potential of the movie but also the share of that potential that has not yet materialized, that is, the part of the total audience that is likely to see the movie at that theater, but that has not yet done so. To incorporate such demand factors, we include in our model of movie tenure the following variable:

$$NLEFT_{ijt} = N_{ij} - \sum_{\omega=1}^{t-1} n_{ij\omega} \tag{3.18}$$

Thus defined, $NLEFT_{ijt}$ is an estimate of the movie audience for movie i in theater j that has not yet seen the movie at that theater by week t. We expect a positive effect of $NLEFT_{ijt}$ on the probability of running the movie for another week: if managers believe that the movie still has a substantial untapped potential, they will keep the movie for another week.

We also expect managers to consider not only whether a movie has a significant untapped potential, but also whether it as a greater potential than other available movies. To account for these competitive factors, and as an indicator of the attractiveness of new movies, we include $NewSC_{it}$ which is defined as the total number of screens allocated to new releases in the benchmark market (market MB). We expect that in weeks where there are better alternatives available (even if not yet released in this market), the probability of cutting a movie will be higher. Since the total number of screens in the benchmark market increased during the observation period, we mean-adjust the $NewSC$ variable.

3.5.2. Audience Model Variables (Z_{ijt})

The Gamma diffusion baseline of the audience model can be adjusted for demand shocks that are time dependent. Previous research has found that the level of movie competition has a significant impact on a movie's box-office revenue (see for example Ainslie et al. 2005). In fact, in weeks characterized by the release of very popular movies, or of a significant number of movies, it is likely to detect a reduction in the expected level of audience for movies currently on show. To capture these effects, for a given movie i being shown in theater j during week t, we define REL_{ijt} as the number of screens that were assigned in the benchmark market to the movies being released in that theater and week.

To better understand this covariate consider our empirical setting of two chains (Chain 1 and Chain 2). Chain 1 is releasing three movies (a, b, c) in week t, and Chain 2 is releasing two (a, d). Both chains are currently running movie i, which we assume to be the focal movie. In such case, for Chain 1, REL_{i1t} is the sum of the number of screens on the opening week for movies (a, b, c) in the benchmark market (market MB). For Chain 2, REL_{i2t} is the sum of the number of screens on the opening week for movies (a, d) in the benchmark market. Note that, we do not add the screens during the release of movie i (i.e. a movie does not compete against itself). Note also that the opening week in the benchmark market could be different from the one in which the movies are being released in the market under analysis. Finally, we also mean-centered REL_{ijt} variable to obtain a zero-mean error for the aggregate of the movies.[5]

One other variable used in the audience model is $BANKHOL_{it}$, a dummy variable that equals to one if during the calendar week that corresponds to the t^{th} week of movie i there

[5]We test for different ways of accounting for the impact of the launching of new movies. For example, we tried for a similar variable for movies released only in competing theater, and the lagged REL_{ijt} variable; none of these variables were significant.

is a Bank Holiday (Christmas, Labour day, etc.), and zero otherwise. We expect more movie attendance in a given week if there is more spare time to do so.

3.5.3. Hierarchical Variables of the Audience Model ($X_{\tau(i)}$, Q_j, and $BSTR_i$)

The vector of movie-specific covariates, $X_{\tau(i)}$, provides the benchmark of the expected audience of movie i, irrespective of theater venue and its assortment. Several could be the variables used to provide such benchmark. For example, movie descriptors that might influence box-office performance include whether the movie is or not a sequel, its budget, genre and rating, the presence of stars and critics reviews (for information on how these variables might affect box-office revenue see for example the work of Litman 1983, Litman and Kohl 1989, Litman and Ahn 1998, Prag and Casavant 1994, Ravid 1999, Ravid and Basuroy 2004, Kamakura et al. 2005).

In this study, we are unable to use such measures. Though many of the movies we study are mainstream and were produced in Hollywood, with freely available information on many of these variables, this is not the case for all the movies. For a significant number of the movies in our database, specially when European-based and independent, there is little publicly-available information. In addition, when this information is indeed available, it is often not equivalent to the one of mainstream movies (e.g., due to the use of different classifications systems for genre or ratings). However, we note that this is not a limitation of our study. Our work does not have forecasting purposes. As a result, there is no need to relate movie performance to the predictive variables mentioned above.

Instead, in this study, we build the benchmark that accounts for the movie's intrinsic performance levels (independent of the distribution layout of the current market), using aggregate sales measures observed in a separate market (which we call market MB) during

the same time period. This benchmark market should have similar audience characteristics as to the under analysis, and should be bigger and completely separate. We note that in a bigger market any potential distribution effects will be averaged out among the different (and more varied) retailers. Aggregate sales in this other market will then provide a good image of the intrinsic performance potential of each movie, independent of the distribution effects in the focal market (which will include, for example, the impact of assortment decisions).

In the theatrical movie industry it is relatively easy to find box-office figures with some level of aggregation (e.g. national/regional sales). As a result, this approach can be easily implemented (we also believe it can be used more generally whenever there is the need of comparing the effect of retailers on brand performance). We note that this approach is similar to the analysis we conducted when interpreting Table 3.3. There we used the aggregate performance observed in a benchmark market, for the unique releases of each chain, to better understand whether the movies in each chain were indeed different *a priori*, or whether any performance differences could be possibly due to quality of the exhibitors.

Hence, we define $LSCRN_i$ as the log of the maximum number of screens that were running movie i at the same time in market MB (in most instances, it corresponds to data from the opening week). We define $LBOR_i$ as the log of total admissions, divided by the maximum number of screenings of movie i, in market MB. With these two variables, we capture the overall baseline success of the movie and its the distribution scope. In addition, by using data from a different market to build this baseline, we avoid possible endogeneity of these benchmark measures. Finally, we also define $COMREL_i$ as a dummy variable that takes the value of one if the movie is a common release, and takes the value zero otherwise. With this variable we want to account for the differing potential of a movie when it is released by both chains simultaneously, compared to when a movie is released only by one of the two chains.

	Min	Mean	Max
Movie Specific Covariates $X_{\tau(i)}$			
$LBOR_i$: Log of the average per screen of total admissions of movie i in market MB.	4.12	7.38	9.82
$LSCRN_i$: Log of the maximum number of screens that simultaneously run movie i in market MB.	0.00	3.14	5.04
$BSTR_i$: Total Box office revenue of movie i in market MB (Mean centered in MM €)	-0.15	0.00	1.6
$COMREL$: Dummy variable for movies released in both theaters. If Common $COMREL = 1$	0	0.58	1
Calendar Week covariates Z^*_{ijt}			
REL_1 : Number of screens in the opening week in market MB for movies released in Chain1 during week t	-0.98	-0.03	1.35
REL_2 : Number of screens in the opening week in market MB for movies released in Chain2 during week t	-1.36	-0.06	2.20
$BANKHOL$: Dummy variable for weeks with bank holidays If there is a bank holiday $BANKHOL = 1$	0	0.18	1
Tenure decision covariates W_{ijt}			
$NewSC_{it}$: Total number of screens for new releases in market MB during week t	-2.08	0.00	1.30
$NLEFT_{ijt}$: Estimate of the audience that has not yet attended the movie (it will depend on the parameter N_{ij})	n.a.	n.a.	n.a.

Table 3.4. Variable Descriptive Statistics

For the theater-specific, consider our empirical setting with two chains ($S = 2$). We then use a single dummy variable, Q_j, such that:

$$Q_j = \begin{cases} 1 \; if \quad j = 2 \\ 0 \; if \quad j = 1 \end{cases} \tag{3.19}$$

Finally, to test for the interaction between the theater fixed effect with the popularity of a movie We define the variable $BSTR_i$ as the mean-centered total box-office revenue of movie i in market MB.[6]

Table 3.4 presents the definition and summary statistics of all variables. We note that $NLEFT$ is determined during model estimation and the summary statistics will depend on the final estimates.

[6]We also run the proposed model with $BSTR_i^2$ to test for U-shape relationships. We will discuss the results of that model in the following section.

3.5.4. Estimation

We estimate the Type II Tobit model of movie audiences at individual theaters with Markov chain Monte Carlo (MCMC) methods. In Appendix D, we provide the full-conditionals and the priors for the parameters of the model and describe the algorithm used in the estimation. As recommended in Bayesian literature (Gelman et al. 2003), we used proper but uninformative priors that exert little influence on the final results. We ran the Markov chain for 25,000 draws, using the first 20,000 iterations as a burn-in period and the last 5,000 to evaluate parameter estimates. We checked that the Markov chain was stationary and converged to the same values from different starting points. We relied on Pseudo Bayes Factors (PSBF) to compare model formulations and to test for the inclusion of alternative model variables.

3.6. Results

We estimated several variations of the proposed model. Specifically, we estimate both the Full Tobit Model we propose and a model that includes only the audience part, and does not incorporate the decision to keep/cut the movie (i.e., the movie audience modeled by itself; we call this model the Audience Model). In addition, we considered alternative specifications for the independent variables (e.g., we tried removing or introducing different variables and we tried quadratic forms of the variables). The results we report on Tables 3.5 and 3.6 are for the best fitting model which is the Full Tobit.[7] We note that the cross validation prediction density of the Full Tobit Model is -746, versus -842 for the Audience model. This comparison reveals that the Full Tobit Model fits the data better (i.e. it has the best Pseudo Bayes Factor) and it provides evidence that indeed the decision to run a movie

[7]We note that the main conclusions obtained were similar for the different variations of the model estimated. Results are available from the authors upon request.

