The Demand for Pharmaceutical Drugs under the New Regulatory Framework:

a Theoretical and Empirical Approach

A Ph.D. Thesis presented by

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Abstract

"The Impact of the Reference Price System on the Pharmaceutical Market: a Theoretical Approach"

This paper studies the impact of the reference price (RP) system on the price-setting strategies of pharmaceutical firms. The main objective of such reimbursement mechanism is to contain pharmaceutical spending through the promotion of price competition and the rise of generic usage. This can be achieved by making patients more "cost aware" via saving incentives when they ask for generics. In particular, the RP system is equivalent to setting an additional but avoidable copayment for those drugs whose price exceeds the reference level. Using a vertical product differentiation model, we show that branded producers decrease prices substantially after the introduction of this new copayment regime while generic prices remain more or less constant. As a consequence, price competition increases under the new regulatory framework, however, market share for generic drugs remain constant or even decreases. We can finally conclude that, although the social planner succeeds in promoting price competition, it completely fails in raising generic usage among population. Both the implementation of the RP system and the potential entrance of generics constitute a sufficiently credible threat to make brand-name producers decrease price, thus fostering effective competition.

"Demand for Pharmaceutical Drugs: a Choice Modelling Experiment"

Despite the importance of supplier inducement and brand loyalty in the drug purchasing process, little empirical evidence is found about the influence that those factors exert on patients' decisions. Under the new scenario of easier access to information, patients become more demanding and are even capable to question physician's prescription. Furthermore, new regulation also encourages patients to adopt an active role in the decision between trade-name and generic drugs. Using a stated preference model based on a choice survey, I find evidence of how significant physician's prescription and pharmacist's recommendation become along the drug purchase process and, to what extent, brand loyalty influences final decision. As far as we know, this paper is the first to take explicitly into account consumers' preferences instead of focusing on the behavior of health professionals.

**"Eliciting Consumers Preferences Using Stated Preference Discrete Choice Models:
Contingent Ranking versus Choice Experiment"**

The aim of this paper is twofold: firstly, to undertake a theoretical review about the most recent stated preference techniques used for eliciting consumers preferences and secondly, to compare the empirical results of two different stated preference discrete choice approaches. They differ in the measurement scale for the dependent variable and, therefore, in the estimation method, despite both use a multinomial logit. One of the approaches uses a complete ranking of full-profiles (contingent ranking), that is, individuals must rank a set of alternatives from the most to the least preferred, and the other uses a first-choice rule in which individuals must select the most preferred option from a choice set (choice experiment). From the results we realize how important the measurement scale for the dependent variable becomes and, to what extent, procedure invariance is satisfied.

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Introduction

In this thesis, I analyze the demand for pharmaceutical drugs from different perspectives. The first chapter explores, from a theoretical point of view, the impact of a new reimbursement mechanism, the RP system, on the demand for pharmaceuticals and effective price competition. The second chapter uses a stated preference database with the aim to examine the importance of supplier inducement and brand loyaty in the process by which patients decide among commercial drugs at the chemist's. Finally, the third chapter proceeds to compare two stated preference discrete choice approaches that differ in the measurement scale for the dependent variable.

Under the new scenario of easier access to information, patients become more demanding and are even capable to question physician's prescription. Furthermore, new regulation also encourages patients to adopt an active role in the decision between trade-name and generic drugs. In this sense, health care systems are transitioning from a physician-directed system to a patient-directed one and consumers preferences become an interesting issue of analysis not only for healh economists but also for new empirical industrial organization economists.

Chapter 1 studies the impact of the reference price (RP) system on the price-setting strategies of pharmaceutical firms. Several European countries have already established this new reimbursement mechanism as a regulatory measure aimed to contain national pharmaceutical spending through the promotion of price competition and the rise of generic usage. Although there exist several variations in the RP calculation method, we take into

account a general expression that could adjust to all European versions; therefore, our conclusions could be extrapolated to those countries with similar regulatory framework.

We analyze two different scenarios: (i) we first solve quality and price equilibrium before RP system enters into force; in this case, we assume that consumers must pay a constant copayment rate k for both branded and generic drugs and (ii) in the second scenario, we introduce the effect of the RP system that entails an additional but avoidable copayment for those drugs whose price exceeds the reference price.

Until now, several economists have examined what happens to the prices of innovator drugs when generic versions enter the market and, although the majority of them agree that the effect is quite small, there is some dispute about its direction. However, once the price competition has been distorted due to the implementation of the RP system, previously reached conclusions are not valid any more because they were obtained under the assumption of free market. We now require a different scenario where a new regulation is introduced.

According to a recent review on RP system, the existing literature about the impact of the RP system has been mainly descriptive and the absence of a common theoretical framework hindered the design of an optimal regulatory measure. However, in the last period, few authors have looked into the problem from a theoretical and empirical point of view.

Cabrales (2003) and Mestre-Ferrándiz (2003) are closer to ours in the sense that they both use a differentiation model and introduce RP system as a market distortion. Notwithstanding, the assumptions about product differentiation and reference price construction

substantially differ. We use a *vertical product differentiation model* with two firms operating the market: one firm produces the brand-name drug whose patent has already expired (B) and the other produces the corresponding generic version (G). We assume a two-stage game where, in the first stage, firms choose the "perceived" quality of the good they want to produce and, in the second stage, a competitive process occurs where firms set prices.

We find that, under the RP system, branded producers decrease prices substantially in order to adapt to the new competitive situation while generic prices remain more or less constant. In Bertrand models, market shares do not change after the introduction of reference prices while in Stackelberg models, the market share of branded drugs even increases and that of generics decreases. In both cases, the brand-name producers compensate the decline of profits by selling greater quantities instead of charging higher prices. Our theoretical results are in the line of Pavcnik's empirical findings. We also undertake a social welfare analysis and compare price competition under RP system and Ramsey pricing. We find that the reference price system maximizes price competition when the penetration of generic drugs overcomes 70% of the market; otherwise, Ramsey prices can better ensure price competition and maximization of social welfare.

Chapter 2 explores the importance of supplier inducement and brand loyalty in the process by which patients decide among commercial drugs at the chemist's. The purchase of pharmaceutical drugs is more than a "purchasing act in itself" because it involves a multistage process in which, firstly, physician writes a drug prescription, secondly, pharmacist dispenses and substitutes and, finally, patient consumes. The existence of *informa-*

tion asymmetries between physicians and patients and *uncertainty* on drugs effectiveness generate supplier inducement and brand loyalty respectively.

The new pharmaceutical framework makes interesting the analysis of patients preferences, however the empirical literature on pharmaceuticals demand is very limited and has always been focused on the behavior of either physicians or pharmacists. Furthermore, all of them use revealed preference data to estimate the objective utility function.

As far as we know, this paper is the first to explore consumers' preferences for commercial drugs using stated preference data obtained from a choice survey. We carry out a choice modelling experiment to understand how patients develop preferences for commercial drugs. This method is based on the premise that consumers evaluate the convenience of a product by combining the separate amounts of utility provided by each attribute. In our case, a representative sample of 439 individuals are surveyed and asked to rank a set of commercial drugs alternatives according to their preferences.

The parameters of our utility function are estimated using a *rank ordered logit* - a generalization of McFadden's conditional logit- and will determine the significance of brand loyalty, laboratory reputation and reliance upon health experts along the decision-making process

The "main effects" model shows the significant importance of experts' inducement - although physician's prescription is always more reliable than pharmacist's recommendation- and, to what extent, both brand loyalty and laboratory reputation influence the final decision. Using interactions between attributes and characteristics of the respondents, I find that age is a relevant variable in the decision between a trade-name and a generic drug at the

chemist's. The old firmly trust incumbent brands and doctor's prescription; on the contrary, the youngest are easily influenced by pharmacist's recommendation and, despite not being loyal to incumbent brands, they value laboratory reputation. In addition, those patients exhibiting high switching costs firmly trust doctor's opinion and are reluctant to switch to other drugs different than the incumbent. On the contrary, those that have already tested and learnt about generics are more easily influenced by pharmacist's recommendation and laboratory reputation

Chapter 3 has a twofold objective: firstly, to undertake a theoretical review about the most recent stated preference techniques used for eliciting consumers preferences and, secondly, to empirically compare two stated preference approaches and discuss their main strengths and weaknesses.

Although *revealed preference* data have been traditionally used to estimate consumers' valuation for attributes, *stated preferences* hold important advantages when historical data do not suit the objective function. Notwithstanding, there are many ways to elicit stated preferences from individuals -contingent valuation, conjoint analysis, discrete choice methods- and recently, a great debate has emerged focusing on the pros and cons of each of them, mainly between conjoint analysis and choice methods.

The empirical aim of this paper is to compare the results of two particular stated preference discrete choice model (SPDCM) approaches and assess the validity and reliability of each of them. They differ in the measurement scale for the dependent variable and therefore in the estimation method, despite both use a multinomial logit. One of the approaches uses a complete ranking of full-profiles (contingent ranking) in which individuals must rank

a set of alternatives from the most to the least preferred, and the other uses a first-choice rule in which individuals must select the most preferred option from a choice set (choice experiment). From the results we realize how important the measurement scale for the dependent variable becomes and, to what extent, procedure invariance is satisfied; that is, two different measurement methods used to measure the same thing should yield the same outcome. However, inconsistency occurs when different methods for measuring a preference yield different results. This inconsistency is called *procedure preference reversal.*

Chapter 1
The Impact of the Reference Price System on the Pharmaceutical Market: a Theoretical Approach

Abstract[1]

This paper studies the impact of the reference price (RP) system on the price-setting strategies of pharmaceutical firms. The main objective of such reimbursement mechanism is to contain pharmaceutical spending through the promotion of price competition and the rise of generic usage. This can be achieved by making patients more "cost aware" via saving incentives when they ask for generics. In particular, the RP system is equivalent to setting an additional but avoidable copayment for those drugs whose price exceeds the reference level. Using a vertical product differentiation model, we show that branded producers decrease prices substantially after the introduction of this new copayment regime while generic prices remain more or less constant. As a consequence, price competition increases under the new regulatory framework, however, market share for generic drugs remain constant or even decreases. We can finally conclude that, although the social planner succeeds in promoting price competition, it completely fails in raising generic usage among population. Both the implementation of the RP system and the potential entrance of generics constitute a sufficiently credible threat to make brand-name producers decrease price, thus fostering effective competition.

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1.1 Introduction

Several European countries have already established this new reimbursement mechanism, RP system, as a regulatory measure aimed to contain national pharmaceutical spending through the promotion of price competition and the rise of generic usage. Although there exist several variations in the RP calculation method, we take into account a general expression that could adjust to all European versions; therefore, our conclusions could be extrapolated to those countries with similar regulatory framework.

We analyze two different scenarios: (i) we first solve quality and price equilibrium before RP system enters into force; in this case, we assume that consumers must pay a constant copayment rate k for both branded and generic drugs and (ii) in the second scenario, we introduce the effect of the RP system that entails an additional but avoidable copayment for those drugs whose price exceeds the reference price.

Until now, several economists have examined what happens to the prices of innovator drugs when generic versions enter the market and, although the majority of them agree that the effect is quite small, there is some dispute about its direction (Section 1.2.1). However, once the price competition has been distorted due to the implementation of the RP system, previously reached conclusions are not valid any more because they were obtained under the assumption of free market. We now require a different scenario where a new regulation is introduced (Section 1.2.2).

According to a recent review on RP system (López-Casasnovas and Puig-Junoy, 2001), the existing literature about the impact of the RP system has been mainly descriptive and the absence of a common theoretical framework hindered the design of an optimal

regulatory measure. However, in the last period, few authors have looked into the problem from a theoretical and empirical point of view.

Aronsson et al (1997) empirically analyze the impact of the RP system in Sweden and find that it lowered the price of the original relative to the price of the generics. The negative effect of the RP system appears to be reasonable since the introduction of this system may have provided strong incentives for manufacturers of brand name products to lower their prices.

Cabrales (2003) studies oligopolistic competition in off-patent pharmaceutical markets using a vertical product differentiation model. His model can explain the observation that countries with stronger regulation have smaller generic market shares. He assumes a price ceiling that corresponds to a RP system and finds that the relative market share of the high quality good is a decreasing function of the maximum price, that is, the lower the ceiling price, the higher the relative market share of the high quality product. Mestre-Ferrándiz (2003) shows that Spanish RP system achieves the objectives to increase price competition and reduce public pharmaceutical costs only if the reference price is set in a certain interval.

Finally, Pavcnik (2002) empirically examines the link between potential patient out-of-pocket expenses and pharmaceutical pricing using a unique policy experiment from Germany. Using data on oral antidiabetic and antiulcerant drugs, she finds that producers significantly decrease prices after the change in potential out-of-pocket expenses. Price declines are most pronounced for brand name products. Furthermore, branded products that face more generic competitors reduce prices more.

Cabrales (2003) and Mestre-Ferrándiz (2003) are closer to ours in the sense that they both use a differentiation model and introduce RP system as a market distortion. Notwithstanding, the assumptions about product differentiation and reference price construction substantially differ. We use a *vertical product differentiation model* with two firms operating the market: one firm produces the brand-name drug whose patent has already expired (B) and the other produces the corresponding generic version (G). We assume a two-stage game where, in the first stage, firms choose the "perceived" quality of the good they want to produce and, in the second stage, a competitive process occurs where firms set prices.

Furthermore, at each stage of the game, firms make their decisions about quality and prices both simultaneously and sequentially. Therefore, we obtain four different models. We solve the **quality game** taking into account two different assumptions about entry temporality: branded copies or me-too drugs enter the market simultaneously to the original product while generic drugs enter the market after the patent on the corresponding brand-name drug has expired. We solve the **price-setting sub-game** by taking into account Bertrand and Stackelberg price competition. It is widely accepted that price is one of the main strategic variables in the pharmaceutical industry, however, some researchers assume simultaneous price competition while others accept a sequential price competition (Section 1.3).