	FULL TOBIT MODEL		
	$ln(N_{ij})$	γ_{ij}	$ln(\beta_{ij})$
Intercept	**2.30**	0.15	**1.05**
	[1.71 2.87]	[-0.14 0.45]	[0.35 1.71]
LBOR	**0.74**	-0.02	**-0.28**
	[0.67 0.81]	[-0.05 0.02]	[-0.36 -0.20]
LSCRN	**0.45**	0.02	**0.12**
	[0.37 0.54]	[-0.02 0.05]	[0.02 0.20]
COMREL	**-0.23**	0.01	-0.05
	[-0.38 -0.07]	[-0.06 0.08]	[-0.21 0.12]
Q	**-0.18**	0.00	0.09
	[-0.31 -0.06]	[-0.06 0.06]	[-0.04 0.23]
$Q \times BSTR$	**0.40**		
	[0.08 0.72]		

Table 3.5. Results of the Tobit and Audience Model. Movie covariates (Λ)

	FULL TOBIT MODEL			
	Chain 1		Chain 2	
	Post. Mean	95% Prob. interval	Post. Mean	95% Prob. interval
N_{ij}	21,174	[20,586.12; 21,736.13]	16,035	[15,587.18; 16,421.83]
γ_{ij}	0.07	[0.04; 0.11]	0.09	[0.04; 0.15]
β_{ij}	0.48	[0.44; 0.53]	0.63	[0.54; 0.72]
δ_{REL}	**-0.12**	[-0.17; -0.07]	**-0.09**	[-0.13; -0.05]
$\delta_{BANKHOL}$	**0.10**	[0.02; 0.17]	**0.14**	[0.06; 0.23]
$\mu_{Intercept}$	**-0.25**	[-0.41; -0.01]	-0.11	[-0.29; 0.06]
μ_{NewSC}	**-0.26**	[-0.44; -0.05]	**-0.29**	[-0.48; -0.10]
μ_{NLEFT}	**0.02**	[0.01; 0.02]	**0.02**	[0.02; 0.03]
σ_n^2	**0.12**	[0.11; 0.13]		
$\rho = \frac{\sigma_{n\nu}^2}{\sigma_n \sigma_\nu}$	**0.17**	[0.09; 0.21]		

Table 3.6. Results of the Tobit and Audience Model. Parameters

for another week, versus cancel it, conveys information about a movie's performance. This can also be seen by looking at the posterior mean and probability interval of the correlation of the error terms v_{ijt} and ε_{ijt}. As expected, it is more likely for a screen manager to keep showing a movie after an unexpected good week of performance (the posterior mean of the correlation is 0.17, and the 95% probability interval is $[0.09, 0.24]$). Next, we will discuss the detailed results of the Full Tobit Model.

3.6.1. Role of Branding in Channel Management

The main objective of this paper is to empirically test the role of branding in channel management. As we discussed previously, we follow previous research and argue that strong brands can be less dependent on retailers for their performance. By being less dependent, strong brands have a bargaining advantage when compared to weaker brands, which creates another double jeopardy effect for weaker brands (Ehrenberg 1988). We test this contention by (1) measuring the effect of the retail channel (chains) on brand performance, and (2) testing whether strong brands are indeed less dependent on retailers for their performance.

3.6.1.1. Theater-Specifc Effects. Our results reveal that after taking into account possible assortment effects, all else constant, movies will perform differently depending on where they are shown. This is true across all movies, common and unique releases. Indeed, as we can see from Table 3.5, though theater specific effects do not explain differences in speed and peak location, theater specific effects do explain the total demand for a movie in a given theater. The effect is negative ($B_Q^N = -0.18$ with a 95% probability interval that does not cover zero), which means that movies perform worse when shown in Chain 2. The model suggests also that the difference in performance is substantial and on average 16.5%.[8]

3.6.1.2. Theater-Brand Interaction. As described in the model development section, we have allowed in the Full Tobit Model a possible interaction between theater-effects and the brand strength of a movie (which is given in the model by $Q \times BSTR$). Our results do suggest that this interaction is significant and positive ($C_{Q\times BSTR}^N = 0.40$ with a 95% probability interval that does not cover zero). This means that, stronger brands perform

[8]The theater difference for a movie with average audience (i.e. with $LBOR = 0$ given that $LBOR$ is mean centered)is $\exp(B_N) = 0.835$. This mean that Chain 2 should expect to obtain a revenue that is 83.5% of the audience of Chain 1 (all else constant).

equally well in Chain 1 and Chain 2 (the 95% interval of the sum of the theater effect and the theater-brand interaction effect includes zero). Weaker brands will still perform better in Chain 1. We also tested for the inclusion of a quadratic term for the brand strength measure but we did not find improvements in model fit.

In sum, our analysis indicates that Chain1 is superior to Chain2 and, more important, our data supports the contention that the impact of theater quality seems to be less salient for stronger brands. This means that stronger brands are less dependent on the theater's own ability to attract audiences and suggests that stronger brands might have indeed stronger bargaining power due to this effect, as suggested by previous authors.

3.6.2. Results for the Remaining Variables

To check whether the proposed methodology provides sensible estimates for all the variables, next we present in detail and discuss the results for all model variables (including the movie tenure variables).

3.6.2.1. Movie Specific Covariates Entering The Hierarchical Structure. The movie-specific covariates, when significant, have the expected signs. Movies with high attendance per screen and launched in more screens in the market MB also performed better in our focal market ($A^N_{LBOR} = 0.74$ and $A^N_{LSCR} = 0.45$). In contrast, movies that are common releases tend to perform worse in each theater due to the direct competition of the other theater. This is goes against some previous findings in the literature. For example, Davis (2005) report very small business stealing effects across theaters. What we find in our sample is that common releases perform worse in each theater that what would have been expected had they been released only in a single theater. This is logical and it is due to audiences dividing themselves across the two theaters.

We note also that the impact of audience per screen ($LBOR$) on the $\log(\beta_{ij})$ is negative ($A^{\beta}_{LBOR} = -0.28$) which means that movies with high attendance per screen in the benchmark market decay slower in the focal market. It is also noticeable that movies released in more screens in the benchmark market will also decay faster for the same level of audience per screen ($A^{\beta}_{LSCRN} = 0.12$). This could be due to the marketing support of wide distribution movies: movies with wide distribution receive in general more advertising support and as result are likely to concentrate revenues at the beginning of the running period. Movies with similar level of audience per screen but not so widely distributed receive less advertising and are likely to rely more on word of mouth for their diffusion, making the decay process of these movies slower (all else constant). Finally, no clear relationship exists between the peak location and the audiences in the benchmark market.

3.6.2.2. Movie Tenure Decision. As expected, our results reveal that theater managers take into account the movie's audience potential for the subsequent weeks in deciding where to keep showing versus cut the movie: movies with high expected future audience are more likely to be shown for another week in both chains ($\mu^1_{NLEFT} = \mu^2_{NLEFT} = 0.02$ with probability intervals that do not cover 0).[9] In addition, also as expected, a movie will be cut more frequently in weeks with more popular releases available ($\mu^1_{NewSC} = -0.26$ and $\mu^2_{NewSC} = -0.29$ also with 95% probability intervals that do not cover zero)

3.6.2.3. Audience Component of the Model. As in Ainslie et al. (2005), we can see in Table 3.6 that competition among movies has an impact on movie performance: when there is stronger competition a movie's audience suffers ($\delta^1_{REL} = -0.12, \delta^2_{REL} = -0.09$). As pointed out above, we did not find this effect with movies released only in competing theatres. In addition, also as expected, weeks with bank holidays included attract a higher number of moviegoers boosting the audiences of movies irrespective of their chain ($\delta^1_{BANKHOL} = 0.10$,

[9]The super-scripts 1 and 2 denote the parameter for Chain 1 and 2 respectively.

$\delta^2_{BANKHOL} = 0.14$). We note that these parameter values imply differences of $\pm 10\%$ over the baseline for periods of maximum variation. Finally, we report also the average values of the Gamma baseline of the audience model (N_{ij}, γ_{ij}, and β_{ij}). As we can see, all else constant, movies shown in Chain 1 seem to have higher audience that movies shown in Chain 2, movies in Chain 1. As for the speed and peak location, we did not find significant differences with the 95% probability intervals of both chains overlapping substantially.

3.7. Conclusion

Recently, marketing scholars have started to look at branding from the perspective of inter-organizational relationships. Such scholars have suggested that brands might play an important role in the management of such relationships (e.g., Aaker 1991, Anderson and Weitz 1992, Brown et al. 1995, and Davis 2000), though no empirical study has yet provided evidence to support such contention. With this paper we provide a study of retailer effects on brand performance and how these effects interact with brand strength. Our objective is to contribute to the literature on the inter-organizational role of branding by empirically studying the value of manufacturer brands in channel management.

Following previous research, we have argued that strong manufacturer brands are less dependent on retailers for their performance, which can in turn contribute for their bargaining advantage. We test this contention by measuring the effect of the retail channel on brand performance using movie audience data across competing theaters (retailers). We estimate a Tobit model of movie audience and movie tenure decisions using data from a local duopoly market in Europe. The proposed approach accounts for the impact of distribution decisions, brand competition, and assortment effects.

Our results do confirm that, in our empirical setting, retailers have a significant effect on brand performance and that exhibitors expectations of movie performance influence which movies are shown in any given week (i.e., we find evidence of the two-way relationship between performance and distribution as reported by Reibstein and Farris 1995). We also find that the effect of retailers differs between strong and weak brands: though movies shown in Chain 1 perform, on average, consistently better (all else constant, and irrespective of being a common or a unique release) brand strength plays a moderating role as differences in performance across the two chains are smaller for stronger. Hence, these results suggest, as hypothesized by many authors, that weaker brands (i.e., movies with little success) rely more on the quality of the venue chosen for their performance and hence have less bargaining power.

There are several potential explanations for this phenomenon. For example, there could be a percentage of moviegoers that are actually customers of the theater (and in a secondary way are then customers of the movies). That is, they decide first which theater they are going to visit and then what movie are they going to see depending from the assortment in the given location. A "better" theater, (i.e. the one that attracts a higher number of people for its better facilities, location or services provided) could attract more of this type of customers On the other hand, when the moviegoer has decided in advance which movie to go watching (which is more likely for strong movies than for weaker movies), then theater selection becomes secondary. Another explanation for this could be also related with signaling (Basuroy et al. 2006). Releasing a movie in a higher quality venue might signal to a moviegoer that the movie is also of higher quality. In contrast, if the movie is well known because it has been supported with a large advertising campaign or has famous actors, then this effect will be smaller.

Finally, our results are also consistent with the mediating role of brand familiarity in the evaluation of brand alliances (Simonin and Ruth 1998). These results suggest the notion of higher gains "for a less-known brand teaming up with a well-liked and well-known partner brand. Under such a scenario, the less-known brand might contribute little but gain much from the partner..." (p.39). If we think the relationship brand-retailer as analogous to a brand alliance, we can conclude that there are reasons for powerful retailers to claim a higher share of the value created to less popular manufacturers than to manufacturers of powerful brands. In sum, all these explanations suggest that the enhancing effect of a better theater is expected to be more salient for movies in which "quality" is less certain.

Our work provides also specific contributions to the literature on movie audience modeling. Though we follow previous research in terms of functional form and effects considered, we were also required to propose new modeling approaches. For example, unlike previous research, which had focused on market-level and aggregate measures of box-office revenue, we observe and model movie performance at the theater level. This means that we face significant right truncation of movie performance data. To handle this right-truncation of theater-level audience data, we propose to simultaneously model the evolution of box-office revenue and the movie cutting decisions of exhibitors (every week, facing a stream of incoming movies exhibitors have to decide which movies to stop playing at their theaters and which movies to continue showing).

Our results indicate improved descriptive and predictive performance of the proposed joint model of movie audience and tenure decisions. In addition, our proposed approach provides new substantive findings regarding the decision process of theater managers. These findings complement existing theories and anecdotal evidence. For example, consistent with industry reports, we find that theater managers take into consideration the future expected revenues of

movies when making movie tenure decisions. We also find that there are competitive effects across theaters, though these affect only the total demand for a movie at a given theater and not the speed or the peak location of that demand.

There are several limitations of this work that are worthwhile exploring in future research. For example , in our empirical application the measurement of brand strength is simplified due to the specific characteristics of the market under study (e.g., absence of price competition). In other applications this task might provide serious challenges. When brand strength cannot be measured as in our empirical study we recommend the use of the vast literature on brand equity measurement and the many methods previously developed (see Aaker 1993 and Kapferer 1992 for a review). Finally, we note that our study refers only to one market and one country. It would be important to test whether the effects we found generalize to other industries and countries, and what are the moderating factors for the retailer-brand strength interaction we find.

APPENDIX

A. Kalman Filter for the Estimation of the Unobservables θ_{jt}

In this Appendix, I provide the moments of the conditional density $\delta_{jt}|\lambda, \sigma_\mu^2, x_{jt}, \Delta_{t-1}$ and a brief description of the algorithm used in the Kalman Filter estimation. Just recall that, conditional on λ, σ_μ^2, the mean valuations (δ_{jt}) and the unobservables (θ_{jt}) can be written as the state-space representation of a dynamic system with an observation equation $\delta_{jt} = \mu_{0j} + x_{jt}\beta + \theta_{jt} + \xi_{jt}$ and state equation $\theta_{jt} = \rho_{0j} + \rho_{1j}\theta_{jt-1} + \nu_{jt}$. Assuming independence of θ_{jt} with any of the realizations of $\xi_{jt} \sim N(0, \sigma_\xi^2)$ and $\nu_{jt} \sim N(0, \sigma_{\nu_j}^2)$, the random variable $\delta_{jt}|\lambda, \sigma_\mu^2, x_{jt}, \Delta_{t-1}$ is also normally distributed: $\delta_{jt}|\lambda, \sigma_\mu^2, x_{jt}, \Delta_{t-1} \sim N(\overline{\delta}_{jt}, \Sigma_{t|t-1})$ with

$$\overline{\delta}_{jt} = E[\delta_{jt}(x_{jt})|\Delta_{t-1}] = E[\mu_{0j} + x_{jt}\beta + \theta_{jt} + \xi_{jt}|\Delta_{t-1}] = \mu_{0j} + x_{jt}\beta + \theta_{jt|t-1}, \qquad (A.1)$$

since $E[\xi_{jt}|\Delta_{t-1}] = 0$ and $\theta_{jt|t-1}$is the value of the conditional unobservable given Δ_{t-1} The conditional variance $\Sigma_{t|t-1}$can be written as follows:

$$\Sigma_{t|t-1} = Var[\delta_{jt}(x_{jt})|\Delta_{t-1}] = Var[\theta_{jt} + \xi_{jt}|\Delta_{t-1}] = \Psi_{jt|t-1} + \sigma_\xi^2, \qquad (A.2)$$

where $\Psi_{jt|t-1}$ is the covariance matrix of state variable θ_{jt} given $\Delta_{t-1}$to be determined.

The values for $\theta_{jt|t-1}$ and $\Psi_{jt|t-1}$are obtained recursively following this algorithm (see Hamilton 1996; Naik et al. 1998). To start the iteration, we need to impose some initial condition. I impose $\theta_{j1} = 0$. Thus defined, the unobservables θ_{jt} represent changes in utility from period 1 For the initial variance I choose $\Psi_{j1} = 0.01$ or other small number different from zero since $\theta_{j1} = 0$ by construction.

From $t = 2, ..., T$ I iterate over the following sequence for j=contract, prepaid:

First, generate the covariance matrix of $\theta_{jt}|\Delta_{t-1} \Rightarrow \Psi_{jt|t-1} = \rho_{1j}\Psi_{jt-1}\rho_{1j} + \sigma^2_{\nu_j}$

Second, calculate the best estimator of $\theta_{jt}|\Delta_{t-1} \Rightarrow \theta_{jt|t-1} = \rho_{0j} + \rho_{1j}\theta_{jt-1}$

Third, estimate the prediction error of $\delta_{jt}|\theta_{jt|t-1} \Rightarrow \kappa_{jt|t-1} = \delta_{jt} - \mu_{0j} - x_{jt}\beta - \theta_{jt|t-1}$

Fourth, calculate the covariance of the prediction error $\kappa_{jt|t-1} \Rightarrow \Sigma_{t|t-1} = \Psi_{jt|t-1} + \sigma^2_{\xi}$

Fifth, update the value of θ_{jt} after observing $\delta_{jt} \Rightarrow \theta_{jt} = \theta_{jt|t-1} + \Psi_{jt|t-1}(\Sigma_{t|t-1})^{-1}\kappa_{jt|t-1}$

Sixth, update the covariance matrix of $\theta_{jt} \Rightarrow \Psi_{jt} = \Psi_{jt|t-1} - \Psi_{jt|t-1}(\Sigma_{t|t-1})^{-1}\Psi_{jt|t-1}$

Note from step five that the updating of θ_{jt} depends on the factor $\Psi_{jt|t-1}(\Sigma_{t|t-1})^{-1}$. If we develop this expression we have:

$$\Psi_{jt|t-1}(\Sigma_{t|t-1})^{-1} = \frac{\rho_{1j}\Psi_{jt-1}\rho_{1j} + \sigma^2_{\nu_j}}{\rho_{1j}\Psi_{jt-1}\rho_{1j} + \sigma^2_{\nu_j} + \sigma^2_{\xi}} \qquad (\Lambda.1)$$

So, the updating process depends basically in the relationship $\frac{\sigma^2_{\nu_j}}{\sigma^2_{\nu_j}+\sigma^2_{\xi}}$. In some empirical applications it will be difficult to identify properly $\sigma^2_{\nu_j}, \sigma^2_{\xi}$ but one can still identify the relationship in a typical problem of scaling. For these reasons, I found useful to set σ^2_{ξ} as a fixed number different from 0. In the empirical application I set $\sigma^2_{\xi} = 1$.This assumption seemed to be justified since the likelihood for $\sigma^2_{\xi} = 1$ and the likelihood with an unrestricted σ^2_{ξ} was very similar.

APPENDIX

B. Multinomial Nested Logit and Binomial Models

1. Multinomial Nested Logit Model

I model the physician decision of drug choice for each patient visit given a drug prescription in the focal therapeutic category (in our case the SSRI category). I model this decision as a two-level process: physicians select which molecule to prescribe and which version. This decision process creates a nested structure that can be represented by a two-level tree, with molecule choice in the first level and version choice in the second.

Consider a physician deciding which drug to prescribe to her patient among the available alternatives in the market to treat a specific condition. Define V_{ijt} as physician i's valuation of drug j for a prescription in visit t as:

$$V_{ijt} = X_{ijt}\beta_{ij} + G_{ij} + \varepsilon_{ijt} \quad \text{for } i = 1,\ldots,N,\ j = 1,\ldots,J, \text{and } t = 1,\ldots,T_i, \tag{B.1}$$

where X_{ijt} is a $(1 \times k)$ vector of explanatory variables (e.g., marketing activity and previous prescription history), β_{ij} is the corresponding $(k \times 1)$ vector of physician specific parameters, J is the number of alternative drugs, N is the number of physicians observed, T_i is the number of patients seen by physician i, and ε_{ijt} is a general extreme value distributed error term (Train 2003). The term G_{ij} is an extra factor that is only present if the molecule is available in generic form. It represents the change in valuation due to the trade-off between the significant price discounts of generic versions and their perceived quality.

If we assume that physicians prescribe the drug with the maximum valuation, we obtain a nested multinomial logit model. Physician's i probability of prescribing molecule j at occasion t is then defined as:

$$p_{ijt} = \frac{\exp(X_{ijt}\beta_{ij} + \lambda_i I_{ijt})}{\sum_{l=1}^{J} \exp(X_{ilt}\beta_{ij} + \lambda_i I_{ilt})} \tag{B.2}$$

The term I_{ijt} is the "inclusive value" of physician i, which is equal to $\ln 1 + \exp\left(\frac{G_{ij}}{\lambda_i}\right)$ if a generic version is available for molecule j at patient visit t, or equal to zero if a generic is not available; λ_i is the physician-specific inclusive value parameter. Note that these inclusive value parameters should lie between zero and one. If λ_i is negative, an increase in the utility of an alternative in the nest (which should increase the probability of the nest being chosen), actually diminishes the probability of selecting the nest (in virtually all choice modeling situations, this is implausible). If λ_i is greater than one, an increase in the utility of an alternative in the nest not only increases its selection probability but also the selection probability of the rest of the alternatives in the nest. Though this may be plausible under certain limited conditions, it is generally not applicable to a wide variety of choice modeling situations. Therefore, the nesting structure that provides inclusive value parameter estimates between zero and one is generally adopted as long as the structure offers a plausible behavioral framework and interpretation.

For those molecules available under generic and brand-name formulations, the probability of prescribing molecule j under generic version is:

$$p_{iG_jt} = p_{ijt}\frac{\exp\left(\frac{G_{ij}}{\lambda_i}\right)}{1 + \exp\left(\frac{G_{ij}}{\lambda_i}\right)} \tag{B.3}$$

and the probability of prescribing molecule j under brand version is:

$$p_{iG_jt} = p_{ijt}\frac{1}{1+\exp\left(\frac{G_{ij}}{\lambda_i}\right)} \tag{B.4}$$

From these expressions we can see that the final choice probability is decomposed in two parts: one is the probability of selecting the molecule (p_{ijt}) which corresponds to the upper level nests, and the other is the probability of selecting the format of the molecule given molecule choice (choice of format within the molecule nest). Each part corresponds to the two levels of the tree depicted in Figure 2.1.