We find that, under the RP system, branded producers decrease prices substantially in order to adapt to the new competitive situation while generic prices remain more or less constant. In Bertrand models, market shares do not change after the introduction of reference prices while in Stackelberg models, the market share of branded drugs even increases

and that of generic drugs decreases. In both cases, the brand-name producers compensate the decline of profits by selling greater quantities instead of charging higher prices. Our theoretical results are in the line of Pavcnik's empirical findings (Section 1.4). We also undertake a social welfare analysis and compare price competition under RP system and Ramsey pricing. We find that the reference price system maximizes price competition when the penetration of generic drugs overcomes 70% of the market; otherwise, Ramsey prices can better ensure price competition and maximization of social welfare (Section 1.5).

This paper is organized as follows. Section 1.2 deeply describes the main regulatory framework and the characteristics of demand and supply in the pharmaceutical market. Section 1.3 introduces the assumptions about product differentiation models both simultaneous and sequential. Section 1.4 explores the impact of the RP on the price and quantity strategies and Section 1.5 presents a social welfare analysis and calculates the Ramsey prices. Finally, Section 1.6 summarizes the results and concludes.

1.2 Characteristics of the Pharmaceutical Market

The purpose of this paper is to examine the impact of the reference price (RP) system on the price-setting strategies of pharmaceutical firms, both branded and generic drugs producers. RP is a regulatory measure aimed to contain pharmaceutical spending by promoting the usage of lower-cost generic drugs. Although we mainly focus on the Spanish case due to proximity, we are able to extend our conclusions to those European countries with similar regulatory framework.

The entry process of generic drugs follows parallel patterns worldwide however, and due to different political, social and cultural contexts, some countries exhibit high penetration rates while others could not reach a significant market share.[2] Several European countries, such as Denmark, Germany, Island, Norway, Sweden, Spain and The Netherlands, have introduced different types of RP mechanisms with substantial variations among them. However, the principle remains always the same: the price paid by the third-party is established by reference to interchangeable drugs, with any excess cost being borne by the consumer as an out-of-pocket payment.

1.2.1 Generics Entry

One of the primary goals of Law 13/96 was to set up a competitive framework in the Spanish pharmaceutical market by promoting the availability of lower-cost generic drugs.[3] The so-called generic drugs are those medicines that contain the same active ingredient as a brand-name drug and enter the market once the patent on the latter has expired.

Generic drugs cost less than their innovator counterparts because of their lower R&D initial investment. In this sense, they become very attractive for national health systems because they are expected to play an active role in holding down pharmaceutical spending. The rise of pharmaceutical spending in the last decade has led governments to encourage

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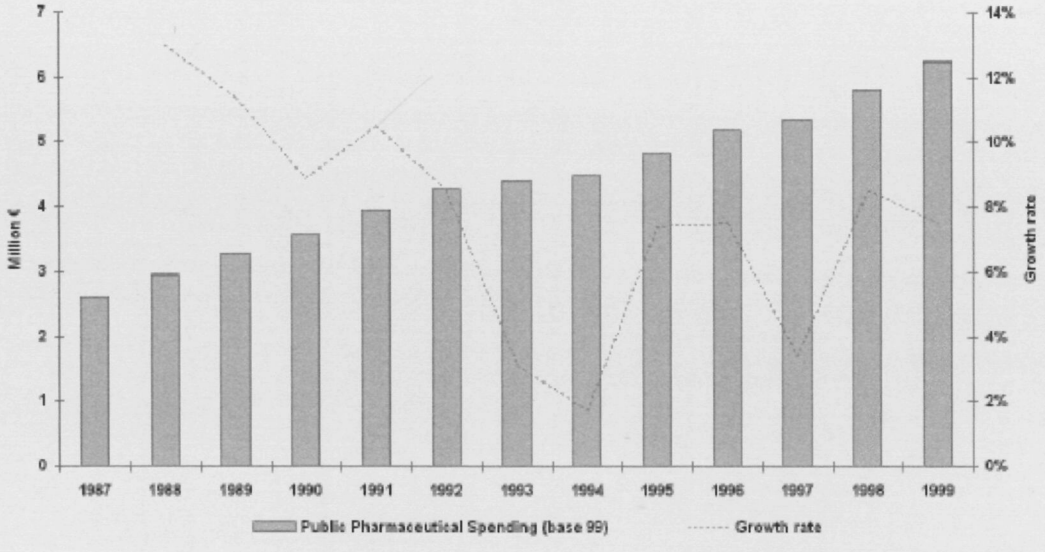
[2] Countries such as Germany (32%), The Netherlands (39.9%) and UK (46.45%) enjoy a high "generics over total drugs" ratio while Belgium (1%), France (4%), Italy (0.75%) and Spain (3.6%) are characterized by low generic drugs penetration rates *(Source: "Gasto Farmacéutico (I) en Europa. Comparación del Año 2000", El Global, 2001; available at www.elglobal.net).*

[3] Law 13/96, 30 December, entitled "Medidas administrativas, fiscales y del orden social" that modifies Law 25/1990 called "Ley del Medicamento". In the USA, the commonly known as the Waxman-Hatch Act intented to reduce expenditures on prescription drugs by encouraging generic entry. It eliminated the strict requirements for FDA approval of generic substitutes and replaced it with one that requires much less stringent testing.

the use of those cheaper drugs among population and medical centres with the aim of fostering price competition between branded and generic versions (Figure 1.1).[4]



Source: Spanish Ministry of Health (data available at www.pmfarma.com)

Figure 1.1. Public Pharmaceutical Spending in Spain (1987-1999)

In order to obtain the official approval from *Agencia Española del Medicamento*, generic versions are only required to certify "bioequivalence" to the corresponding innovator drug; in other words, to show that the active ingredient is released and absorbed at the same rate for the generic drug as for the corresponding innovator.[5] However, although brand-name drugs and their corresponding generic versions are supposed to be perfect substitutes in terms of quality and therapeutic effects, in fact, from the consumers and physicians' point of view, they are not.

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[4] Accumulated growth rate of the Spanish public pharmaceutical spending for the period 1987-1999 is 140%.

[5] The task of *Agencia Española del Medicamento* in Spain corresponds to that of the Food and Drug Administration (FDA) in the USA. Generally speaking, generic drugs obtain official approval under a shorter process than innovator drugs.

Demand Side: Once generics enter the market, it raises uncertainty about their quality. Consumers tend to re-use those medicines that have worked for them in preference for taking the risk of trying drugs that they have not tested before and that may not suit them. In pharmaceutical markets, a consumer behaves as if he faces a switching cost equal to the maximum premium that he would be willing to pay to be guaranteed a product of the same value as a product he has previously purchased (Klemperer, 1995). That is, a product of unknown quality is inherently riskier than a product of known quality. Because it is less risky, consumers will pay a higher price for the product of the known quality (Conrad, 1983).

In our model, we assume that a fraction of consumers face high switching costs and manifest strong preferences for brand-name drugs while the remainder is more price-sensitive and show negligible switching cost. Loyal consumers are extremely committed to brand-name drugs and exhibit a state dependence in their purchasing patterns because their preferences depend on the past history of prescriptions (Coscelli, 2000). This uncertainty about quality creates an *artificial vertical differentiation* that segments consumers' demand.

Doctors are also responsible for this artificial product differentiation because they are relevant decision-makers in the drug purchasing process. As Hellerstein (1998) found, almost all physicians prescribe two types of drugs, but some of them are more likely to prescribe generic drugs while others are more likely to prescribe brand-name versions. The latter exhibit habit persistence, in other words, tendency to prescribe repeatedly the same brand-name drug (Coscelli, 2000). There could be several reasons why physicians do not

prescribe generic drugs more often but the more outstanding one is the lack of information about the availability and efficacy of generic versions.

Under the new regulatory framework, pharmacists play also an important role:[6] if physicians prescribe a brand-name drug whose price exceed the reference price, the pharmacists are able to substitute it by its corresponding generic version as long as consumer agrees. Masson and Steiner (1985) have performed an analysis of the initial period after the new state substitution law in the United States and found that these new laws have indeed increased the market's price sensitivity and the amount of generic usage in the market.

There exists a close relationship between experts -both physicians and pharmacists- and patients. Patients firmly trust their doctors' opinion and are reluctant to switch to generics if physicians do not advise them to do so. The asymmetric information between doctors and patients certainly suggests the possibility that the former could use their position of superior knowledge for their own financial benefit. In the absence of incentives, physicians are more likely to stand prescribing brand-name drugs instead of generic versions. In Health Economics, this phenomenon is commonly known as the *supplier-induced-demand effect.*

Therefore, under the new regulatory scenario, the demand for drugs can be characterized as follows: the physician prescribes, the pharmacist dispenses and substitutes whenever possible, patient consumes and pays a fraction of the drug cost as an out-of-pocket payment and finally the third-party pays the rest. In this framework, there is an agency relationship between physician and patient and another between pharmacist and patient,

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[6] In Spain, Law 66/1997, 30 December, entitled "Medidas Fiscales, Administrativas y del Orden Social" that modified article 94 of Ley del Medicamento.

however, their analysis is beyond the scope of this article. In our model, we assume that patients are the unique decision-makers. Chapter 2 explores, from an empirical point of view, the importance of physicians and pharmacists' demand inducement.

Supply Side: The supply side in pharmaceutical markets is characterized by a *first mover pricing leadership*. Once a breakthrough drug is introduced, its manufacturer enjoys a period of exclusivity until the patent expires. Several authors have argued that a pioneering brand is able to establish a reputation which later entrants cannot overcome without large promotional expenditures or drastic price cuts.

The period of exclusivity grants some *monopoly rents* and market advantages for the innovator such as high market shares, locked-in consumers and high-quality products reputation. Furthermore, this period of exclusivity allows the brand-name producer to enjoy a future price leadership. Once a patent expires, all interested producers can manufacture the generic version and enter the market. Generally speaking, we can assume that there exist relatively small barriers to entry because the generic approval process does not take longer, it is not very costly and producers of generic drugs do not need to duplicate research costs.

Impact of Generics Entry on Pricing Strategies

The impact of generic entry on the price strategies of brand-name producers has been a source of controversy. Actually, several economists have examined what happens to the prices of innovator drugs when generic copies enter the market and, although the majority of them agree that the effect is quite small, there is some dispute about its direction. Another

point to emphasize is the fact that all empirical studies use data from the United States market, thus assuming no price regulation.

Grabowski and Vernon (1992) found that prices continued to rise faster than inflation after generic entry. On the contrary, Caves et al (1991) attempted to control for the rate of price increase that would have occurred without generic entry and concluded that although the prices of many brand-name drugs continued to rise after generic entry, those prices were still lower than they would have been otherwise.

Frank and Salkever (1997) found that brand-name prices increased more quickly than if generic entry had not occurred. More recently, Mestre-Ferrándiz (1999) found that brand-name producer also has incentives to produce its generic alternative; this leads to an increase in the price of the brand-name drug produced by this firm. Ching (2000) argues that consumer heterogeneity in terms of price elasticity has the potential to explain the pricing pattern that brand-name prices increase in response to generic entry. Those studies assumed *demand market segmentation*; that is, when generics enter the market, price sensitive consumers switch to low cost versions and, consequently, the brand-name firm faces a more price inelastic demand and hence can raise its price. This is called the *Generic Competition Paradox.*

On the other hand, Ellison et al (1997) found that in one antibiotic market, demand for a brand-name drug is more sensitive to changes in the price of its generic substitutes than to changes in the price of a competing brand-name drug.

1.2.2 Reference Price System and Promotion of Generics

The rise of national pharmaceutical spending in the last decade has led governments to adopt several regulatory measures aimed to promote price competition through generics entry, control sale prices and margins and establish new reimbursement mechanisms. The lower price of generic drugs with respect to branded versions has encouraged public administration to promote generics usage as a mechanism to contain national pharmaceutical spending and monitor quality of pharmaceutical care. Each country has implemented slightly different pharmaceutical policy mechanisms and their success has been closely related to political, social and cultural context within which each health care systems operates. One of the most popular measures has been the promotion of prescribing, dispensing and consuming lower-price generic drugs through the introduction of reference prices and substitution laws (Table 1.1).

	A	B	DK	FIN	F	G	GR	IC	IRL	I	L	NL	N	P	S	Sw	CH	GB
Laboratory sale price control	-	■	-	■	-	-	■	■	-	-	■	-	■	■	■	-	-	-
New drugs reimbursement control	■	■	■	■	■	-	■	-	-	■	■	■	■	■	■	■	■	-
International comparison	■	■	■	■	■	-	■	■	■	■	■	■	■	■	■	■	■	-
Reference price system	-	-	■	-	-	■	-	■	-	-	-	■	■	-	■	■	-	-
Devolution/contracts	■	-	-	-	■	-	-	-	■	■	-	-	-	-	■	■	-	■
Profits control	-	-	-	-	-	-	-	-	-	-	-	-	-	-	■	-	-	■
Promotional spending control	-	-	-	-	■	-	-	-	-	-	-	-	-	-	■	-	-	■
Prescription drugs budget	-	-	-	-	-	■	-	-	■	-	-	-	-	-	-	-	-	■
Pharmaco-economic evidence recommendation	-	-	-	■	-	-	-	-	-	■	-	■	■	■	-	■	-	■
Wholesaler fixed margins	■	■	-	-	■	■	■	-	■	■	■	-	-	■	■	-	■	■
Pharmacists fixed margins	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
Generic substitution	-	-	■	■	■	-	-	■	-	■	■	■	■	-	■	-	-	-
Copayment rates	■	■	■	■	■	■	■	■	■	■	■	-	■	■	■	■	■	■
OTC price control	-	■	-	-	-	-	■	-	-	-	■	-	-	-	-	-	-	-
Price control for hospital use drugs	-	■	-	-	-	-	■	-	-	■	-	-	-	-	■	-	-	-

A=Austria; B=Belgium; DK=Denmark; FIN=Finland; F=France; G=Germany; GR=Greece; IC=Iceland; IRL=Ireland; I=Italy; L=Luxembourg; NL= Netherlands; N=Norway; P=Portugal; S=Spain; SW=Sweden; CH=Switzerland; GB=Great Britain.