Finally, I adopt a random effects formulation to model physician-specific effects and estimated the final model via Bayesian simulation methods (estimation details presented in Appendix C). Random effects are commonly used in economics and management to account for differences across individual units. Previous models of pharmaceutical demand have also used a random effects formulation to account for heterogeneity (e.g., Manchanda et al. 2004; Manchanda and Chintagunta 2004; Narayanan et al. 2005). Specifically, we assume that physician-specific parameters are normally distributed, $\beta \sim MVN(\overline{\beta}, \Sigma)$, where $\overline{\beta}$ is the $(k \times 1)$ vector of population level means and Σ is the corresponding $(k \times k)$ variance-covariance matrix.

2. Binomial Models

I use binomial models to analyze within- and between-molecule competition once generic versions of fluoxetine are introduced in the market. Define p_i as physician i probability of prescribing the option u_1 in Period 2 across all prescriptions occasions. The likelihood for each physician is then given by:

$$l(n_i, r_i, p_i) = \frac{n_i!}{(n_i - r_i)!} p_i^{r_i}(1-p_i)^{n_i - r_i}, \tag{B.5}$$

where, r_i is the number of prescriptions of option u_1 for physician i during Period 2 and n_i is the number of prescription occasions. We make p_i a function of observable and unobservable physician characteristics, such that:

$$p_i = \frac{\exp(s_i + \alpha + Z_i\theta)}{1 + \exp(s_i + \alpha + Z_i\theta)}, \tag{B.6}$$

where Z_i is a $(1 \times q)$ vector of physician specific characteristics (observable and unobservable), and θ is the corresponding $(q \times 1)$ vector of parameters; the term s_i represents a prescription baseline.

Depending on the definition of u_1 and n_i I can study within- or between-molecule competition. In addition, depending on the baseline used I can either analyze changes from Period 1 to Period 2 or I can simply analyze Period 2 prescription decomposition. Hence, I estimate four alternative models that correspond to Models I through IV summarized in Table B.1.

Table B.1 Binomial Models	**With Baseline Prescription Changes**	**With No Baseline Prescription Level**
Between Molecule Competition	**Model I**	**Model II**
u_1 = Fluoxetine (branded+generics)	$s_i^I = \ln\left(\frac{SHARE_i}{1+SHARE_i}\right)$	
u_0 = All other molecules	$SHARE$ = share of Fluoxetine	$s_i^{II} = 0$
n_j = Number of times u_j is prescribed	across all SSRIs prescriptions	
Within Molecule Competition	**Model IV**	**Model III**
u_1 = Generic versions of Fluoxetine	$s_i^{IV} = \ln\left(\frac{SHARE_i}{1+SHARE_i}\right)$	
u_0 = Branded Fluoxetine	$SHARE$ = share of generic	$s_i^{III} = 0$
n_j = Number of times u_j is prescribed	across all Fluoxetine prescriptions	

When $s_i = 0$ (Models II and III) I obtain a descriptive model: I describe how the individual level characteristics influence prescription. In Models I and IV, I analyze the change from Period 1 to Period 2 associated to generic entry. Finally, in Models I and II I study between-molecule competition, that is, how often was fluoxetine (as a whole) prescribed vis-à-vis other SSRIs; in Models III and IV I study within-molecule competition: how often

where generic versions of fluoxetine prescribed across all fluoxetine prescriptions. Parameters of Equations B.5 and B.6 will have the superscript B for the between-molecule models and the superscript W for the within-molecule models.

The proposed models are estimated via maximum likelihood. Variables are tested for inclusion using a 5% significance level and if deemed non-significant are removed from the final model. Results presented include only the significant variables.

APPENDIX

C. Specification of Priors: Random Coefficient Nested Logit

I specify a multivariate normal prior for the between-physician conditional mean parameters and an inverted Wishart for the variance-covariance matrix of the random coefficient nested logit model. I take diffuse priors to induce a mild amount of shrinkage. The setting of prior parameters has the potential to influence the physician level parameters. I did a robustness check estimating the models with three different priors. The conclusions of the analyses were the same regardless of the prior used.

The likelihood for physician i with the proposed random coefficient nested logit model has the following form:

$$L(\beta_i|data) = \prod_{i=1}^{N}\prod_{t=1}^{T_i} p_{iG_jt}^{y_t} p_{iB_jt}^{y_t}, \tag{C.1}$$

with the probabilities defined in Equations B.3 and B.4 and y_t defined as a dummy variable equal to one when drug j in generic/brand version was chosen by physician i in prescription occasion t. Heterogeneity is introduced in the model as $\beta \sim MVN(\overline{\beta}, \Sigma)$ and I take:

- Prior for $\overline{\beta} \sim MVN(a_0, b_0)$ where $a_0 = \overline{0}_k$ and $b_0 = 100I_k$ and $k = 11$ (# of parameters)
- Prior for $\Sigma \sim IW(n_0, s_0)$ where $n_0 = k + 2 = 13$ and $s_0 = \frac{n_0}{10} I_k$

1. Full conditionals and simulation algorithm

First, set starting values for the unknown parameters.

Second, draw from a Metropolis-Hasting algorithm with a random walk chain. Let us denote the previous draw for and the candidate draw. The acceptance probability of the candidate draw is given by:

$$\pi_i = \min\left[\frac{\exp\left[-\frac{1}{2}\left(\beta_i^n - \overline{\beta}\right)\Sigma^{-1}\left(\beta_i^n - \overline{\beta}\right)L_i(\beta_i^n)\right]}{\exp\left[-\frac{1}{2}\left(\beta_i^p - \overline{\beta}\right)\Sigma^{-1}\left(\beta_i^p - \overline{\beta}\right)L_i(\beta_i^p)\right]}, 1\right] \tag{C.2}$$

Third, draw from the conditional distribution:

$$\overline{\beta}|\beta_i, \Sigma \sim MVN\left(\sum_{i=1}^{N}\frac{\beta_i}{N},\ \left(\frac{N}{\Sigma} + b_0^{-1}\right)^{-1}\right) \tag{C.3}$$

Fourth, draw from the conditional distribution:

$$\Sigma|\overline{\beta}, \beta_i \sim IW\left(N + n_0,\ \left(\sum_{i=1}^{N}\left(\beta_i - \overline{\beta}\right)\left(\beta_i - \overline{\beta}\right)' + s_0^{-1}\right)^{-1}\right) \tag{C.4}$$

APPENDIX

D. Priors and Simulation Algorithm of the Type II Tobit Model

We specify multivariate normal priors for the conditional mean parameters of the different elements of the Tobit Model. I distinguish the following sets of parameters:

First, let us denote $D_N = (A_N, B_N, C_N)$ the set of parameters for the hierarchical model related to $\log(N)$ described in Equation (3.14). Likewise, define $D_\beta = (A_\beta, B_\beta, C_\beta)$ and $D_\gamma = (A_\gamma, B_\gamma, C_\gamma)$ as the parameters for $\log(\beta)$ and γ. We constrained the interaction parameters (C) to be zero when the main effect was non-significant. The random effect ω_{ij} is zero mean and has a diagonal covariance matrix with elements $(\sigma_N^2, \sigma_\beta^2, \sigma_\gamma^2)$. The election of this constrained model is supported by the fact that it has a better PSBF than an unrestricted model with full variance-covariance matrix. Then, let us impose:

- $D_N \sim MVN(a_N, b_N)$ where $a_N = \overline{0}_k$ and $b_N = 100 I_k$ and $K = 6$ (# of parameters)
- $D_\beta \sim MVN(a_\beta, b_\beta)$ where $a_\beta = \overline{0}_k$ and $b_\beta = 100 I_k$ and $K = 5$
- $D_\gamma \sim MVN(a_\gamma, b_\gamma)$ where $a_\gamma = \overline{0}_k$ and $b_\gamma = 100 I_k$ and $K = 5$
- $\sigma_m^2 \sim IG(a_0/2, b_0/2)$ where $a_0 = 0.001$ and $b_0 = 0.001$ for $m = N, \beta, \gamma$
- From $Z_{ijt}\delta_j$ (4 parameters) and $W_{ijt}\mu_j$; (6 parameters) $\Psi = [\mu\ \delta\ ] \sim MVN(a_\Psi, b_\Psi)$ where $a_\Psi = \overline{0}_k$ and $b_\Psi = 100 I_k$ and $K = 10$

Finally, as pointed out, the errors of the model $(\varepsilon_{ijt}, v_{ijt})$ follow a multivariate normal distribution. There are two free parameters in the covariance matrix (the covariance is symmetric and the error $v_{ijt} \sim N(0,1)$ for identification issues). As in Ansari, et al. (2005), I decompose the covariance as $\Delta = DRD$ where D is a diagonal matrix with the standard

deviations of Δ, and R is the correlation matrix where we have to identify the off-diagonal parameter η.constrained between [−1 1]. The other element to identify is σ_n. I apply the following transformations:

- $\sigma_n = \exp(\psi_1)$
- $\rho = \frac{\exp(\psi_2)-1}{\exp(\psi_2)+1}$

Then I choose a multivariate prior for $(\psi_1 \ \psi_2) \sim MVN(a_\psi, b_\psi)$ where $a_\psi = \overline{0}_k$ and $b_\psi = 5I_k$ and $K = 2$.With these priors $\sigma_n > 0$ and $\rho \in$ [-1 1]. These priors are proper and induce a mild amount of shrinkage.

1. Full Conditionals and Simulation Algorithm

The data likelihood of the Tobit Model for movie i at theater j during weeks after release $T = 1, 2, ...t$ is based on Equations (3.5), (3.11) and (3.12). Hence, given weekly audiences n_{ijt} and the augmented data y_{ijt} (utilities of the probit model) we write:

$$\nu_{ijt} = y_{ijt} - W_{ijt}\mu_j \tag{D.1}$$

$$\varepsilon_{ijt} = \ln(n_{ijt}) - \ln(\widehat{n}_{ijt}) \tag{D.2}$$

$$(\nu_{ijt}, \varepsilon_{ijt}) \sim MVN\left((0\ 0), \begin{pmatrix} 1 & \sigma^2_{\nu n} \\ \sigma^2_{\nu n} & \sigma^2_n \end{pmatrix}\right) \tag{D.3}$$

The likelihood function is, therefore, the multivariate normal probability density function of the errors $(\nu_{ijt}, \varepsilon_{ijt})$ given data G (audiences (n_{ijt}) , running decisions (C_{ijt}),augmented data (y_{ijt}), and market data (W_{ijt}, Z_{ijt})) and parameters $\Omega = (\mu_j, \overline{\delta}_j, \Theta_{ij}(\ln(N_{ij}), \gamma_{ij}, \ln(\beta_{ij})), \Delta)$. Thus, for the total length of the showing of a movie i a theater j:

$$L_{ij} = \prod_{\tau=1}^{t} \phi(\nu_{ij\tau}\ \varepsilon_{ij\tau} \mid G, \Omega) \tag{D.4}$$

where $\phi(\cdot)$ is the density function of the Multivariate Normal distribution. Once defined these expressions the simulation algorithm can be implemented iterating the following steps:

(1) Set starting values for the unknown parameters.

(2) Simulate utilities of the decision keep/stop the showing of the movie (y_{ijt})

$$y_{ijt} \mid G, \Omega \sim \text{ truncated } N(\xi_{ijt}, m_0), \tag{D.5}$$

where $\xi_{ijt} = W_{ijt}\mu_j + \sigma^2_{\nu n}(\sigma^2_n)^{-1}(\varepsilon_{ijt} \mid D, \Omega)$ and $m_0 = 1 - \sigma^2_{\nu n}(\sigma^2_n)^{-1}\sigma^2_{\nu n}$ are the conditional mean and variance of a multivariate normal given $\varepsilon_{ijt} \mid X, \Omega$. To simulate the utilities y_{ijt}, we draw from the truncated distribution such that if $C_{ijt} = 1$ then $y_{ijt} \geq 0$ and if $C_{ijt} = 0$ then $y_{ijt} < 0$

(3) Draw $\Theta_{ij}(\ln(N_{ij}), \gamma_{ij}, \ln(\beta_{ij}))$ from a Metropolis-Hasting algorithm with a random walk chain. Let us denote Θ^p_{ij} the previous draw for Θ_{ij} and Θ^n_{ij} the candidate draw. The acceptance probability of the candidate draw is given by:

$$\pi_{ij} = \min\left[\frac{\exp\left[-\frac{1}{2}\left(\Theta^n_{ij} - \overline{\Theta}_{ij}\right)\Sigma^{-1}\left(\Theta^n_{ij} - \overline{\Theta}_{ij}\right)L_{ij}(\Theta^n_{ij})\right]}{\exp\left[-\frac{1}{2}\left(\Theta^p_{ij} - \overline{\Theta}_{ij}\right)\Sigma^{-1}\left(\Theta^p_{ij} - \overline{\Theta}_{ij}\right)L_{ij}(\Theta^p_{ij})\right]}, 1\right] \tag{D.6}$$

where $\overline{\Theta}_{ij} = \Phi_{1i} + \Phi_{2j} + \Phi_{3ij}$

(4) Define $E^* = \Theta_{ij} - \overline{\Theta}_{ij}$ as the mean difference for the random coefficients. For $m = N, \beta, \gamma$,draw as follows

$$D_m \mid X, \sigma^2_m, G, \Omega \sim MVN(A_m, \Sigma_m), \tag{D.7}$$

$$\text{where } \Sigma_m = \left(\frac{1}{\sigma^2_m}X'X + b_m^{-1}\right)^{-1} \text{ and } A_0 = \Sigma_m\left(\frac{1}{\sigma^2_m}X'E^*_m + b_m^{-1}a_m\right)$$

(6) With the new parameters D_m, recalculate the errors, $H = \Theta_{ij} - \overline{\Theta}_{ij}$. Then draw σ_m^2 from the conditional distribution

$$\sigma_m^2 \mid G, X, D, \Omega \sim IG(R_m/2, f_s/2), \tag{D.9}$$

$$\text{where } R_m = \left(H_m' H_m + s_0^{-1}\right)^{-1} \text{ and } f_s = a_0 + 295 \text{ (number of movies)}$$

(7) To draw the parameters $\Psi = [\mu \ \delta]$ we use the results of the Seemingly Unrelated Regression (SUR) model (Koop 2003, p.138). and proceed as follows:

- Define $\ln(n_{ijt})^* = \ln(n_{ijt}) - \ln\left(N_{ij}\frac{1}{\beta_{ij}^{\alpha_{ij}}\Gamma(\alpha_{ij})}t^{\alpha_{ij}-1}\exp(-\frac{t}{\beta_{ij}})\right)$
- Construct the dependent variable J stacking the pairs $(y_{ijt}, \ln(n_{ijt})^*)$ in one column ($nobs = 1270$, number of observations)
- Construct the covariates matrix L as a block matrix:

$$\text{L}=\begin{pmatrix} W_{1,1} & \dots & \dots & W_{1,6} & 0 & \dots & 0 \\ \vdots & & & \vdots & \vdots & & \vdots \\ W_{nobs,1} & \dots & \dots & W_{nobs,6} & 0 & \dots & 0 \\ 0 & \dots & \dots & 0 & Z_{1,1} & \dots & Z_{1,4} \\ \vdots & & & \vdots & \vdots & & \vdots \\ 0 & \dots & \dots & 0 & Z_{nobs,1} & \dots & Z_{nobs,4} \end{pmatrix}$$

- Construct the error ξ stacking the pairs $(\nu_{ijt}, \varepsilon_{ijt})$ in one column.
- Now, we can write the model as: $J = L\Psi' + \xi$ as a linear model with inverse covariance matrix $N^{-1} = I_{nobs} \otimes \Delta^{-1}$. With this specification we can draw Ψ from the formulas of the linear regression model with known covariance as follows:

$$\Psi \mid D, \Omega \sim MVN(A_\Psi, \Sigma_\Psi), \tag{D.10}$$

$$\text{where } \Sigma_\Psi = \left(L' N^{-1} L + b_\Psi^{-1}\right)^{-1} \text{and } A_\Psi = \Sigma_\Psi (L' N^{-1} J + b_\Psi^{-1} a_\Psi)$$

- Finally, we obtain the two free parameters (σ_n, η) of the error matrix through a Metropolis-Hastings step. Let us denote Δ^p the previous draw for Δ and Δ^n the candidate draw. The acceptance probability of the candidate draw is given by:

$$\pi = \min \left[\frac{L(\Delta((\psi_{1,}\psi_2)^n)\phi\left[(\psi_{1,}\psi_2)^n\right]}{L(\Delta((\psi_{1,}\psi_2)^p\phi\left[(\psi_{1,}\psi_2)^p\right]}, 1 \right] \tag{D.11}$$

where $\phi\left[(\psi_{1,}\psi_2)^n\right]$ is the probability density function of the prior multivariate normal distribution evaluated at $(\psi_{1,}\psi_2)^n$.With the transformations $\sigma_n(\psi_1)$, $\eta(\psi_2)$, we assure that the parameters are inside the proper boundaries. We also have to impose the joint restriction that Δ is positive definite.

References

[1] Aaker, D. A. (1991). *Managing brand equity: Capitalizing on the value of a brand name.* New York: Free Press.

[2] Aaker, D.A., and K.L. Keller (1990), "Consumer Evaluations of Brand Extensions", *Journal of Marketing*, 54(1), 27–41.

[3] Abrahamson, Eric and Lori Rosenkopf (1997), "Social Network Effects on the Extent of Innovation Diffusion: a Computer Simulation", *Organization Science*, 8 (May-June), 289-309.

[4] Ailawadi, K. and P. Farris (1999), "Trade Promotion Essential to Selling Through Resellers", *Sloan Management Review*, 41(1), 83–92.

[5] Ailawadi, K., D.R. Lehmann, and S.A. Neslin (2003), "Revenue Premium as an Outcome Measure of Brand Equity", *Journal of Marketing*, 67 (October), 1–17.

[6] Ailawadi, K., L. Kusum, N. Borin, and P. Farris (1995), "Market Power and Performance: a Cross-Industry Analysis", *Journal of Retailing*, 71(3), 211–249.

[7] Ainslie, Andrew, Xavier Dreze and Fred Zufryden (2005), "Modeling Movie Lifecycles and Market Share", *Marketing Science*, 24 (3), 508-517 .

[8] Amemiya, T. (1984), *Advanced Econometrics.* Cambridge, MA: Harvard University Press.

[9] Anderson, E. and B. Weitz (1992), "The Use of Pledges to Build and Sustain Commitment in Distribution Channels", *Journal of Marketing Research,* 29(1), 18–34.

[10] Anderson, J. C. and J.A. Narus (1999), *Business Market Management: Understanding, Creating and Delivering Value*, Upper Saddle River, NJ: Prentice Hall Inc.

[11] Ansari, Asim, Carl Mela and Scott Neslin (2005), "Customer Channel Migration," forthcoming in *Journal of Marketing Research.*

[12] Aronsson, Thomas, Mats Bergman and Niklas Rudholm (2001), "The Impact of Generic Drug Competition on Brand Name Market Shares - Evidence from Micro Data", *Review of Industrial Organization*, 19 (December), 425-435.

[13] Bae, J. (1997), "Drug Patent Expirations and the Speed of Generic Entry", *Health Services Research* , 87–101.

[14] Bass, Frank M. (1969), "A New Product Growth for Model Consumer Durables," .*Management Science*, 15, 215-227.

[15] Basuroy, Suman, Kalpesh Kaushik Desai, and Debabrata Talukdar, (2006), "An Empirical Investigation of Signaling in the Motion Picture Industry" *Journal of Marketing Research*, 43(May), 287-295.

[16] Basuroy, Suman, Subimal Chatterjee and S.A. Ravid (2003), "How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets", *Journal of Marketing*, 67 (October), 103-117.

[17] Bell, D.R., J.Chiang, and V. Padmanabhan (1999), "The Decomposition of Promotional Response: An Empirical Generalization", *Marketing Science*, 18(4), 508-526.

[18] Ben-Akiva, M. and S.R. Lerman (1985), *Discrete Choice Analysis: Theory and Application to Travel Demand*, The MIT Press. Cambridge.

[19] Berry, L. L. (2000), "Cultivating Service Brand Equity", *Journal of the Academy of Marketing Science*, 28(1), 128-137.

[20] Berry, Steven T. (1994), "Estimating Discrete-Choice Models of Product Differentiation", *RAND Journal of Economics*, 25 (Summer), 242-262.

[21] Berry, Steven T., John Levinsohn and Ariel Pakes (1995), "Automobile Prices in Market Equilibrium", *Econometrica*, 63, 841-890.

[22] Besanko, D., J.P. Dubé, and S. Gupta (2005), "Own-Brand and Cross-Brand Retail Pass-Through", *Marketing Science*, 24(1), 123-137.