Source: "Diagnóstico y Perspectiva del Gasto Farmacéutico en España", NERA. Report published by Farmaindustria.

Table 1.1. Main Mechanisms to Control Pharmaceutical Spending in European Countries

Reference Price System

In Spain, Royal Decree 1035/1999 regulates the mechanism by which government calculates the reference price for those drugs funded by Social Security and included in the submarket of drugs whose patent has already expired. Since the introduction of the RP system in Germany in 1989, different versions have been implemented in various European countries with substantial modifications. However the principle remains always the same: the price paid by the third-party is established by reference to interchangeable drugs, with any excess cost being borne by the consumer as an out-of-pocket payment.

The main objectives of a RP system are to increase price competition and, ultimately, reduce public expenditure on pharmaceuticals. The first aim can be achieved by making patients more "cost aware" via saving incentives when they ask for generics. In particular, the RP system is equivalent to setting an *avoidable* copayment for those drugs whose price is superior to the reference price. This new regulatory measure would presumably reduce the costs of the third-party or Social Security.

Most of the countries first to introduce the RP system have three characteristics in common:(i) pharmaceutical prices are not directly regulated; (ii) generic drugs account for a significant market share and (iii) public pharmaceutical spending accounts for more than half of total drugs sales. Although Spain satisfies the third feature, the first two are not accomplished. These drawbacks could explain why the Ministry of Health had repeatedly postponed the introduction of reference prices until December 2000.

In Germany, the reference price (maximum reimbursement) is taken to be the price of the least expensive generic drug in an homogenous group and costs are only reimbursed

up to this maximum; that is, if the retail price exceeds the maximum reimbursement, the patient bears the excess cost. Otherwise, the patient does not need to copay. The pharmacist is not allowed to substitute to a generic product unless the doctor explicitly permits it on the prescription pad (Pavcnik, 2002). The Swedish RP system came into effect on January 1, 1993 and specifies that any cost exceeding the price of the least expensive generic version by more than 10% must be borne by the patient (Aronsson et al, 1997).

In Spain, the reference price is determined endogenously as a function of both brand-name and generic versions prices: (i) the reference price is defined for each homogeneous group (in each homogeneous group there is at least one generic), then the reference price is calculated as the weighted-average of the minimum prices until 20% of the market sales are covered; (ii) in those cases where the difference between the reference price and the maximum market price is less than 10%, the reference price will be set at 90% of the maximum price; (iii) if the difference between the maximum price and the reference price is greater than 50%, the reference price will be set at 50% of the maximum price and (iv) in any case, the reference price can not be lower than the minimum supplier price and it will be revised every year.

Under this new regulatory framework, conclusions shown in previous section about the impact of generic entry on pricing strategies are not valid any more because they were obtained under the assumption of free market. We now require a different scenario where a new reimbursement mechanism is able to distort price competition. Few economists have recently studied this phenomenon.

Aronsson et al (1997) empirically analyze the impact of the RP system in Sweden and find that it lowered the price of the original relative to the price of the generics. The negative effect of the RP system appears to be reasonable since the introduction of this system may have provided strong incentives for manufacturers of brand name products to lower their prices.

Cabrales (2003) studies oligopolistic competition in off-patent pharmaceutical markets using a vertical product differentiation model. His model can explain the observation that countries with stronger regulation have smaller generic market shares. He assumes a price ceiling that corresponds to a RP system and finds that the relative market share of the high quality good is a decreasing function of the maximum price, that is, the lower the maximum price, the higher the relative market share of the high quality product. Mestre-Ferrándiz (2003) shows that Spanish RP system achieves the objectives to increase price competition and reduce public pharmaceutical costs only if the reference price is set in a certain interval.

Finally, Pavcnik (2002) empirically examines the link between potential patient out-of-pocket expenses and pharmaceutical pricing using a unique policy experiment from Germany. Using data on oral antidiabetic and antiulcerant drugs, she finds that producers significantly decrease prices after the change in potential out-of-pocket expenses. Price declines are most pronounced for brand name products. Furthermore, branded products that face more generic competitors reduce prices more.

Cabrales (2003) and Mestre-Ferrándiz (2003) are closer to ours in the sense that they both introduce RP system as a market distortion. Notwithstanding, the assumptions about

product differentiation and reference price construction substantially differ. Our theoretical results are in the line of Pavcnik's empirical findings.

1.3 The Model

We analyze two different scenarios: (i) we first solve quality and price equilibrium before RP system enters into force; in this case, we assume that consumers must pay a constant copayment rate k for both type of drugs and (ii) in the second scenario, we introduce the effect of the RP system. As explained above, the RP system is a reimbursement mechanism that sets an additional but avoidable copayment for those drugs whose price exceeds the reference price.

We use a *vertical product differentiation model* with two firms operating the market: one firm produces the brand-name drug whose patent has already expired (B) and the other produces the corresponding generic version (G). We assume a two-stage game where, in the first stage, firms choose the "perceived" quality of the good they want to produce and, in the second stage, a competitive process occurs where firms set prices.

Although there are no administrative barriers to enter the market once the patent on the breakthrough product has expired, both the low margins in the generic submarket and the initial lack of confidence make potential competitors reluctant to enter. Therefore, there exists a transition period during which the market is duopolistic. Two different scenarios can happen; either the innovator firm decides to produce also the generic version applying *third degree price discrimination* or a third company decides to enter the market producing the generic version. In our case, we assume the existence of a third company.

Demand Side: Consumers have the same utility function however they differ in their tastes described by parameter v

$$\begin{array}{c} U(v\ \theta_i) = v\theta_i - kp_i \text{ if consumer buys one unit} \\ U(v\ \theta_i) = 0 \text{ otherwise} \end{array} \quad i = B\,G \tag{1.1}$$

Let consumers' taste for drug "perceived" quality be denoted by v and assume a continuum of consumers indexed by their valuation v on the interval $[0\ 1]$. The benefit from purchasing one unit from producer i (B,G) is $v\theta_i$ where θ_i is the "perceived" quality for each producer. The perception of quality can be either high or low. High perceived quality is associated to brand-name drug (θ_B) and low perceived quality is associated to its generic version (θ_G). Consumers with a higher v are more willing to pay for a higher quality good, that is, they are relatively insensitive to price variations and exhibit high switching costs or brand loyalty. Those consumers with lower v, instead, react to small changes in the relative price of the two goods and thus exhibit low switching costs. The cost is kp_i where k is the copayment rate paid by the consumer and p_i is the sale price set by the company.[7]

$U(v\ \theta_i)$ should be thought as the *surplus* derived from the consumption of the good. The utility is separable in quality and price. We assume that consumers always have enough money to buy one unit if it is optimal to do so and when a consumer is indifferent between buying and not buying, he buys and when he is indifferent between buying the two types of drugs, he buys the brand-name drug. In order to obtain the demand functions for brand-name and generic drugs, we maximize utility function as follows:

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[7] In Spain, there is a copayment of 40% of the sale price for both the brand-name and the generic drug. The rest is paid by the third-party.

Consumer buys the brand-name drug as long as:

$$\begin{array}{c} v\theta_B - kp_B \geq v\theta_G - kp_G \Longrightarrow v^* \geq \frac{k(p_B - p_G)}{\theta_B - \theta_G} \text{ and} \\ v\theta_B - kp_B \geq 0 \Longrightarrow v^- \geq \frac{kp_B}{\theta_B} \end{array} \tag{1.2}$$

Consumer buys the generic version if:

$$\begin{array}{c} v\theta_G - kp_G > v\theta_B - kp_B \Longrightarrow v^* < \frac{k(p_B - p_G)}{\theta_B - \theta_G} \text{ and} \\ v\theta_G - kp_G \geq 0 \Longrightarrow v_- \geq \frac{kp_G}{\theta_G} \end{array} \tag{1.3}$$

Taking into account that $v \in [0\ 1]$, the demand functions for high and low quality firms are given respectively by:

$$q_B = 1 - \frac{k(p_B - p_G)}{\theta_B - \theta_G} \text{ and } q_G = \frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G} \tag{1.4}$$

Otherwise, consumer will not buy.

Supply Side: The competition between the two firms takes place in two stages. In the first stage, they decide on the quality θ to be produced with $1 \geqslant \theta_B > 0\,5 > \theta_G > 0$ There is no a priori upper bound to the level of quality, but we assume that there exists a lower bound to it. The latter can be interpreted as a *Minimum Quality Standard* (MQS) requirement (Ronnen, 1991). In our model, the MQS refers to the bioequivalence test that generic firms should obtain before entering the market and the minimum advertising investment needed to obtain a position in the market. On the other hand, branded firms should engage in R&D and advertising to improve perceived quality. Therefore, each firm incurs a fixed cost of quality improvement while variable costs do not change with quality (Motta, 1993):

$$C_i = \frac{\theta_i^2}{2} \qquad i = B\,G \tag{1.5}$$

We assume that, at each stage of the game, firms make their decisions about quality and prices both simultaneously and sequentially. Therefore, we obtain four different models (Figure 1.2).

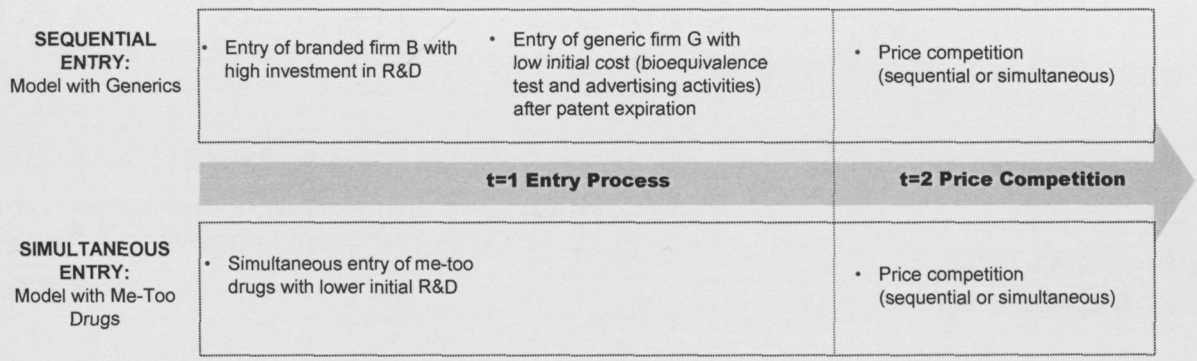

Figure 1.2. Two-stage Game: Entry Process and Price Competition

We solve the quality game taking into account two different assumptions about entry temporality. In the first model, we assume that firm B (innovator) registers the breakthrough drug but, due to the lack of product patent protection, firm G can enter the market simultaneously with a copy of the original product. This is the case of me-too drugs or branded copies.[8] In the second model, we assume that the product patent protection is accomplished and, therefore, firm G enters the market with the generic version after the patent on the branded drug has expired, thus implying a sequential entry.

In the second stage, firms set prices. Costs of quality development have been already sunk and constant unit production costs are incurred. Without loss of generality, we take these costs to be zero (Motta, 1993). We solve the price-setting sub-game by taking into account Bertrand and Stackelberg price competition. It is widely accepted that price is one

[8] This is a consequence of an unusual patent system. For example, in Spain, under the old patent system, only processes for the preparation of new chemical entities were patentable. Under the new patent system, processes, and probably uses, have been patentable since 1986 but products only since 1992.

of the main strategic variables in the pharmaceutical industry, however, some researchers assume simultaneous price competition while others accept a sequential price competition. For example, Zweifel and Crivelli (1996) suppose a simple duopoly model where both, innovator and generic imitator, regard price as their strategic variable, thus resulting in a Bertrand equilibria. On the other hand, several economists have studied the existence of first-mover pricing advantages in the pharmaceutical industry and concluded that first movers have brand loyalty advantages that permit them to charge higher prices and retain substantial market shares in the future.

In summary, we solve four different models taking into account all possible combinations (Table 1.2). We look for the sub-game perfect Nash equilibrium of the game. As usual, this will be obtained by backward induction. As stated before, we solve these four models taking into account the copayment scenario and the RP scenario, therefore we are able to compare how firms respond to a change from a copayment system to a reference price system.

Model	Quality Game	Price Competition
Model 1	Simultaneous (branded copies)	Sequential (Stackelberg)
Model 2	Sequential (generic drugs)	Sequential (Stackelberg)
Model 3	Simultaneous (branded copies)	Simultaneous (Bertrand)
Model 4	Sequential (generic drugs)	Simultaneous (Bertrand)

Table 1.2. Simultaneous and Sequential Models

1.3.1 Stackelberg Model

In this section,we solve models 1&2 where the characteristic in common is the sequential price competition. Actually, we assume first mover advantage where brand-name producer

is the price *leader* (B) and generic producer is the *follower* (G). The quality game is solved both simultaneously (branded copies) and sequentially (generic drugs).