[23] Bloom, P.N. and V. Perry (2001), "Retailer Power and Supplier Welfare: The Case of Wal-Mart", *Journal of Retailing*, 77(3), 379-397.

[24] Bloom, P.N., G.T. Gundlach, J.P. Canon (2000), "Slotting Allowances and Fees: Schools of Thought and the Views of Practicing Managers", *Journal of Marketing*, 64(2), 92-108.

[25] Braun, Michael, Peter S. Fader, Eric T Bradlow and Howard Kunreuther (2006), "Modeling the 'Pseudodeductible' in Insurance Claims Decisions", *Management Science*, 52 (8) 1258-1272

[26] Bronnenberg, B. and C. Mela (2004), "Market Roll-Out and Retailer Adoption for New Brands", *Marketing Science*, 23 (4), 500-518.

[27] Bronnenberg, B. and C. Sismeiro (2002), "Using Multimarket Data to Predict Brand Performance in Markets for Which No or Poor Data Exist", *Journal of Marketing Research*, 39 (February), 1-17.

[28] Bronnenberg, B., V. Mahajan, and W.R. Vanhonacker (2000), "The Emergence of Market Structure in New Repeat-Purchase Categories: The Interplay of Market Share and Retailer Distribution", *Journal of Marketing Research*, 37 (February), 16-31.

[29] Brown, J. R., R.F Lusch, and C.Y. Nicholson (1995), "Power and Relationship Commitment: Their Impact on Marketing Channel Member Performance", *Journal of Retailing*, 71(4), 363-392.

[30] Bucklin, Randolph E. and Sunil Gupta (1992), "Brand Choice, Purchase Incidence, and Segmentation: An Integrated Modeling Approach", *Journal of Marketing Research*, 29 (May), 201-215.

[31] Bucklin, Randolph and Catarina Sismeiro (2003), "A Model of Web Site Browsing Behavior Estimated on Clickstream Data", *Journal of Marketing Research*, 40 , 249-267.

[32] Cane, Alan (1997), "UK: Mobile phone market grow slows by half", *Financial Times*. (10 November 1997)

[33] Caves, Richard E., Michael D. Whinston and Mark A. Hurwitz (1992), "Patent Expiration, Entry and Competition in the U.S. Pharmaceutical Industry: An Exploratory Analysis", *Brookings Papers on Economic Activity, Microeconomics*, 1-48.

[34] Chatterjee, Rabikar and Jehoshua Eliashberg (1990), "The Innovation Diffusion Process in a Heterogeneous Population: A Micromodeling Approach", *Management Science*, 36 (September), 1057-1079.

[35] Chintagunta, Pradeep (2002), "Investigating Category Pricing Behavior at a Retail Chain", *Journal of Marketing Research*, 39 , p.141.

[36] Corstjens, M., T. Johnson and R. Steele (2004), "Hey Retailers, If Your are So Powerful Why Aren't You More Profitable?" INSEAD working paper.

[37] Coscelli, A (1998), "Entry of New Drugs and Doctors" mimeo, University College London.

[38] Currie, Gillian and Sangin Park (2002). "The Effects of Advertising and Cosumption Experience on the Demand for Antidepressant Drugs" Working paper.

[39] Danaher, Peter J., Bruce G.S. Hardie and William P. Putsis JR. (2001), "Marketing-Mix Variables and the Diffusion of Successive Generations of a Technological Innovation", *Journal of Marketing Research*, 38 , 501-514.

[40] Danzon, Patricia M. and Li-Wie Chao (2000), "Does Regulation Drive Out Competition in Pharmaceutical Markets?", *Journal of Law and Economics*, 43 , 311-257.

[41] Davis, Peter (2005), "The Effect of Local Competition on Retail Prices: The US Motion Picture Exhibition Market", *Journal of Law and Economics*, 48 (2)

[42] Davis, S. (2000), *Brand Asset Management: Driving Profitable Growth Through Your Brands*, San Francisco: Jossey-Bass Inc.

[43] Dekimpe, Marnik G, Philip M. Parker and Miklos Sarvary (1998), "Forecasting the Diffusion Pattern of Cellular Telecommunications on the Country-level Using a Staged Estimation Approach", *Technological Forecasting and Social Change*, 57 , 105-132.

[44] Department of Health and the Association of the British Pharmaceutical Industry (2002), "The Study into the Extent of Competition in the Supply of Branded Medicines to the NHS". National Health Service Report. London.

[45] DeSarbo, Wayne S. and Jungwhan Choi (1999), "A Latent Structure Double Hurdle Regression Model for Exploring Heterogeneity in Consumer Search Patterns", *Journal of Econometrics*, 89 (1-2), 423-55.

[46] Donohue, J.M and Ernst.R Berndt (2004), "Effects of Direct-to-Consumer Advertising on Medication Choice: the Case of Antidepressants", *Journal of Public Policy and Marketing*, 23 (Fall), 115-127.

[47] Dubin, Jeffrey A. (1998), *"Studies in Consumer Demand-Econometric Methods Applied to Market Data"*. Kluwer Academic Publishers, Boston.

[48] Dukes, A.J., E. Gal-Or, and K. Srinivasan (2006), "Channel Barganing With Retailer Assymetry", *Journal of Marketing Research*, 43(February), 84-97.

[49] Duncan, T., and S.E. Moriarty (1998), "A Communication-Based Marketing Model for Managing Relationships", *Journal of Marketing*, 62(2), 1-13.

[50] Economist, The (2004), "Je ne texte rien," July 8th.

[51] Ehrenberg, A.S.C. (1988), *Repeat Buying: Facts, Theory and Applications*, London, Oxford University Press.

[52] Elberse, A. and J. Eliashberg (2003), "Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures", *Marketing Science*, 22(3), 329-354.

[53] Eliashberg, Jehoshua, Anita Elberse and Mark A.A.M. Leenders (2006), "The Motion Picture Industry: Critical Issues in Practice, Current Research & New Research Directions", .*Marketing Science* 25(6), 638-661

[54] Eliashberg, J., S. Swami, C.B. Weinberg, B. Wierenga (2001), "Implementing and Evaluating SilverScreener: A Marketing Management Support System for Movie Exhibitors", *Interfaces*, 31(3), S108-S127.

[55] Ellison, Sara Fisher, Iain Cockburn, Zvi Griliches and Jerry Hausman (1997), "Characteristics of Demand for Pharmaceutical Products: An Examination of Four Cephalosporins," *RAND Journal of Economics*, 28 , 426-446.

[56] Erdem, T., and J. Swait (1998), "Brand Equity as a Signalling Phenomenon", *Journal of Consumer Psychology*, 7(2), 131-157.

[57] Farris, P. and K. Ailawadi (1992), "Retail Power Monster or Mouse?", *Journal of Retailing*, 68(4), 351-369.

[58] Ferrándiz, Jorge Mestre (1999), "The Impact of Generic Goods in the Pharmaceutical Industry", *Health Economics*, 8 , 599-612.

[59] Fildes, Robert and V. Kumar (2002), "Telecommunications Demand Forecasting - a Review", *International Journal of Forecasting*, 18 , 489-522.

[60] Fischer, Michael A. and Jerry Avorn (2003), "Economic Consequences of Underuse of Generic Drugs: Evidence from Medicaid and Implications for Prescription Drug Benefit Plans", *Health Service Research*, 38 , 1051-1064.

[61] Fourt, Louis A. and Joseph W. Woodlock , "Early Prediction of Market Success for New Grocery Products", *Journal of Marketing*, 25, (2), 31-38.

[62] Frank, Richard G. and David S. Salkever (1992), "Pricing, Patent Loss and the Market for Pharmaceuticals", *Southern Economic Journal*, 165-179.

[63] Frank, Richard G. and David S. Salkever (1997), "Generic Entry and the Pricing of Pharmaceuticals", *Journal of Economics and Management Strategy*, 6 , 75-90.

[64] Frazier, G.L., and K. Antia (1995), "Exchange Relationships and Interfirm Power in Channels of Distribution", *Journal of the Academy of .Marketing Science*, 23(4), 321–326.

[65] Gaski, J. F. (1984), "The Theory of Power and Conflict in Channels of Distribution", *.Journal of Marketing*, 48(3), 9–29.

[66] Gelman, Andrew, John Carlin, Hal Stern and Donald Rubin (2003), *Bayesian Data Analysis,* Chapman & Hall, New York.

[67] Geyskens, I., J.-B. Steenkamp, and N. Kumar (1998), "Generalizations About Trust in Marketing Channel Relationships Using Meta-Analysis", *International Journal of Research in Marketing*, 15(3), 223–248.

[68] Ghosh, M., and G. John (1999), "Governance Value Analysis and Marketing Strategy", *Journal of Marketing*, 63(Special Issue), 131–145.

[69] Gil, Ricard. (2006), "Demand Shifts and Changes in Competition: Evidence from the Movie Theater Industry", *International Journal of Economics of Business*,13(3), 407-428.

[70] Gleckman , H. (2002), "The Backlash Against Big Pharma", *Business Week Online*, (May 27). <http://www.businessweek.com/>.

[71] Goldenberg, Jacob , Barak Libai and Eitan Muller (2002), "Riding the Saddle, How cross-Market Communications Creates a Major Slump in Sales", *Journal of Marketing*, 66 (April), 1-16.

[72] Golvin, Charles S. (2005), "US Mobile Growth Defies Conventional Wisdom", *Forrester Research Report* (22nd March).

[73] Gönül, Fusun, Franklin Carter, Elina Petrova and Kannan Srinivasan (2001), "Promotion of Prescription Drugs and its Impact on Physicians' Choice Behaviour", *.Journal of Marketing*, 65 , 79-90.

[74] Grabowsky, Henry and James Vernon (1992), "Brand Loylaty; Entry, and Price Competition in Pharmaceuticals after the 1984 Drug Act", *Journal of Law and Economics*, 35.

[75] Grabowsky, Henry and James Vernon (1996), "Longer Patents for Increased Generic Competition: The Waxman-Hatch after One Decade", *PharmacoEconomics*, 10 , 110-123.

[76] Hall, Kenji, Cliff Edwards and Ronald Grover (2006), "This Playstation May Play Too Much", *Business Week.* (20th February), pp.48.

[77] Hamilton, James D. (1996), *Time Series Analysis*, Princeton University Press. New Jersey.

[78] Heide, J.B. (1994), "Interorganisational Governance in Marketing Channels", *Journal of Marketing*, 58(January), 71-85.