Price-setting Game

In the second stage, firms choose prices under the assumption that costs of quality development have been already sunk. Therefore, firms' profits are given by:[9]

$$\Pi_B = p_B\left[1 - \frac{k(p_B - p_G)}{\theta_B - \theta_G}\right] \text{ and } \Pi_G = p_G\left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right] \tag{1.6}$$

Firm G's price-setting problem is:

$$\underset{p_G}{Max}\ \Pi_G(p_B p_G) = p_G\left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right] \tag{1.7}$$

and the first-order condition (FOC) is:

$$\frac{\partial\Pi(p_G p_B)}{\partial p_G} = \left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right] + p_G\left[\frac{-k}{\theta_B - \theta_G} - \frac{k}{\theta_G}\right] = 0 \tag{1.8}$$

The *reaction function* that gives the optimal choice of p_G as a function of p_B is:[10]

$$p_G = \frac{\theta_G}{2\theta_B} p_B \tag{1.9}$$

Then the leader, firm B, maximizes the following expression subject to G's reaction function:

$$\begin{aligned} &\underset{p_B}{Max}\ \Pi_B(p_B p_G) = p_B\left[1 - \tfrac{k(p_B - p_G)}{\theta_B - \theta_G}\right] \\ &\text{s.t.} \quad p_G = \tfrac{\theta_G}{2\theta_B} p_B \end{aligned} \tag{1.10}$$

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[9] We assume that firms' profits are equal to $\prod_i = p_i q_i$ where q_i is consumers' demand derived from the maximization of utility function and p_i is the sale price. Therefore, we obtain the profit function by summing up the direct revenues from the consumers $k * p_i q_i$ and those paid by the third-party$(1-k) * p_i q_i$ This model focuses on the publicly funded pharmaceutical drugs.

[10] Notice that from this equation, it can be verified that $v^* > v^-$ and $v^* > v_-$

whose FOC is given by:

$$\frac{\partial \Pi_B}{\partial p_B} = \left[1 - \frac{kp_B - k\frac{\theta_G}{2\theta_B}p_B}{\theta_B - \theta_G}\right] + p_B\left[\frac{-k}{\theta_B - \theta_G} + \frac{k\frac{\theta_G}{2\theta_B}}{\theta_B - \theta_G}\right] = 0 \tag{1.11}$$

We solve p_B and substitute in order to get p_G :

$$p_B = \frac{\theta_B(\theta_B - \theta_G)}{k(2\theta_B - \theta_G)} \text{ and } p_G = \frac{\theta_G(\theta_B - \theta_G)}{2k(2\theta_B - \theta_G)} \tag{1.12}$$

Substituting the price equilibrium levels into the quantity equations yields the following market shares:

$$q_B = \frac{1}{2} \text{ and } q_G = \frac{\theta_B}{2(2\theta_B - \theta_G)} \tag{1.13}$$

The relative price ratio, $\frac{p_B}{p_G} = \frac{2\theta_B}{\theta_G}$, shows that the brand-name price is always higher than the generic price due to price leadership effect. The relative market share ratio, $\frac{q_B}{q_G} = \frac{2\theta_B - \theta_G}{\theta_B}$, displays that the demand for brand-name drugs is always higher than that for generic drugs due to first mover advantage. Those features fit quite well the Spanish pharmaceutical market.

Quality Game

We now look for the solutions of the quality game. We assume fixed costs of quality improvement and zero variable costs. This may be thought of as a situation where firms should engage in high initial R&D and advertising activities to improve quality and strengthen market position. In particular, generics or branded copies firms (G) should pass the bioequivalence test to obtain permission to enter the market and invest in promotional activities to get market reputation. On the other hand, branded firms (B) should engage in R&D and advertising activities to launch new chemical products. As expected, the cost of the bioequivalence test is not comparable to the cost associated to R&D activities necessary

to bring up a new chemical compound. The advertising and promotional spending oriented to health professionals, both physicians and pharmacists, is translated to consumers through *supplier inducement.*

Firms will choose their quality specification to maximize their profits:

$$\Pi_B = \frac{\theta_B(\theta_B - \theta_G)}{2k(2\theta_B - \theta_G)} - \frac{\theta_B^2}{2} \text{ and } \Pi_G = \frac{\theta_B\theta_G(\theta_B - \theta_G)}{4k(2\theta_B - \theta_G)^2} - \frac{\theta_G^2}{2} \tag{1.14}$$

Firstly, we solve the model taking into account the **simultaneous** decision of qualities, that is, we assume the entry of an imitator firm at the same time than the innovator company launches the new chemical compound without product patent protection. The FOCs are:

$$\frac{\partial \Pi_B}{\partial \theta_B} = \frac{2\theta_B - \theta_G}{2k(2\theta_B - \theta_G)} - \frac{\theta_B(\theta_B - \theta_G)}{k(2\theta_B - \theta_G)^2} - \theta_B = 0 \tag{1.15}$$

$$\frac{\partial \Pi_G}{\partial \theta_G} = \frac{\theta_B\theta_G(\theta_B - \theta_G)}{2k(2\theta_B - \theta_G)^3} + \frac{\theta_B^2 - 2\theta_B\theta_G}{4k(2\theta_B - \theta_G)^2} - \theta_G = 0 \tag{1.16}$$

Now, we rewrite (1.15) and (1.16) by bringing θ_B and θ_G on the right-hand side of their respective equalities. After substituting and rearranging and taking into account that $k =$ 0 4, we obtain:

$$6\ 875\theta_B^3\theta_G + 5\theta_G^3\theta_B - 7\ 5\theta_B^2\theta_G^2 - 1\ 25\theta_G^4 - 1\ 25\theta_B^4 = 0 \tag{1.17}$$

Set $\theta_G = \mu\theta_B$ with $\mu \leqslant 1$ (recall that θ_B is the higher quality which allow us to do this transformation), so that we can rewrite (1.17) as:[11]

$$6\ 875\mu + 5\mu^3 - 7\ 5\mu^2 - 1\ 25\mu^4 - 1\ 25 = 0 \tag{1.18}$$

[11] We use the same idea as Motta (1993), however, instead of assuming $\theta_B = \mu\theta_G$ with $\mu \geqslant 1$, we do it the way round.

The only solution in real numbers and lower than one is $\mu = 0\ 2319$ By substituting this value back into the first order condition, we obtain:[12]

$$\theta_B = 0\ 6358 \text{ and } \theta_G = 0\ 1475 \tag{1.19}$$

and

$$p_B = 0\ 6904 \text{ and } p_G = 0\ 0800 \tag{1.20}$$

We also solve the quality game **sequentially.** We assume that the entry of the generic firm occurs once the patent of the corresponding brand-name drug has expired. In this case, the solution is more complicated and requires the application of Newton's interpolation with Mathematica.[13] We obtain:

$$\theta_B = 0\ 6240 \text{ and } \theta_G = 0\ 1471 \tag{1.21}$$

and

$$p_B = 0\ 6758 \text{ and } p_G = 0\ 0797 \tag{1.22}$$

In both models 1&2, the second order derivatives are negative and there are no incentives for firm G to leapfrog the rival firm and itself produce the highest quality. Therefore, we can ensure we have found Nash equilibrium.

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12 We obtain the same results with Mathematica.

13 In this case, we maximize:
$\underset{\theta_B}{Max} \prod_B = p_B q_B - \frac{\theta_B^2}{2}$
s.t. $\frac{\partial \prod_G}{\partial \theta_G} = 0$

1.3.2 Bertrand Model

In this section,we solve models 3&4 where firms compete à la Bertrand by choosing prices simultaneously. The quality game is also solved simultaneously (branded copies) and sequentially (generic drugs).

Price-setting Game

Under Bertrand competition, we have to maximize the profit functions of brand-name and generic drugs producers simultaneously:

$$\underset{p_B}{Max}\ \Pi_B(p_B p_G) = p_B\left[1 - \frac{k(p_B - p_G)}{\theta_B - \theta_G}\right] \tag{1.23}$$

$$\underset{p_G}{Max}\ \Pi_G(p_B p_G) = p_G\left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right] \tag{1.24}$$

The FOC of the branded firm B is:

$$\frac{\partial \Pi_B}{\partial \theta_B} = \left[1 - \frac{k(p_B - p_G)}{\theta_B - \theta_G}\right] + p_B\left[\frac{-k}{\theta_B - \theta_G}\right] = 0 \Longrightarrow p_B = \frac{(\theta_B - \theta_G) + kp_G}{2k} \tag{1.25}$$

The FOC of the generic firm G is:

$$\frac{\partial \Pi_G}{\partial \theta_G} = \left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right] + p_G\left[\frac{-k}{\theta_B - \theta_G} - \frac{k}{\theta_G}\right] = 0 \Longrightarrow p_G = \frac{\theta_G}{2\theta_B}p_B \tag{1.26}$$

Substituting, we get the both *price reaction functions*:

$$p_B = \frac{2\theta_B(\theta_B - \theta_G)}{k(4\theta_B - \theta_G)} \text{ and } p_G = \frac{\theta_G(\theta_B - \theta_G)}{k(4\theta_B - \theta_G)} \tag{1.27}$$

Quantities are:

$$q_B = \frac{2\theta_B}{4\theta_B - \theta_G} \text{ and } q_G = \frac{\theta_B}{4\theta_B - \theta_G} \tag{1.28}$$

In Bertrand models, we obtain a constant market share ratio, $\frac{q_B}{q_G} = 2$, so that the penetration of the branded product always doubles that of the generic drugs.

Quality Game

Firms will choose their quality specification to maximize their profits:

$$\Pi_B = \frac{4\theta_B^2(\theta_B - \theta_G)}{k(4\theta_B - \theta_G)^2} - \frac{\theta_B^2}{2} \text{ and } \Pi_G = \frac{\theta_B\theta_G(\theta_B - \theta_G)}{k(4\theta_B - \theta_G)^2} - \frac{\theta_G^2}{2} \tag{1.29}$$

Firstly, we solve the model taking into account the **simultaneous** decision of qualities, that is, we assume the entry of an imitator firm at the same time than the innovator company launches the new chemical compound without product patent protection. The FOCs are:

$$\frac{\partial\Pi_B}{\partial\theta_B} = \frac{12\theta_B^2 - 8\theta_B\theta_G}{k(4\theta_B - \theta_G)^2} - \frac{32\theta_B^2(\theta_B - \theta_G)}{k(4\theta_B - \theta_G)^3} - \theta_B = 0 \tag{1.30}$$

$$\frac{\partial\Pi_G}{\partial\theta_G} = \frac{\theta_B^2 - 2\theta_B\theta_G}{k(4\theta_B - \theta_G)^2} + \frac{2\theta_B\theta_G(\theta_B - \theta_G)}{k(4\theta_B - \theta_G)^3} - \theta_G = 0 \tag{1.31}$$

Now, we rewrite (1.30) and (1.31) by bringing θ_B and θ_G on the right-hand side of their respective equalities. After substituting and rearranging and taking into account that $k =$ 0 4, we obtain:

$$5\theta_B\theta_G^3 - 35\theta_B\theta_G^2 + 62\ 5\theta_B^2\theta_G - 5\theta_B^2\theta_G^2 + 20\theta_G^3 - 10\theta_B^3 = 0 \tag{1.32}$$

Set $\theta_G = \mu\theta_B$ with $\mu \leqslant 1$ (recall that θ_B is the higher quality which allow us to do this transformation), so that we can rewrite (1.32) as:

$$25\mu^3 - 40\mu^2 + 62\ 5\mu - 10 = 0 \tag{1.33}$$

The only solution in real numbers and lower than one is $\mu =$ 0 1780 By substituting this value back into the first order condition, we obtain:[14]

$$\theta_B = 0\ 6332 \text{ and } \theta_G = 0\ 1205 \tag{1.34}$$

[14] We obtain the same results with Mathematica.

and

$$p_B = 0\ 6729 \text{ and } p_G = 0\ 0640 \tag{1.35}$$

We also solve the quality game **sequentially.** We assume that the entry of the generic firm occurs once the patent of the corresponding brand-name drug has expired. In this case, the solution is more complicated and requires the application of Newton's interpolation with Mathematica.[15] We obtain:

$$\theta_B = 0\ 6129 \text{ and } \theta_G = 0\ 1195 \tag{1.36}$$

and

$$p_B = 0\ 6484 \text{ and } p_G = 0\ 0632 \tag{1.37}$$

In both models 3&4, the second order derivatives are negative and there are no incentives for firm G to leapfrog the rival firm and itself produce the highest quality. Therefore, we can ensure we have found Nash equilibrium.

Just to summarize, we present a comparison of the results in Table 1.3:

Model	θ_B	θ_G	$\theta_B - \theta_G$	p_B	p_G	$p_B - p_G$	$\frac{q_B}{Q}$	$\frac{q_G}{Q}$
Model 1	0.6357	0.1474	0.4883	0.6904	0.0800	0.6104	58%	42%
Model 2	0.6240	0.1471	0.4769	0.6758	0.0797	0.5961	59%	41%
Model 3	0.6332	0.1205	0.5127	0.6729	0.0640	0.6089	67%	33%
Model 4	0.6129	0.1195	0.4934	0.6484	0.0632	0.5851	67%	33%

Table 1.3: Results Comparison

Generally speaking, when firms compete à la Bertrand (model 3&4), the degree of quality differentiation is larger than in Stackelberg models (model 1&2) and, paradoxically, firms also compete more aggressively in prices. In Stackelberg models, new entrants (G)

[15] In this case, we maximize:
$\underset{\theta_B}{Max} \prod_B = p_B q_B - \frac{\theta_B^2}{2}$
s.t. $\frac{\partial \prod_G}{\partial \theta_G} = 0$

choose both quality and prices in order to be positioned closer to incumbent firms (Figure 1.3).

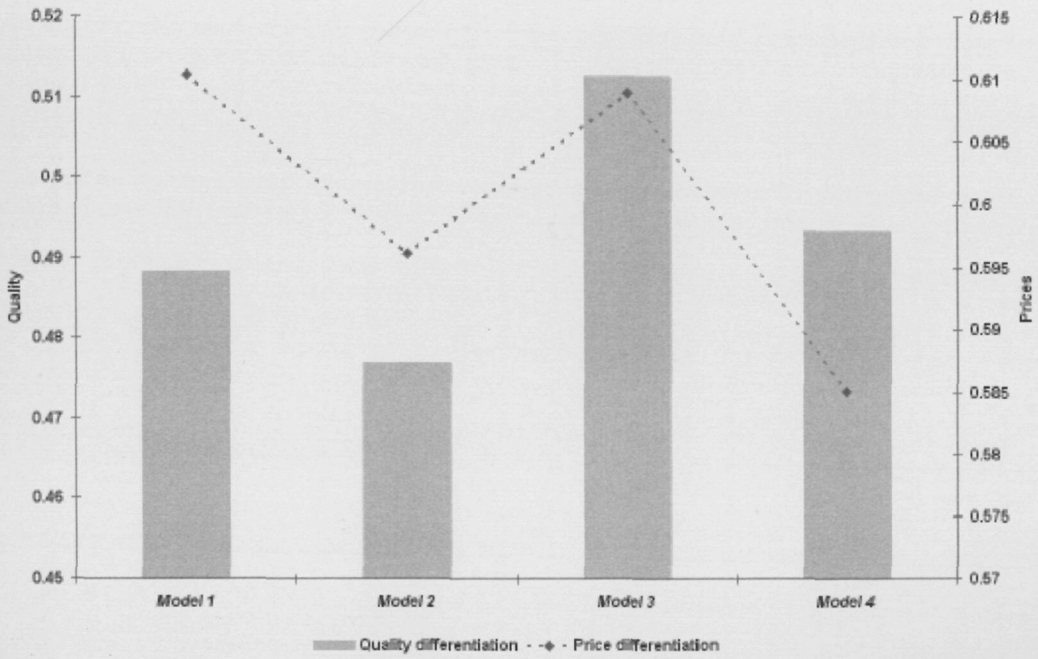

Figure 1.3. Quality and Price Differentiation

Models 1&3 solve the quality game simultaneously, thus assuming the entrance of branded copies, while models 2&4 solve the quality game sequentially taking into account the generic drugs entry. The degree of differentiation is always higher in branded copies scenarios than in generic scenarios. This is not always satisfied in pharmaceutical markets where imitator laboratories try to be confused with original ones. Market shares are more extreme in Bertrand's models -67% branded drugs and 33% generic drugs- than in Stackelberg -52% branded drugs and 48% generic drugs. In Bertrand models, market share distribution remains constant because branded producers decrease prices in order to maintain market penetration.

1.4 The Reference Price System

It is clear from Royal Decree 1035/1999 that the reference price for each homogeneous group is determined endogenously using the previous-year drug prices. For simplicity, we work in one shot period and assume that the reference price is a linear function of both branded and generic prices; in particular, it takes the following form where α and β are exogenous weights that represent respective market shares:

$$p_R = \alpha p_G + \beta p_B \tag{1.38}$$

This is a general expression and, therefore, it can be adjust to other RP system variations, for example, assuming $\alpha = 0$ and $\beta = 1$ $(p_R = p_B)$, $\alpha = 1$ and $\beta = 0$ $(p_R = p_G)$ or a fixed proportion of both.

We also assume that $\alpha > k$ what let us ensure that the reference price will be never lower than the generic price. This is the reason why we can consider an additional but avoidable copayment for the branded product but no additional copayment for the generic drug. Therefore, the RP system modifies the demand function for both branded and generic drugs as follows.

Consumer buys the brand-name drug as long as:

$$\begin{aligned} v\theta_B - kp_B - (p_B - \alpha p_G - \beta p_B) \geq v\theta_G - kp_G \implies v^* \geq \tfrac{(k+1-\beta)p_B-(k+\alpha)p_G}{(\theta_B-\theta_G)} \text{ and} \\ v\theta_B - kp_B - (p_B - \alpha p_G - \beta p_B) \geq 0 \implies v^- \geq \tfrac{(k+1-\beta)p_B-\alpha p_G}{\theta_B} \end{aligned} \tag{1.39}$$

Consumer buys the generic drug if:

$$\begin{aligned} v\theta_G - kp_G > v\theta_B - kp_B - (p_B - \alpha p_G - \beta p_B) \implies v^* < \tfrac{(k+1-\beta)p_B-(k+\alpha)p_G}{(\theta_B-\theta_G)} \text{ and} \\ v\theta_G - kp_G \geq 0 \implies v_- \geq \tfrac{kp_G}{\theta_G} \end{aligned} \tag{1.40}$$

Substituting and rearranging, we obtain the new demand functions:

$$q_B = 1 - \frac{(k+1-\beta)p_B - (k+\alpha)p_G}{(\theta_B - \theta_G)} \text{ and } q_G = \frac{(k+1-\beta)p_B - (k+\alpha)p_G}{(\theta_B - \theta_G)} - \frac{kp_G}{\theta_G} \tag{1.41}$$

Changes in patient out-of-pocket expenses affect the demand conditions prevailing on the market and might alter the markup that pharmaceutical firms charge over marginal cost (Pavcnik, 2002). According to our model, price competition is now distorted due to the implementation of a new regulatory framework. At this stage, quality game is over and fixed quality costs are already sunk, therefore, firms can only react through price movements. We solve again the price-setting subgame taking into account new demand functions.

Using the same procedure as before, we obtain the following price equilibrium for Stackelberg and Bertrand respectively:

$$p_B = \frac{(\theta_B - \theta_G)(k\theta_B + \alpha\theta_G)}{(k+1-\beta)\left[(\alpha-k)\theta_G + 2k\theta_B)\right]} \text{ and } p_G = \frac{\theta_G(\theta_B - \theta_G)}{2\left[(\alpha-k)\theta_G + 2k\theta_B)\right]} \tag{1.42}$$

$$p_B = \frac{2(\theta_B - \theta_G)(k\theta_B + \alpha\theta_G)}{(k+1-\beta)\left[4(\alpha\theta_G + k\theta_B) - \theta_G(k+\alpha)\right]} \text{ and } p_G = \frac{\theta_G(\theta_B - \theta_G)}{4(\alpha\theta_G + k\theta_B) - \theta_G(k+\alpha)} \tag{1.43}$$

According to the assumptions about α and β we could have a great number of scenarios for each model. In Table 1.4, we just consider two different scenarios: one in which α and β take the market shares values existing before the introduction of the RP system (Table 1.3), and another in which an ideal situation where branded and generic drugs share the market is assumed ($\alpha = \beta = 0\ 5$)

Model	θ_B	θ_G	$\theta_B - \theta_G$	α	β	p_B	p_G	p_R	$\frac{q_B}{Q}$	$\frac{q_G}{Q}$
Model 1	0.6357	0.1474	0.4883	0.42	0.58	0.3681	0.0704	0.2430	62%	38%
Model 1	0.6357	0.1474	0.4883	0.50	0.50	0.3400	0.0688	0.2044	61%	39%
Model 2	0.6240	0.1471	0.4769	0.41	0.59	0.3644	0.0701	0.2437	62%	38%
Model 2	0.6240	0.1471	0.4769	0.50	0.50	0.3332	0.0683	0.2007	61%	39%
Model 3	0.6332	0.1205	0.5127	0.33	0.67	0.3797	0.0570	0.2732	67%	33%
Model 3	0.6332	0.1205	0.5127	0.50	0.50	0.3118	0.0539	0.1829	67%	33%
Model 4	0.6129	0.1195	0.4934	0.33	0.67	0.3660	0.0561	0.2637	67%	33%
Model 4	0.6129	0.1195	0.4934	0.50	0.50	0.3006	0.0531	0.1768	67%	33%

Table 1.4: Results Comparison with Reference Price

Doing comparative statics and using the scenario $\alpha = \beta = 0\ 5$ as a benchmark , we could get some insights into how firms react when parameters of the model change. In our model, the higher the generic weight (α), the lower the branded weight (β) and, therefore, the lower the reference price (remember that $p_B > p_G$); as a consequence, both branded and generic firms decrease prices ($\frac{\partial p_B}{\partial \alpha} < 0$ and $\frac{\partial p_G}{\partial \alpha} < 0$) On the other hand, the higher the branded weight, the higher the reference price and, as a consequence, both branded and generic firms increase prices ($\frac{\partial p_B}{\partial \beta} > 0$ and $\frac{\partial p_G}{\partial \beta} > 0$)

	p_B	p_G	$\frac{q_B}{Q}$	$\frac{q_G}{Q}$
Model 1				
Before	0.6904	0.0800	58%	42%
After	0.3681	0.0704	62%	38%
Model 2				
Before	0.6758	0.0797	59%	41%
After	0.3644	0.0701	62%	38%
Model 3				
Before	0.6729	0.0640	67%	33%
After	0.3797	0.0570	67%	33%
Model 4				
Before	0.6484	0.0632	67%	33%
After	0.3660	0,0561	67%	33%

Table 1.5. Before and After RP System

Under the RP system, branded producers decrease prices substantially in order to adapt to the new competitive situation while generic prices remain more or less constant.

In Bertrand models (3&4), market shares do not change after the introduction of reference prices while in Stackelberg models (model 1&2), the market share of branded drugs even increases and that of generic drugs decreases. In both cases, the brand-name producers compensate the decline of profits by selling greater quantities instead of charging higher prices (Table 1.5).

We contrast our theoretical results with Pavcnik's empirical findings and realize that conclusions are in the same line. She found that producers significantly decrease prices after the change in patient out-of-pocket expenses and, furthermore, these price declines are most pronounced for brand-name products.

1.5 Social Welfare Analysis: Ramsey Prices

Comparing the relative price ratio prevailing before and after the introduction of the RP system, it is clear that price competition has increased. In this sense, government has achieved one of the main objectives supposedly to be accomplished by this new reimbursement mechanism.

$$(\frac{p_B}{p_G})_{\text{copayment}} > (\frac{p_B}{p_G})_{\text{RP system}} \tag{1.44}$$

Unfortunately, actual regulation often deviates considerably from an optimal regulation that aims to limit market inefficiencies and maximize social welfare. The problem of how to set prices so as to maximize social welfare whilst ensuring that all costs are covered can arise in many contexts. Ramsey prices are designed to address the situation where it is necessary to increase prices above the level of marginal cost. In particular, the standard Ramsey pricing rule says that "in order to maximize social welfare, prices in different

market segments should be set such that the mark-up over marginal cost in each segment is inversely proportional to the price sensitivity of demand".

Social welfare is defined as the sum of consumer and producer surplus and profits are equal to the sum of revenues in each demand segment less the cost (without loss of generality, we assume variable costs to be zero, however, we introduce a minimum profit level). In particular:

$$CS_B = (v\theta_B - kp_B)\left[1 - \frac{k(p_B - p_G)}{\theta_B - \theta_G}\right] \text{ and } CS_G = (v\theta_G - kp_G)\left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right] \tag{1.45}$$

and the profit functions are:

$$\Pi_B = p_B q_B = p_B\left[1 - \frac{k(p_B - p_G)}{\theta_B - \theta_G}\right] \text{ and } \Pi_G = p_G q_G = p_G\left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right] \tag{1.46}$$

Although there exist two different firms in the market, the innovator and the generic imitator, we sum up their profits as if only one firm produces the two types of drugs:

$$\Pi_T = p_B\left[1 - \frac{k(p_B - p_G)}{\theta_B - \theta_G}\right] + p_G\left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right] \tag{1.47}$$

We maximize consumer surplus subject to the constraint that profits must achieve at least a pre-specified minimum profit level Π :

$$\begin{aligned} \underset{p_B p_G}{Max}\ CS &= (v\theta_B - kp_B)\left[1 - \tfrac{k(p_B - p_G)}{\theta_B - \theta_G}\right] + (v\theta_G - kp_G)\left[\tfrac{k(p_B - p_G)}{\theta_B - \theta_G} - \tfrac{kp_G}{\theta_G}\right] \\ \text{s.t. } \Pi &\leq p_B\left[1 - \tfrac{k(p_B - p_G)}{\theta_B - \theta_G}\right] + p_G\left[\tfrac{k(p_B - p_G)}{\theta_B - \theta_G} - \tfrac{kp_G}{\theta_G}\right] \end{aligned} \tag{1.48}$$

We solve the maximization problem using Kuhn-Tucker theorem. Set up the Lagrangian:

$$\pounds = (v\theta_B - kp_B)\left[1 - \frac{k(p_B - p_G)}{\theta_B - \theta_G}\right] + (v\theta_G - kp_G)\left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right] - \\ -\lambda\left[\Pi - p_B\left[1 - \frac{k(p_B - p_G)}{\theta_B - \theta_G}\right] - p_G\left[\frac{k(p_B - p_G)}{\theta_B - \theta_G} - \frac{kp_G}{\theta_G}\right]\right] \tag{1.49}$$

where λ is the Lagrange multiplier that measures the value, in terms of social welfare, of relaxing the profit constraint by a small amount.

We take derivatives with respect to prices and finally get:

$$p_{BRamsey} = \frac{\theta_B(\lambda - k - kv)}{2k\lambda - 2k^2} \text{ and } p_{GRamsey} = \frac{\theta_G(\lambda - k - kv)}{2k\lambda - 2k^2} \tag{1.50}$$

Now, we proceed to compare the degree of price competition under two different regulations: RP system and Ramsey. Therefore, we calculate the relative price ratio under both scenarios: [16]

$$(\frac{p_B}{p_G})_{RP} = \frac{2(k\theta_B + \alpha\theta_G)}{(k + 1 - \beta)\theta_G} \text{ and } (\frac{p_B}{p_G})_{Ramsey} = \frac{\theta_B}{\theta_G} \tag{1.51}$$

Price competition will be stronger under Ramsey pricing as long as:

$$(\frac{p_B}{p_G})_{RP} > (\frac{p_B}{p_G})_{Ramsey} \implies 2\theta_G + \theta_B(k - 1 + \beta) > 0 \tag{1.52}$$

and competition will be stronger under RP system when the expression above becomes negative. Table 1.6 shows that Ramsey pricing should be the optimal regulation as long as the penetration of generic drugs is not very high while RP system should become the most efficient price control mechanism once the generic market share has reached an outstanding percentage. Under Stackelberg price competition (models 1&2), RP system will be the most efficient regulation as long as generic market share overcomes 80% ($\alpha = 0\ 8$) while this threshold decreases to 70% under Bertrand price competition models.[17]

[16] The relative price ratio under Bertrand and Stackelberg models coincide.