[79] Hellerstein, Judith K. (1998), "The Importance of the Physician in the Generic versus Trade-Name Prescription Decision", *RAND Journal of Economics*, 29 , 108-136.

[80] Herzog, Christof (2005), "Europe's Mobile Consumer", *Forrester Research Report*, (16th June).

[81] Hoch, S. and S. Banerjee (1993), "When do Private Labels Succeed", *Sloan Management Review*, 34(4), 57-67.

[82] Hoeffler, S. and K.L. Keller (2003), "The Marketing Advantages of Strong Brands", *Journal of Brand Management*, 10 (6), 421-445.

[83] Horsky, Dan (1990), "A Diffusion Model Incorporating Product Benefits, Price, Income and Information", *Marketing Science*, 9 (Fall), pp.342.

[84] Horsky, Dan and Paul Nelson (1992), "New Brand Positioning and Pricing in an Oligopolistic Market", *Marketing Science*, 11 (Spring), pp.133.

[85] Hunt, Shelby D. and John R. Nevin (1974), "Power in a Channel of Distribution: Sources and Consequences", *Journal of Marketing Research*, 11(2), 186-193.

[86] Hurwitz, Mark A and Richard E. Caves (1988), "Persuasion or Information? Promotion and the Shares of Brand Name and Generic Pharmaceuticals", *Journal of Law and Economics*, 31 (October), 299-320.

[87] Islam, Towhidul and Nigel Meade (1997), "The Diffusion of Successive Generations of a Technology: A More General Model", *Technological Forecasting and Social Change*, 56 , 49-60.

[88] Jain, Dipak C., Eitan Muller and Naufel J. Vilcassim (1999), "Pricing Patterns of Cellular Phones and Phonecalls: A Segment-Level Analysis", *Management Science*, 45 (February), 131-141.

[89] Janakiraman, Ramkumar, Shantanu Dutta, Catarina Sismeiro and Phil Stem (2005), "Are they all the same? Physicians' Persistence and its Implications for Marketing Communication" Working paper.

[90] Jayachandran, Satish, Jennifer L. Nevins and William O. Bearden (2003), "Market Share Retention after Generic Entry in a Complex Buying System: The Case of Pharmaceutical Brands" Working paper.

[91] Jones, Adam (2005), "France's Top Mobile groups fined" *Financial Times*, December 2nd.

[92] Jones, J. Morgan, Christopher J. Ritz (1991), "Incorporating Distribution into New Product Diffusion Models", *International Journal of Research in Marketing*, 8(June), 91-112.

[93] Jun, Duk B., Seon K. Kim, Yoon S. Park, Myoung H. Park and Amy R. Wilson (2002), "Forecasting Telecommunication Service Subscribers in Substitutive and Competitive Environments", *International Journal of Forecasting*, 18 , 561-581.

[94] Kadiyali, V., P. Chitagunta, and N. Vilcassim (2000), "Manufacturer-Retailer Channel Interactions and Implications for Channel Power: An Empirical Investigation of Pricing in a Local Market", *Marketing Science*, 19 (2), 127–48.

[95] Kalish, S., V. Mahajan, E. Muller.(1995), "Waterfall and Sprinkler New-Product Strategies in Competitive Global Markets", *International Journal of Research in Marketing*, 12 105–119.

[96] Kamakura, Wagner A., Suman Basuroy, and Peter Boatwright (2005), "Is Silence Golden? An Inquiry into the Meaning of Silence in Professional Product Evaluations," *Quantitative Marketing and Economics*, 4(2), 119-141

[97] Kapferer, J.N. (1992), *Strategic Brand Management: New Approaches to Creating and Evaluating Brand Equity*, The Free Press, New York, NY.

[98] Katz, Michael L and Carl Shapiro (1985), "Network Externalities, Competition, and Compatibility", *American Economic Review*, 75 , p.424.

[99] Keller, K. L. (1993), "Conceptualising, Measuring, Managing Customer Based Brand Equity", *Journal of Marketing*, 57(1), 1–22.

[100] Kim, Namwoon, Rajendra K. Srivastava and Jin K. Han (2001), "Consumer Decision-Making in a Multi-Generational Choice Set Context," *Journal of Business Research*, 53 , 123-136.

[101] Koop, Gary (2003), *Bayesian Econometrics*, John Wiley & Sons. Chichester, England.

[102] Krider, Robert, Tieshan Li, Yong Liu and Charles Weinberg (2005), "The Lead-Lag Puzzle of Demand and Distribution: A Graphical Method Applied to Movies", *Marketing Science*, 24, (4) , 635-645 .

[103] Krishnan, Trichy V., Frank M. Bass and V. Kumar (2000), "Impact of a Late Entrant on the Diffusion of a New Product/Service", *Journal of Marketing Research*, 37 (May), 269-278.

[104] Kumar, V., and Trichy V Krishnan,.(2002), "Multinational Diffusion Models: An Alternative Framework", *Marketing Science*, 21: 318-330

[105] Kumar, V. , J. Ganesh and R. Echambadi (1998), "Cross-National Diffusion Research: What We Know and How Certain Are We?" , *Journal of Product Innovation Management*, Vol. 15(3), May, pp 255-268.

[106] Kyle, Margaret K. (2003), "Pharmaceutical Price Controls and Entry Strategies," Working paper.

[107] Lal, R. and C. Narasimhan (1996), "The Inverse Relation Between Manufacturer and Retailer Margins: A Theory", *Marketing Science*, 15(2), 132–151.

[108] Lattin, James and John H. Roberts (1988), "Modeling the Role of Risk-Adjusted Utility in the Diffusion of Innovations" Working paper #1019, Stanford University.

[109] Leffler, K.B (1981), "Persuation or Information? The Economics of Prescription Drug Advertising", *Journal of Law and Economics*, 24 , 45-74.

[110] Lehmann, Donald R., and Charles B. Weinberg (2000), "Sales Through Sequential Distribution Channels: An Application to Movies and Videos", *Journal of Marketing*, 64(July), 18–33.

[111] Lemon, K. and S.M. Nowlis (2002), "Developing Synergies Between Promotions and Brands in Different Price-Quality Tiers", *Journal of Marketing Research*, 39(2), 171–185.

[112] Lexchin, Joel (2004), "The Effect of Generic Competition on the Price of Brand-Name Drugs", *Health Policy*, 68 , 47-54.

[113] Lichtenberg , Frank and Tomas Philipson (2000), "Creative vs. Uncreative Destruction of Innovative Returns: An Empirical Examination of the U.S. Pharmaceuticals Market" *NBER Working paper* , 46935.

[114] Litman, B.R. (1983), "Predicting the Success of Theatrical Movies: An Empirical Study", *Journal of Popular Culture*, 17 (Spring), 159–75.

[115] Litman, B.R. and H. Ahn (1998), "Predicting Financial Success of Motion Pictures" in *The Motion Picture Mega Industry*. Needham Heights, MA: Allyn Bacon, 172–97.

[116] Litman, B.R. and L.S. Kohl (1989), "Predicting Financial Success of Motion Pictures: The '80s Experience", *Journal of Media Economics*, 2, 35–50.

[117] Lundin, Douglas (2000), "Moral Hazard in physician prescription behaviour", *Journal of Health Economics*, 19 , 639-662.

[118] McCarthy, Clare (2000), "Bullish Lundbeck Forges Ahead," *Financial Times*, August, 16th.

[119] Macé, S. and S.A. Neslin (2004), "The Determinants of Pre- and Postpromotion Dips in Sales of Frequently Purchased Goods", *Journal of Marketing Research*, 41 (August), 339–350.

[120] Magazzini, Laura, Fabio Pammolli and Massimo Riccaboni (2004), "Dynamic Competition in Pharmaceuticals: Patent Expiry, Generic Penetration, and Industry Structure", *European Journal of Health Economics*, 5 , 175-182.

[121] Mahajan, Vijay , Eitan Muller and Jerry Wind (2000), *New Product Diffusion Models.*, Kluwer Publishers , Norwell, Massachusetts.

[122] Manchanda, Puneet and Pradeep K. Chintagunta (2004), "Responsiveness of Physician Prescription Behavior to Salesforce Effort: An Individual Level Analysis" *Marketing Letters*, 15 , 129-145.

[123] Manchanda, Puneet, Peter E. Rossi and Pradeep K. Chintagunta (2004), "Response Modeling with Non-Random Marketing Mix Variables", *Journal of Marketing Research*, 41 , 467-478.

[124] McFadden, Daniel (1999), "Computing Willingness-to-Pay in Random Utility Models" in J.Moore, R. Riezman, and J.Melvin (eds.), *Trade, Theory and Econometrics: Essays in honour of John S. Chipman.* Routledge, London.

[125] McLaughlin, R., and Vithala Rao. (1991), *Decision Criteria for New Product Acceptance and Success*, Quorum Books, New York.

[126] Merrill Lynch Equity Research Department (2006), "*Global Wireless Matrix 4Q06*" Research Report.

[127] Messinger, P. R. and C. Narasimhan (1995), "Has Power Shifted in the Grocery Channel?", *Marketing Science*, 14(2), 189-223.

[128] Miravete, Eugenio J. (2002), "Estimating Demand for Local Telephone Service with Asymmetric Information and Optional Calling Plans", *Review of Economic Studies*, 69, 943-971.

[129] Mizik, Natalie and Robert Jacobson (2004), "Are Physicians Easy Marks?: Quantifying the Effects of Detailing and Sampling on New Prescriptions", *Management Science*, 50, 1704-1715.

[130] Montgomery, D.B. (1975), "New-Product Distribution: An Analysis of Supermarket Buyer Decisions", *Journal of Marketing Research*, 12(3), 255–264.

[131] Moore, Geoffrey (1998), *Crossing the Chasm: Marketing and Selling High-Tech Products to Mainstream Customers*, Harper. New York.

[132] Moul, Charles (2005), "Measuring Market Power in the Theatrical Distribution of Movies" Working paper.

[133] Naik, Prasad A., Murali K. Mantrala and Alan G. Sawyer (1998), "Planning Media Schedules in the Presence of Dynamic Advertising Quality", *Marketing Science*, 17 , 214-235.

[134] Narayanan, Sridhar and Puneet Manchanda (2006), "Heterogeneous Learning and the Targeting of Marketing Communication for New Products" Working paper.

[135] Narayanan, Sridhar, Punet Manchanda and Pradeep Chintagunta (2005), "Temporal Differences in the Role of Marketing Communication in New Product Categories", *Journal of Marketing Research*, 42 , 278-290.