[17] "The share of generic drugs must increase if we want the reference price system to work properly", Gaceta de los Negocios, November 1998.

α	β	Model 1	Model 2	Model 3	Model 4
0	1	+	+	+	+
0.1	0.9	+	+	+	+
0.2	0.8	+	+	+	+
0.3	0.7	+	+	+	+
0.4	0.6	+	+	+	+
0.5	0.5	+	+	+	+
0.6	0.4	+	+	+	+
0.7	0.3	+	+	-	-
0.8	0.2	-	-	-	-
0.9	0.1	-	-	-	-
1	0	-	-	-	-

Table 1.6. Optimal Price Regulation

1.6 Concluding Remarks

This paper analyzes the impact of the RP system on the price-setting strategies of pharmaceutical firms. Several European countries have already established this new reimbursement mechanism as a regulatory measure aimed to contain national pharmaceutical spending through the promotion of price competition and the rise of generic usage. Although there exist several variations in the RP calculation method, we take into account a general RP expression that could adjust to all European versions; therefore, our conclusions could be extrapolated to other countries with similar regulatory framework.

We analyze two different scenarios: (i) we first solve quality and price equilibrium before RP system enters into force; in this case, we assume that consumers must pay a constant copayment rate k for both branded and generic drugs and (ii) in the second scenario, we introduce the effect of the RP system that entails an additional but avoidable copayment for those drugs whose price exceeds the reference price.

We use a *vertical product differentiation model* with two firms operating the market: one firm produces the brand-name drug whose patent has already expired (B) and the other produces the corresponding generic version (G). We assume a two-stage game where, in the first stage, firms choose the "perceived" quality of the good they want to produce and, in the second stage, a competitive process occurs where firms set prices.

Furthermore, at each stage of the game, firms make their decisions about quality and prices both simultaneously and sequentially. Therefore, we obtain four different models. We solve the **quality game** taking into account two different assumptions about entry temporality: branded copies or me-too drugs enter the market simultaneously to the original product while generic drugs enter the market after the patent on the corresponding brand-name drug has expired. We solve the **price-setting sub-game** by taking into account Bertrand and Stackelberg price competition. It is widely accepted that price is one of the main strategic variables in the pharmaceutical industry, however, some researchers assume simultaneous price competition while others accept a sequential price competition.

Model	Quality Game	Price Competition
Model 1	Simultaneous (branded copies)	Sequential (Stackelberg)
Model 2	Sequential (generic drugs)	Sequential (Stackelberg)
Model 3	Simultaneous (branded copies)	Simultaneous (Bertrand)
Model 4	Sequential (generic drugs)	Simultaneous (Bertrand)

Generally speaking, when firms compete à la Bertrand (model 3&4), the degree of quality differentiation is larger than in Stackelberg models (model 1&2) and, paradoxically, firms also compete more aggressively in prices. In Stackelberg models, new entrants (G) choose both quality and prices in order to be positioned closer to incumbent firms. Models 1&3 solve the quality game simultaneously, thus assuming the entrance of branded copies,

while models 2&4 solve the quality game sequentially taking into account the generic drugs entry. The degree of differentiation is always higher in branded copies scenarios than in generic scenarios. This is not always satisfied in pharmaceutical markets where imitator laboratories try to be confused with original ones. Market shares are more extreme in Bertrand's models -67% branded drugs and 33% generic drugs- than in Stackelberg -52% branded drugs and 48% generic drugs.

Price competition is now distorted due to the implementation of the RP system. At this point, quality game is over and fixed quality costs are already sunk, therefore, firms can only react through price movements. Changes in the copayment regime affect the demand conditions prevailing on the market and might alter the markup that pharmaceutical firms charge over marginal cost. We solve again the price-setting subgame taking into account new demand functions.

We find that, under the RP system, branded producers decrease prices substantially in order to adapt to the new competitive situation while generic prices remain more or less constant. In Bertrand models (3&4), market shares do not change after the introduction of reference prices while in Stackelberg models (model 1&2), the market share of branded drugs even increases and that of generic drugs decreases. In both cases, the brand-name producers compensate the decline of profits by selling greater quantities instead of charging higher prices. We contrast our theoretical results with Pavcnik's empirical findings and realize that conclusions are in the same line. She found that producers significantly decrease prices after the change in patient out-of-pocket expenses and, furthermore, these price declines are most pronounced for brand-name products.

We also undertake a social welfare analysis and compare price competition under RP system and Ramsey pricing. We find that the reference price system maximizes price competition when the penetration of generic drugs overcomes 70% of the market; otherwise, Ramsey prices can better ensure price competition and maximization of social welfare.

Finally, we can conclude that, from a theoretical point of view, the RP system achieves the objective of increasing price competition, however, we can not say anything about the impact on the public pharmaceutical spending because it is beyond the scope of this paper. An outstanding remark is the fact that, although the social planner succeeds in promoting price competition between branded and generic drugs, it completely fails in raising generic usage among population. Actually, both the implementation of the RP system and the potential entrance of generic drugs constitute a sufficiently credible threat for branded producers to decrease prices. Therefore, it is not necessary to account for an effective large generic market share for price competition to increase. In this sense, generic firms in Spain and other countries with similar regulatory framework could feel disappointed with a regulatory measure that do not promote *de facto* the use of lower-cost generic drugs.

Chapter 2
Demand for Pharmaceutical Drugs: a Choice Modelling Experiment

Abstract[18]

Despite the importance of supplier inducement and brand loyalty in the drug purchasing process, little empirical evidence is found about the influence that those factors exert on patients' decisions. Under the new scenario of easier access to information, patients become more demanding and are even capable to question physician's prescription. Furthermore, new regulation also encourages patients to adopt an active role in the decision between trade-name and generic drugs. Using a stated preference model based on a choice survey, I find evidence of how significant physician's prescription and pharmacist's recommendation become along the drug purchase process and, to what extent, brand loyalty influences final decision. As far as we know, this paper is the first to take explicitly into account consumers' preferences instead of focusing on the behavior of health professionals.

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2.1 Introduction

The purchase of pharmaceutical drugs is more than a "purchasing act in itself" because it involves a multistage process in which, firstly, physician writes a drug prescription, secondly, pharmacist dispenses and substitutes and, finally, patient consumes. The existence of *information asymmetries* between physicians and patients and *uncertainty* on drugs effectiveness generate supplier inducement and brand loyalty respectively. In this traditional framework, physicians are the core of the system, however, under the new scenario of easier access to information, patients become more demanding and are even capable to question physician's prescription. Furthermore, new regulation also encourages patients to adopt an active role in the decision between ttrade-name and generic drugs. in this sense, health care systems are transitioning from a physician-directed system to a patient-directed one (Section 2.2).

The new pharmaceutical framework makes interesting the analysis of patients preferences, however the empirical literature on pharmaceuticals demand is very limited and has always been focused on the behavior of either physicians or pharmacists. Furthermore, all of them use revealed preference data to estimate the objective utility function (Section 2.3).

As far as we know, this paper is the first to explore consumers' preferences for commercial drugs using stated preference data obtained from a choice survey. This method is based on the premise that consumers evaluate the convenience of a product by combining the separate amounts of utility provided by each attribute. In our case, a representative sample of 439 individuals are surveyed and asked to rank a set of commercial drugs alternatives according to their preferences (Section 2.4).

The parameters of our utility function are estimated using a *rank ordered logit* - a generalization of McFadden's conditional logit- and will determine the significance of brand loyalty, laboratory reputation and the reliance upon health care experts along the decision-making process

The main effects model shows the significant importance of experts' inducement - although physician's prescription is always more reliable than pharmacist's recommendation- and, to what extent, both brand loyalty and laboratory reputation influence the final decision. Using interactions between attributes and characteristics of the respondents, I find that age is a relevant variable in the decision between a trade-name and a generic drug at the chemist's. The old firmly trust incumbent brands and doctor's prescription; on the contrary, the youngest are easily influenced by pharmacist's recommendation and, despite not being loyal to incumbent brands, they value laboratory reputation. In addition, those patients exhibiting high switching costs firmly trust doctor's opinion and are reluctant to switch to other drugs different than the incumbent. On the contrary, those that have already tested and learnt about generics are more easily influenced by pharmacist's recommendation and laboratory reputation (Section 2.5).

The remainder of the paper is organized as follows. The nature of pharmaceutical demand and the role of consumers preferences is deeply described in Section 2.2. Section 2.3 introduces the most recent methodologies used in the estimation of consumers preferences. Section 2.4 describes the stages involved in an experimental design from the identification of attributes and levels to the collection of data. Section 2.5 summarizes the results and, finally, Section 2.6 concludes.

2.2 The Nature of Pharmaceutical Demand

Demand for pharmaceutical drugs is unusual in the sense that consumer is typically not the one deciding which product to consume and often not the one paying for it. Indeed, the purchase of pharmaceutical products is more than a "purchasing act in itself" because it involves a multistage process in which, firstly, physician writes a drug prescription; secondly, pharmacist dispenses and substitutes whenever possible (*diagnosis and treatment*) and, finally, patient pays and consumes (*drug consumption*).[19] Therefore, we can not disconnect the drug purchase act from the visit to health experts.[20] Figure 2.4 displays two different levels of bilateral relationships: those between experts -physicians and pharmacists- and patients and those between each of the agents and drugs.

[19] The role of the pharmacist in the dispensing stage is determined by the nature of *national substitution laws* and the amount to be paid by the patient depends on the *pharmaceuticals reimbursement mechanism* that apply to each country.

[20] This is not the case for OTC drugs, available at drugstores without physician prescription.

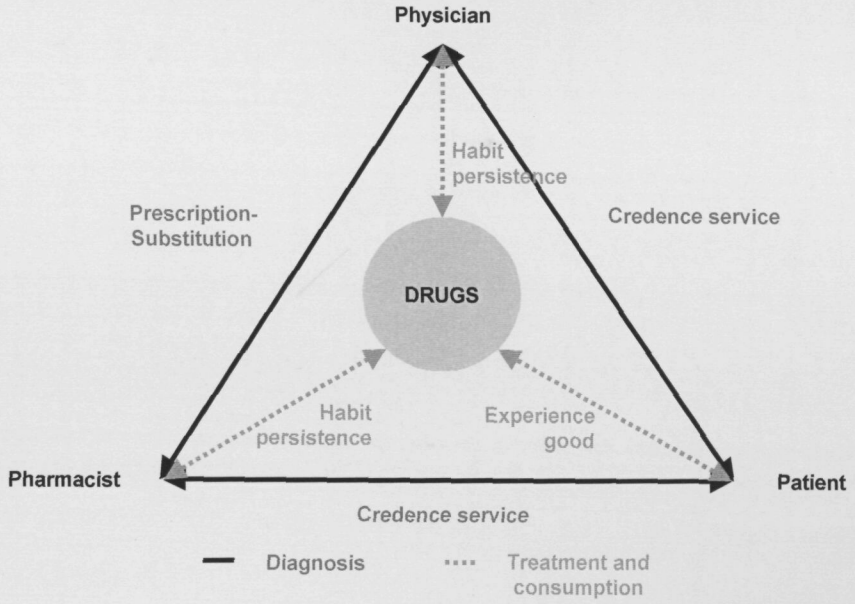

Figure 2.4. Bilateral Relationships in the Pharmaceutical Market

The drug purchase process is characterized by the existence of *information asymmetries* between physicians and patients and *uncertainty* on drugs effectiveness. Because medical knowledge is so complicated, the information hold by the physician regarding the consequences and possibilities of treatment is necessarily very much greater than that of the patient, or at least, so it is believed by both parties. On the other hand, since most drugs differ both in their effectiveness and incidence of side effects across patients, uncertainty is also an important and long-recognized component of drug consumption (Arrow, 1963). Diagnosis and treatment services provided by heath professionals fulfil the definition of *credence service* and generates supplier inducement. On the other hand, drug consumption satisfies the characteristics of *experience good* and raises brand loyalty among consumers.

2.2.1 Supplier Inducement

Credence goods have the characteristics that, even when consumers can observe the utility they derive from the product/service *ex-post*, they cannot judge whether the quality they received is the *ex-ante* needed one. Therefore, sellers act as experts determining customer's requirements. This information asymmetry between buyer and seller obviously creates strong incentives for opportunistic seller behavior (Edmons, 1997). If this expert also supplies the customer with the treatment then the "expert fraudulent" problem can emerge, that is, the expert prescribes excessive use of the product to the consumer. This is usually the case between health professionals and patients. Under the new regulatory framework, pharmacists are allowed to substitute a therapeutically equivalent drug for the one written on the physician prescription.[21] Therefore, pharmacists play a new role in the treatment process and turn also into an expert. As consumers are aware of the expert fraudulent problem, they face a *psychological switching cost* of changing from an expert they believe they can trust (Klemperer, 1995).[22] As a consequence, trust becomes a key element in the relationship between the consumer and the expert. Patients firmly trust their doctors' and pharmacists' opinions and are reluctant to switch to other treatment if experts do not advise them to do so.

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[21] Most of the American states have adopted "permissive substitution laws" that allow a pharmacist to substitute a therapeutically equivalent drug for the one written on the prescription. In Europe, several countries have also approved mandatory substitution laws. Those countries are: Denmark, Finland, France, Iceland, Italy, Luxembourg, The Netherlands, Norway and Spain (NERA, 2001).

[22] Psychological switching costs appear when the use of a product can induce a person to change their tastes so that he prefers that product to a functionally identical one. Psychological switching costs can also arise when the good in question is a credence good, that is, a product or service whose uselfulness or necessity is not directly measurable by the consumer, even after the consumption, and may only be known by the expert seller. One example of credence goods is the medical services.

Two problems have been the focus of research in the credence goods literature: (i) provision of an inefficient treatment and (ii) charging for a more expensive treatment than provided. The first problem can be of two types: on the one hand, it is inefficient if a consumer receives a cheap treatment, when he actually needs an expensive one. This inefficiency is labelled *undertreatment.* On the other hand, it is inefficient if a consumer receives an expensive treatment when a cheap one would be enough to solve this problem. This inefficiency is labelled *overtreatment.* The second potential problem is that an expert might claim to have supplied an expensive treatment even if he has only provided a cheap one. This kind of fraud is labelled *overcharging* (Dulleck and Kerschbamer, 2001). In Health Economics, the phenomenon of overtreatment is commonly known as *supplier-induced demand.*[23] Professional ethics encourages supplier inducement in the interest of the patient, because the latter often has insufficient information to judge what treatment will improve his health.

2.2.2 Brand Loyalty

As mentioned previously, drug consumption shares the characteristics of experience goods. An experience good is a product whose quality or suitability for the buyer is only discoverable after consumption. When the buyer knows more about the quality of one good the longer he has consumed it, the option to switch is not an attractive one because of the risk it involves. Consequently, in order to switch, buyers may have to be compensated for this uncertainty. As stated by Klemperer (1995), consumers tend to re-use those medicines that

[23] Demand inducement exists when a health care provider, usually a physician, influences a patient's demand for care against his own's interpretation of the best interest of the patient (McGuire, 2000).

have already worked for them, in preference for taking the gamble of trying drugs that they have not tested before and that may not suit them. In pharmaceutical markets, a consumer behaves as if he faces a switching cost equal to the maximum premium that he would be willing to pay to be guaranteed a product of the same value as one he has previously purchased.

As noted by Klemperer (1987), the existence of *switching costs* can make ex-ante identical and homogenous products heterogenous ex-post. Consequently, switching costs lead to a form of *"artificial" product differentiation*, which has implications for firms' strategy and consumer behavior.

2.2.3 The New Role of Consumers Preferences

Several recent studies stated that patients are becoming active participants in the drug decision-making process getting the power to question and even override doctors' decisions. This is mainly due to the fact that patients have greater access to information than before. Under these conditions, health care systems are transitioning from a physician-directed system to a patient-directed one (Matthews, 2001). The drug decision-making process consists of two stages: first, physician chooses the active ingredient and afterwards the commercial name -trade-name or generic version-is prescribed and dispensed. Although it would be rare that patients influence the election of the chemical compound, it is getting more common the participation of patients in the decision of commercial names.

An evidence of this transition process is the recent and increasing importance of the *Direct-To-Consumers Advertising* (DTCA) in those countries where legislation allows it.

Advertising is a vehicle for getting information to customers and tells them about product availability, quality and cost. This spending on DTCA reflects a widespread belief within the pharmaceutical industry that patients may influence the choice of prescription drugs (Coscelli, 2000).

The wedge between the interests and preferences of the patient and the actual behavior of the physician raises the concept of *patient compliance or noncompliance.* After receiving a drug prescription from a physician, patients choose whether or not to fill the prescription (purchase compliance), whether or not to consume the drug in accordance to doctor's prescription (use compliance) and whether or not to maintain the prescription over the life of refills and follow-up (sustained compliance). Ellickson et al (1999) reviewed evidence that noncompliance rates are astonishingly high, reaching up 70%, and found that there is substantial variation in the compliance rate, depending on the type of drug and disease being treated.

Armantier and Namoro (2002) examined the prescription behavior of doctors and compliance on the part of patients in an agency model that accounts for the interplay between patient uncompliance, direct-to-consumer advertising and drug promotion toward doctors. They found that doctors' prescriptions are directly influenced by the probability of patients' noncompliance as well as advertising aimed at doctors and patients.

Finally, other factor that stimulates the patient to become a decision-maker at the chemist's shop is the implementation of substitution laws. In some sense, this legal framework encourages the *use noncompliance*, that is, although patients are not able to choose

among active ingredients, they can indeed decide between generic and brand-name version of the same drug.

In several European countries, governments introduced the *reference price system*, a reimbursement mechanism aimed to motivate those price-sensitive consumers to replace expensive brand-name drugs by their corresponding lower-cost generic versions. The aim of the Health Ministries is then to mitigate the habit persistence and brand loyalty of consumers providing economic incentives through a minus cost in the purchase of pharmaceutical drugs (Chapter 1).

In conclusion, under the scenario of easier access to information, patients become more demanding and are even capable to reject physician's prescription. Furthermore, new regulation also encourages patients to adopt an active role in the decision-making process between trade-name and generic drugs.

2.3 Estimation of Consumers Preferences

The aim of this paper is to estimate consumers preferences for commercial drugs using a choice modelling experiment. As mentioned before, the new pharmaceutical framework makes interesting the analysis of patients preferences, however, the empirical literature on pharmaceuticals demand is very limited and have been always focused on the behavior of either physicians or pharmacists. Moreover, all of them use revealed preference data to estimate the degree of supplier inducement in the drug purchasing process; that is, these models use historical data of the choices effectively done by physicians or pharmacists.[24]

[24] The empirical work by Ellison et al (1997) analyzed the prescription and dispensing process and therefore

As far as we know, this paper is the first to explore consumers' preferences along the drug purchasing process using stated preference data obtained from a choice survey.[25] In this special type of surveys, customers are asked to respond a list of socio-economic questions and rank, according to their preferences, a series of alternatives that represent real or hypothetical products. Although economists typically display scepticism about relying on what consumers say they will do compared with observing what they actually do, there are many situations in which one has little alternative but to take consumers at their word. The premise of this article is that stated preference surveys can produce data consistent with economic theory, from which econometric models can be estimated which are indistinguishable from their revealed preference data counterparts.

Traditionally, the majority of econometric models have used revealed preferences (RP) to estimate consumers preferences, however, stated preference (SP) data has been extensively used in market research and, more recently, in discrete choice modelling techniques. In some cases, the use of SP has important advantages: (i) SP allows the estimation of consumer preferences in those situations where information on the choices made by individuals is not available; (ii) in addition, it is possible to estimate the preferences of individuals for attributes or characteristics of products that are currently non-existent; (iii) SP solves the problem of collinearity that exist between product characteristics when RP is used. This is probably the most common limitation of RP data and one might well wonder

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the preferences of physicians and pharmacists. Using micro-data, Hellerstein (1998) examined physicians' prescription behavior and found evidence of persistence , even after controlling for observable characteristics of physicians and patients. Lundin (2001) found the existence of moral hazard in the physician prescription behavior. Coscelli (2000) used a panel daa on both doctors and patients so as to analyze the importance of their preferences in the prescription decision.

[25] By choice survey we mean any form of data collection involving the elicitation of preferences.

why many economists would argue that severely ill-conditioned RP data are superior to SP data just because they reflect "true" market choices and (iv) SP allows the range of possible values in product characteristics to be extended. In many cases, RP is limited by the little variability of some product characteristics (such as price) that prevent the parameters of the utility function from being estimated efficiently.

In our case, all conditions are satisfied up to a certain extent. For example, in Spain, there is not enough market information about the choice made by patients at the chemist's shop. Moreover, we include in the experiment non-existing alternatives (i.e. generic drugs more expensive than branded products) to be able to capture trade-off among attributes.

Despite advantages, SP data are not always considered to be valid for model estimation due to uncertain reliability of the elicited information under hypothetical scenarios. SP data may contain biases and large random errors if the decision making protocol exercised in a hypothetical situation differs from that exercised in a real choice context. Some of the difficulties we can face are the following (Morikawa et al, 2002): (i) the respondent considers only the most important attribute of the alternatives (the prominence hypothesis); (ii) the response is influenced by an inertia of the current actual choice; (iii) the respondent uses the questionnaire as an opinion statement for his or her own benefit; (iv) the respondent does not consider situational constraints and (v) the respondent misinterprets or ignores an attribute if the attribute value lacks reality.

In order to avoid all these problems, it becomes crucial to perfectly design the experiment. That implies to correctly identify the attributes and their corresponding levels,

construct choice sets and alternatives, determine dominance criteria and present a realistic scenario.

2.3.1 Choice Modelling Methodology

Discrete choice models have been extensively used to analyze consumer's choice behavior because it enables to measure the influence of demand attributes. This class of models is based on the random utility theory (RUT) developed by Thurnstone in 1927; however, current theory and methods owe most of their legacy to McFadden who extended Thurstone's original theory for comparisons of pairs of alternatives to multiple comparisons and choices.

RUT leads to families of probabilistic discrete choice models that describe the behavior of individuals in response to changes in choice attributes and/or factors that measure differences in individuals. Families of probabilistic discrete choice models can be derived by specifying a particular probability distribution for ε_{ij} McFadden postulated that the random components were i.i.d.extreme value type I what leads to the multinomial or conditional logit model (Chapter 3).[26]

In this paper, we use a generalization of the well-known conditional logit regression model introduced by McFadden (1973). In the economics literature, the generalization was proposed by Beggs et al (1981) and further developed by Hausman et al (1987) under the name of *rank-ordered logit model.* The model was independently formulated by marketing researchers (Chapman and Staelin, 1982) who called it the *exploded logit model.* They

[26] Historically this distribution has been referred to by several names, including, Gumbel, Weibull or double-exponential.

developed a procedure to enhance the estimation of the parameters of the stochastic utility model by exploiting the additional information contained in preference rank ordering of choice set alternatives.[27]

In a rank ordered logit model, each of the terms in the product has the form of a conditional logit model. The first step is to choose the most preferred item from among the entire set of J items. McFadden's model for the probability of choosing item j^* from among the entire set is:

$$\frac{\exp(X_{ij^*}\beta)}{\sum_{j=1}^{J}\exp(X_{ij}\beta)} \tag{2.53}$$

When that choice has been made, the probability that the respondent will choose item m from among the remaining items is:

$$\frac{\exp(X_{im}\beta)}{\sum_{j=1}^{J}\exp(X_{ik}\beta)-\exp(X_{ij^*}\beta)} \tag{2.54}$$

i.e. the term associated with j^* is removed from the denominator. This continues so that, at each step, the denominator is calculated by substracting the numerator in the previous step from the denominator in the previous step. If the final choice is between items r and s, the probability of choosing r is:

$$\frac{\exp(X_{ir}\beta)}{\exp(X_{ir}\beta)+\exp(X_{is}\beta)} \tag{2.55}$$

Taking the product of all these probabilities, we get:

$$Li=\prod_{j=1}^{J}\frac{\exp(X_{ij^*}\beta)}{\sum_{k=1}^{J}\delta_{ik}\exp(X_{ik}\beta)} \tag{2.56}$$

[27] In Chapter 3, we also call it Contingent Ranking.

where $\delta_{ik} = 1$ if $Y_{ik} \geqslant Y_{ij}$ and 0 otherwise. Let Y_{ij} be the rank given to alternative j by respondent i. If there are J alternatives in each choice set, then Y_{ij} can take integer values from 1 through J, where 1 is the "best" rank and J is the "worst".

In order to obtain efficient estimators it is indispensable for the survey to be designed in a way that minimizes the variance and co-variance matrix of utility function parameter estimates. This requires the design of an experiment from which attributes and their corresponding levels are identified, factorial design and choice sets constructed and questionnaire written.

2.4 Experimental Design

Recently there has been an increasing interest in choice modelling experiments applied to health economics for eliciting individuals' preferences for non-existing health-care programs, relationship between doctor and patient and willingness to pay for different health-care treatments.

In contrast to revealed preferences, stated preference data are generated by some systematic and planned design process in which attributes and levels are pre-defined without measurement error and combined to permit rigorous testing of certain hypotheses of interest. This systematic process is called *factorial design* and consists of the factorial enumeration of all possible combinations of attribute levels, that is, each level of each attribute is combined with every level of all other attributes building different choice alternatives. Afterwards, each individual is presented with a sequence of choice sets and asked to rank their most preferred alternatives in the choice set presented. Each choice set contains sev-

eral alternatives defined by a set of attributes and attribute levels. Individuals' preferences are revealed by their choices (Carlsson et al, 2002).

A natural and important question is how good priors about the parameters in the utility function are. Some indicative information can be obtained from literature review and experts consultation, but running focus groups and pilot studies is also of vital importance. As a preliminary step, focus groups and pilot studies are used to collect information about suitable attributes and attribute levels to include in the experiment. Furthermore, they are often used to test the questionnaire and to give information about how respondents receive and interpret the information presented. Further sections describe in more detail the development of focus groups and pilot test carried out along our choice experiment.

A description of the development of a choice modelling experiment, which is applicable to all types of stated preference surveys is given by Ryan et al (1997), Hanley et al (2001), Carlsson et al (2002) and all of them identified the following stages: (i) selection of attributes and assignment of corresponding levels, (ii) construction of the choice sets by combining the attribute levels in each of the alternatives, (iii) collection of responses and (iv) econometric analysis of data. The first stage consists of identifying the relevant attributes and their corresponding levels of the good to be valued. This is usually done through literature reviews, focus groups discussions and experts consultation. From conclusions, the dependent variables of the utility function are selected. The second stage, which is usually called statistical design, implies the choice of a full factorial versus a fractional factorial design, the construction of choice sets to be presented to the respondents and the choice of a survey procedure to measure individual preferences (ratings, rankings and

choices). The collection of responses implies a fieldwork in which a representative sample of individuals is selected and asked to answer socio-economic questions and ranked the alternatives in each of the choice sets. Finally, once constructed the dataset, maximum likelihood estimation procedure is applied in order to obtain the results.

The present section analyzes the first three stages of the experimental design and additionally selects the active ingredients to which apply the choice survey. Next section summarizes the results of the estimated models including the effects of each of the choice attributes (main effects) and demand segmentation according to socio-economic and habit purchase characteristics (interactions).

2.4.1 Selection of Drugs

We developed two parallel experiments -one referring to a common infection and the other to a chronic disease- with the aim to contrast whether the degree of illness awareness could modify consumers' decision between a trade-name and a generic drug. So as to present a realistic scenario to individuals, we identified two active ingredients that should fulfil some basic conditions.