[136] Neelamegham, R. and P. Chintagunta (1999), "A Bayesian Model to Forecast New Product Performance in Domestic and International Markets", *Marketing Science*, 18(2), 115–136.

[137] Nevo, Aviv (2001), "Measuring Market Power in the Ready-to-Eat Cereal Industry" *Econometrica*, 69 , 307-342.

[138] Newhouse, J.P. (1993), *Free For All? Lessons from the Rand Health Insurance Experiment*, Harvard University Press. Cambridge.

[139] Norton, John A. and Frank M. Bass (1987), "A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products", *Management Science*, 33 (September), pp.1069.

[140] Ofcom. Office of Communications UK (2001), "International Benchmarking Study of mobile services". Printed report. 7 November 2001.

[141] Ofcom. Office of Communications UK (2003), "International Benchmarking Study of mobile services". Online report available from http:www.ofcom.org.uk/static/archive/oftel/publications/research/2003/ benchmob0503.pdf

[142] Orbach, B.Y. (2004), "Antitrust and Pricing in the Motion Picture Industry", *Yale Journal on Regulation*, 21(2), 317–367.

[143] Oren, Samuel S. and Michael H. Rothkopf (1984), "A Market Dynamics Model for New Industrial Products and Its Application", *Marketing Science*, 3 (Summer), 247-265.

[144] Parker, Philip and Hurbert Gatignon (1994), "Specifying Competitive Effects in Diffusion Models: An Empirical Anaysis", *International Journal of Research in Marketing*, 11 , 17-39.

[145] Pauwels, K. and S. Srinivasan (2004), "Who Benefits from Store Brand Entry?", *Marketing Science*, 23(3), 364–390.

[146] Porter, S.S. and C. Claycomb (1997), "The Influence of Brand Recognition on Retail Store Image", *Journal of Product and Brand Management*, 6(6), 373–387.

[147] Prag, J. and J. Casavant (1994), "An Empirical Study of the Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry", *Journal of Cultural Economics*, 18, 217–35.

[148] Ravid, A.S. and S. Basuroy (2003), "Managerial Objectives, the R-Rating Puzzle, and the Production of Violent Films" *Journal of Business*, 77(2), 155-192

[149] Ravid, S.A. (1999), "Information, Blockbusters and Stars: A Study Of The Film Industry", *Journal of Business*, 72(4), 463–492.

[150] Regan, Tracy L. (2002), "Generic Entry and the Price Competition in the Prescription Drug Market-18 Years after the Waxman-Hatch Act", Working paper.

[151] Reibstein, D. J., P. W. Farris (1995), "Market Share and Distribution: A Generalization, a Speculation, and Some Implications", *Marketing Science*, 14(3), 190–202.

[152] Reiffen, David and Michael R. Ward (2003), "Generic Drug Industry Dynamics", *The Review of Economic and Statistics* 87 , 37-49.

[153] Reiss, Peter C. and Frank Wolak (2007), "Structural Econometric Modeling: Rationales and Examples from Industrial Organization", forthcoming in *Handbook of Econometrics*, Edited by J.J. Heckman and E.E. Leamer, Elsevier, North Holland. Available as a Working paper.

[154] Richard, Oliver and Larry Van Horn (2004), "Persistence in Prescriptions of Branded Drugs" *Interational Journal of Industrial Organization*, 22 , 523-540.

[155] Roberts, John H and James Lattin (2000), "Disaggregate-Level Diffusion Models", chapter in Mahajan, Vijay , Eitan Muller and Jerry Wind (2000), *New Product Diffusion Models.*, Kluwer Publishers , Norwell, Massachusetts.

[156] Roberts, John H. and Glen L. Urban (1988), "Modeling Multiattribute Utility, Risk, and Belief Dynamics for New Consumer Durable Brand Choice", *Management Science*, 34 (February), pp.167.

[157] Saloner, Garth and Andrea Shepard (1995), "Adoption of Technologies with Network Effects: an Empirical Examination of the Adoption of Automated Teller Machines", *RAND Journal of Economics*, 26 (Autumn), 479-501.

[158] Sawhney, Mohanbir S. and Jehoshua Eliashberg (1996), "A Parsimonious Model for Forecasting Gross Box-Office Revenues of Motion Pictures", *Marketing Science*, 15 , 113-131.

[159] Scott Morton, Fiona M. (1999), "Entry Decisions in the Generic Drug Industry", *The RAND Journal of Economics*, 30 , 421-440.

[160] Scott Morton, Fiona M. (2000), "Bariers to Entry, Brand Advertising, and Generic Entry in the U.S. Pharmaceutical Industry", *International Journal of Industrial Organization*, 18 , 1085-1104.

[161] Scott Morton, Fiona M. (2002), "Horizontal Integration between Brand and Generic Firms in the Pharmaceutical Industry", *Journal of Economics and Management Strategy*, 11 , 135-168.

[162] Shocker, A. D., R. Srivastava, and R. Ruekert (1994), "Challenges and Opportunities Facing Brand Management: An Introduction to the Special Issue", *Journal of Marketing Research*, 31(2), 149–158.

[163] Simon, C.J. and M.W.Sullivan (1993), "The Measurement and Determinants of Brand Equity: A Financial Approach", *Marketing Science*, 12 (Winter), 28–52.

[164] Simonin, B.L. and J.A. Ruth (1998), "Is a Company Known by the Company It Keeps? Assessing the Spillover Effects of Brand Alliances on Consumer Brand Attitudes", *Journal of Marketing Research*, 35(1), 30–42.

[165] Slotegraaf, R.J., C. Moorman, and J.J. Inman (2003), "The Role of Firm Resources in Returns to Market Deployment", *Journal of Marketing Research*, 40 (August), 295–309.

[166] Slotegraaf, R. and K. Pauwels (2006), "Growing Small Brands: Does a Brand's Equity and Growth Potential Affect its Long-term Marketing Productivity?" Working paper.

[167] Song, Inseong and Pradeep Chintagunta (2003), "A Micromodel of New Product Adoption with Heterogeneous and Forward Looking Consumers: Application to the Digital Camera Category", *Quantitative Marketing and Economics*, 1 , p.371.

[168] Sood, S. and X. Drèze (2006), "Brand Extensions of Experiential Goods: Movie Sequel Evaluations", *Journal of Consumer Research*, 33, 352–360.

[169] Sriram, S., Pradeep K. Chintagunta and Ramya Neelamegham (2006), "Effects of Brand Preference, Product Attributes, and Marketing Mix Variables in Technology Product Markets" .*Marketing Science*, 25(5), 440/456

[170] Stern, S. (1996), "The Demand for Pharmaceuticals", MIT mimeo.

[171] Swami, Sanjeev, Jehoshua Eliashberg and Charles B. Weinberg (1999), "SilverScreener: A Modeling Approach to Movie Screens Management", *Marketing Science*, 18 , 352-372.

[172] Talukdar, D., K. Sudhir, and Andrew Ainslie (2002) "Investigating New Product Diffusion Across Products and Countries", *Marketing Science* 21, (1), 97-114

[173] Tam, Pui-Wing (2004), "Photo Finish: As Cameras Go Digital, a Race to Shape Habits of Consumers" *Wall Street Journal (Eastern Edition)*, November 19th.

[174] Thirtle, Colin G. and Vernon W. Ruttan (1987), *The Role of Demand and Supply in the Generation and Diffusion of Technical Change,* Harwood Academic. New York.

[175] Train, Kenneth (2003), *Discrete Choice Methods with Simulation,* Cambridge University Press. Boston.

[176] Van Arnum, Patricia (2004), "The Generics Onslaught Begins," *Chemical Market Reporter*, Nov. 8th

[177] Van Everdingen, Y., W.B Aghina and Dennis Fok (2005), "Forecasting cross-population innovation diffusion: A Bayesian approach," *International Journal of Research in Marketing*, 22 , 293-308.

[178] Van Heerde, Harald J., Carl F. Mela and Puneet Manchanda (2004), "The Dynamic Effect of Innovation on Market Structure", *Journal of Marketing Research*, 41 (May), 166-183.

[179] Van Veen, Niek and Michelle de Lussanet (2005), "Central and Eastern European Mobile Forecast: 2005 to 2010", *Forrester Research Report.*

[180] Van Veen, Niek, Michelle de Lussanet and Lizet Menke (2005), "European Mobile Forecast: 2005 to 2010", *Forrester Research Report.* December, 23rd.

[181] Verboven, Frank and Randy Brenkers (2006), "Liberalizing a Distribution System: the European Car Market", *Journal of the European Economic Association*, 4 , 216-251.

[182] Villas-Boas, M. and Y. Zhao (2005), "Retailer, Manufacturers, and Individual Consumers: Modeling the Supply Side in the Ketchup Marketplace", *Journal of Marketing Research*, 42(1), 83–95.

[183] Vogel, Harold (2001), *Entertainment Industry Economics: A Guide for Financial Analysis*,.Cambridge University Press, Boston.

[184] Webster, F.E. Jr. (2000), "Understanding the Relationships among Brands, Consumers, and Resellers", *Journal of the Academy of Marketing Science*, 28(1), 17–23.

[185] Weerahandi, S. and S.R. Dalal (1992), "A Choice-Based Approach to the Diffusion of a Service: Forecasting Fax Penetration by Market Segments", *Marketing Science*, 11 (Winter), 39-53.

[186] Weitz, B., and S. Jap (1995), "Relationship Marketing and Distribution Channels", *Journal of the Academy of Marketing Science*, 23(4), 305–320.

[187] Wilkie, W., D. Descrochers, and G. Gundlach (2002), "Marketing Research and Public Policy: The Case of Slotting Fees", *Journal of Public Policy and Marketing*, 21(2), 275–288.

[188] Wittink, Dick R. (2002), "Analysis of ROI for Pharmaceutical Promotions", Unpublished study conducted for the Association of Medical Publications.

[189] Xie, Jinhong, X. Michael Song, Marvin Sirbu and Qiong Wang (1997), "Kalman Filter Estimation of New Product Diffusion Models", *Journal of Marketing Research*, 34 , 378-393.

[190] Yoo, B., N. Donthu, and S. Lee (2000), "An Examination of Selected Marketing Mix Elements and Brand Equity", *Journal of Academy of Marketing Science*, 28(2), 195–211.

[191] Zufryden, F.S. (1996), "Linking Advertising to Box Office Performance of New Film Releases: A Marketing Planning Model", *Journal of Advertising Research*, July–August, 29–41.