The first active ingredient we look for must be used for common infections, such as a throat infection, implying an occasional and non-continuous treatment at individual level but a great consumption among population. For the second experiment, we need a drug for a chronic disease implying a long and repeated treatment along the year. The selected

chronic disease must be widely spread among population however it can not be subject to "price reduction".[28]

For the first experiment, we selected a throat infection and an antibiotic to treat it.[29] The use of an antibiotic could not be repeated and continuous along the year and a throat infection is supposed to hold just occasionally. From the conclusions derived from the focus group discussions and the statistics about consumption of active ingredients, we realized that amoxiciline could be a potential candidate. According to the National Health System (SNS) statistics, although amoxiciline has recently declined positions in the ranking of the most consumed compounds, it is still one of the most relevant by number of packages jointly with paracetamol and acetylsalicylic acid (Table 2.7).[30]

Consumption in volume (# packages)	1996		1997		1998		1999		2000	
	Packages	Ranking	Packages	Ranking	Packages	Ranking	Packages	Ranking	Packages	Ranking
Paracetamol	17,106	1	18,067	1	20,170	1	23,960	1	25,349	1
Annual growth rate			*5.6%*		*11.6%*		*18.8%*		*5.8%*	
Amoxiciline	11,434	2	10,722	2	10,320	3	10,433	3	9,187	5
Annual growth rate			*-6.2%*		*-3.7%*		*1.1%*		*-11.9%*	
Acetylsalicylic Acid	7,928	6	8,835	6	9,821	2	10,833	2	11,467	2
Annual growth rate			*11.4%*		*11.2%*		*10.3%*		*5.9%*	

Source: Spanish Ministry of Health. Statistics available at www.pmfarma.com

Table 2.7. Ranking of Most Consumed Compounds (# packages)

There exist several amoxiciline homogenous groups, each of them differing according to dosage, package and form (i.e. amoxiciline 500 mg 24 capsules, amoxiciline 1 g 12 capsules). In each homogenous group, there are several brand-name drugs (Clamoxyl,

[28] According to Royal Decree 83/1993, patients affected by one of the chronic disease contemplated in the mentioned Royal Decree must just pay a 10% of the total price.

[29] A recent study published at JAMA (2001) found that the great majority of patients that visit the doctor because of a throat infection receives an antibiotic treatment, although this therapy is only appropriate for the 10% of cases *(Correo Farmacéutico, 17/09/2001).*

[30] Spanish Ministry of Health. Statistics available at www.pmfarma.com

Ardine, Amoxi Gobens, Agerpen, Amoxibacter) and, at least, one generic version (Cinfa, Benox, Esteve, Ratiopharm, Mundogen, Geminis, Normon).[31]

We now talk about the second experiment. After an in-depth analysis of various chronic diseases (i.e. hypertension, diabetes, psoriasis), we finally selected high blood cholesterol because it is a widely spread cardiovascular risk factor and cholesterol lowering therapies are not subject to "price reduction". In Spain, some chronic therapies are subject to "price reduction", that is, Social Security (third-party) partly finances the cost of treatment and patients only pay a 10% copayment. In those cases, individuals are less sensitive to price.

The prevalence of hypercholesterolemia among Spanish population is quite high. From 35 to 64 years old, 18% has high blood cholesterol equal or superior to 250 mg/dl and 57.8% equal or superior to 200 mg/dl. Elevated Low Density Lipoprotein (LDL) is a major cause of coronary heart disease (CHD). In Spain, cardiovascular diseases rank as the first cause of death and their demographic, health and social impact is increasing (Plaza Perez et al, 2000). Although high blood cholesterol is considered a severe risk factor, drug therapy is not always recommended. Everyone with elevated LDL cholesterol is treated with therapeutic life-style changes however drug therapy is reserved to those at relatively high risk. Major risk factors are: cigarette smoking, hypertension, low High Density Lipoprotein (HDL) cholesterol, family history of premature coronary heart disease and diabetes.[32]

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[31] Brand-name drugs have commercial names while generic drugs are labelled with the name of the laboratory.

[32] Risk assessment for determining the 10-year risk for developing coronary heart disease is carried out using Framingham risk scores. The risk factors included in the Framingham calculation of 10-year risk are: age, total cholesterol, HDL cholesterol, systolic blood pressure, treatment for hypertension and cigarette smoking.

Statins -HMG CoA reductase inhibitors- are first line drugs for treatment of high blood cholesterol. In moderate-severe hypertriglyceridemia or low HDL-cholesterol, fibrates are preferred.[33] Statins are the most effective and practical class of drugs reducing LDL cholesterol concentrations. Other agents (bile acid sequestrants, nicotinic acid and some fibrates) also can moderately lower LDL levels. Table 2.8. shows the most consumed statins in the Spanish National Health System. Atorvastatin has recently entered the market and obtained a high degree of penetration.

Consumption in value (thousand €)	1997	1998	1999	2000
Simvastatin	65,795	77,826	90,811	102,381
Atorvastatin	2,459	64,733	99,394	121,946
Pravastatin	46,236	49,661	58,928	72,752
Lovastatin	45,547	42,686	n.a.	n.a.

Source: Spanish Ministry of Health. Statistics available at www.pmfarma.com.

Table 2.8. Ranking of Statins Consumption

Both lovastatin and simvastatin are in the reference price system, that is, patent on their trade-name drugs has already expired and generic versions are available in the pharmaceutical market. There exist several lovastatin and simvastatin homogenous groups, each of them differing according to dosage, package and form. In each homogenous group, there are several brand-name drugs (Zocor, Pantok, Nergadan, Mevacor) and, at least, one generic version (Cinfa, Benox, Esteve, Ratiopharm, Mundogen, Geminis, Normon).

[33] Examples of statins: lovastatin, simvastatin, pravastatin, fluvastatin, atorvastatin, cerivastatin. Examples of fibrates: gemfibrozil, fenofibrate and clofibrate.

2.4.2 Attributes and Levels

Neoclassical economic theory assumes that individuals choose the product that provides a greater level of satisfaction. The final decision depends fundamentally on the following factors: (i) product characteristics, (ii) product price, (iii) socio-demograhic characteristics of the consumer (i.e. age, gender, education, income) and (iv) use of the product made by the consumer in the past. Choice modelling estimates the importance of those factors in the decision adopted by the consumer.

Therefore, the first stage of a choice design consists of identifying the relevant attributes -and their corresponding levels- of the good to be valued. Monetary cost is typically one of the factors to be included because it allows the estimation of willingness-to-pay (WTP). The rest of attributes and their levels of variation are identified through literature reviews, focus groups discussions and experts consultation. The attribute levels should be feasible, realistic, non-linearly space and span the range of respondents' preference maps. Kanninen (2002) shows that, in an optimal design, each attribute should only have two levels, even in the case of a multinomial choice experiment and the levels should be set at two extreme points of the distribution of the parameters.

From the literature review, we identify a *priori* set of factors that may influence the consumers' decision among commercial drugs: supplier inducement and brand loyalty. We also conducted two focus groups discussions aimed at collecting participants' opinion and perception about the consumption of drugs and the entry of generic versions into the pharmaceutical market (Appendix 2.A).

We finally identified the following five attributes classified in three different clusters: (i) **price elasticity**: whole price of the drug, that is, price levels are supposed to be the total amount paid by consumers (there is no reimbursement mechanism); (ii) **brand loyalty**: we include "commercial name" -either a trade-name drug (incumbent) or a generic version- and "laboratory reputation", a well-known or an unknown producer and (iii) **supplier inducement**: we include "physician's prescription" and "pharmacist's recommendation".

Table 2.9 shows drugs attributes and levels. The process by which each level of each attribute is combined with every level of all other attributes generates the different alternatives to be valued by individuals.

Attibute	Levels for Amoxiciline	Levels for Statins
Commercial name	Clamoxyl (brand-name)	Brand-name
	Ardine (brand-name)	
	Generic	Generic
Laboratory reputation	Known	Known
	Unknown	Unknown
Price	1 €	6 €
	4 €	16 €
	20 €	40 €
Physician prescription	Prescribed	Prescribed
	Not prescribed	Not prescribed
Pharmacist recommendation	Recommended	Recommended
	Not recommended	Not recommended

Table 2.9. Attributes and Levels

In both experiments, we include the same attributes however, the levels can vary according to the specific active ingredient. Notwithstanding, the levels for "Laboratory reputation", "Physician prescription" and "Pharmacist recommendation" are exactly equal for both amoxiciline and statins experiments. "Laboratory reputation" takes two levels -known and unknown- and catches the reliance of patients on the drug producer. Instead of

making a list using real names of laboratories, we classify them according to popularity. Train et al (2000) uses the same concept in an experiment about electricity suppliers.

"Physician prescription" takes two levels, either it is a commercial brand directly prescribed by physician or it is not. Although we assume that physician always prescribes the active ingredient -amoxiciline or statins-, in some cases, he prescribes the trade-name drug and in others the generic version (Hellerstein, 1998). "Pharmacist recommendation" also takes two levels, either the commercial brand can be recommended by the pharmacist or not. The advise of the pharmacist can coincide with the physician's prescription or not. We introduce the role of the pharmacist because, due to substitution laws, they can actively participate in the prescription and dispensing process.

"Commercial name" and "Price" levels vary according to each active ingredient.

For the amoxiciline experiment, we take as reference the homogenous group of Amoxiciline 500 mg 24 capsules, one of the most standard dosage, package and form. In this case, commercial name can take three different values, two equivalent specialities (EQ) -Clamoxyl and Ardine- and the corresponding generic version (EFG).[34] Clamoxyl and Ardine are incumbent brand-name drugs in the pharmaceutical market and both well-known by population. "Price" ranges from the extreme values of 1 euro to 20 euros being the middle price of 4 euros equal to the reference price for Amoxicline 500 mg 24 capsules.[35]

In the case of statins, the reference is the homogeneous group of Lovastatin 20 mg 28 capsules. "Commercial name" takes only two values, either a brand-name drug or a generic version. Although lovastatin is the reference active ingredient, we consider an

[34] EQ: Especialidad Equivalente. EFG: Especialidad Farmacéutica Genérica.

[35] The reference price for Amoxiciline 500 mg 24 capsules is established by the Spanish Ministry of Health.

extensive list of trade-name drugs in which included Zocor, Cardyl, Mevacor, Taucor, etc. "Prices" ranges from the extreme values of 6 euros to 40 euros being the middle price of 16 euros the reference price for Lovastatin 20 mg 28 capsules.

2.4.3 Statistical Design

Statistical design theory consists of combining the levels of the attributes into a number of alternative scenarios or profiles to be presented to respondents. In the amoxiciline experiment, we have three attributes with two levels of variation and two attributes with three levels of variations which implies a total of 72 $(2^3 * 3^2)$ scenarios. For the statins, we have four attributes with two levels of variation and one attribute, price, with three levels which implies a total of 48 $(2^4 * 3)$ possible alternatives. Such a complete enumeration of all possible combinations is often called a "complete factorial" or a "full factorial".

From the point of view of maximizing the amount of information, it would be desirable if all individuals could rank all possible attribute levels combinations according to their preferences, in our case, 72 and 48 combinations respectively. However, this would be too cognitively demanding as well as time consuming and, hence, the complexity of the choice experiment needs to be reduced. One way is to let the individuals compare a few number of alternatives in a choice set. *Fractional factorial designs* are able to reduce the number of scenario combinations presented with a concomitant loss of estimating power. The profiles identified by the experimental design are then grouped into choice sets to be presented to respondents (Hanley et al, 2001).

The central question is then how to combine the alternatives from the full factorial design into the choice sets (fractional factorial) so that a maximum amount of information is extracted given other constraints such as the number of choice sets in the experiment. In particular, the main objective is to estimate all coefficients with high precision in order to calculate an accurate value of each attribute, that is, to minimize the error around the estimated parameters β:

$$U_{ij} = X_{ij}\beta + \varepsilon_{ij} \tag{2.57}$$

McFadden (1973) shows that the distribution of $\hat{\beta}$ is asymptotically normal with mean β and covariance matrix:

$$\Omega = \sigma^2(X'X)^{-1} \tag{2.58}$$

Thus, the problem of optimal design can be seen as a problem of defining the design matrix X, in such a way that the size of the covariance matrix of the estimator β is minimized. The goodness or efficiency of an experimental design can be quantified. Common measures of design efficiency are based on the information matrix $X'X$. The variance-covariance matrix of the vector of parameter estimates β is proportional to $(X'X)^{-1}$. An efficient design will have a small variance matrix and the eigenvalues of $(X'X)^{-1}$ provide measures of its size. The most prominent efficiency measures are based on the idea of quantifying size by averaging (in some sense) the eigenvalues or variances. Some examples of efficiency measures are A-efficiency, D-efficiency, G-efficiency however the most common is

D-efficiency because it is less computationally burdensome:[36]

$$D - efficiency = \left|\Omega^{\frac{1}{k}}\right|^{-1} \tag{2.59}$$

where k is the number of parameters to estimate. The aim is to maximize D-efficiency and minimize the error measure inversely related to it (Huber and Zwerina, 1996):

$$D - error = \left|\Omega^{-1}\right|^{\frac{1}{k}} \tag{2.60}$$

Huber and Zwerina (1996) identify four properties that characterize efficient choice designs: (i) level balance, (ii) orthogonality, (iii) minimal overlap and (iv) utility balance. A design that satisfies these principles has a maximum D-efficiency (and therefore a minimum D-error). Two of these, level balance and orthogonality, also characterize linear designs. The third, minimal overlap, becomes relevant for choice designs, because each attribute level is only meaningful in comparison to others within a choice set. Utility balance requires that the utility of each alternative in a choice set is equal.[37]

Kuhfeld et al (1994) use a computerized search algorithm to minimize D-efficiency in order to construct an efficient, but not necessarily orthogonal linear design. A modified Federov algorithm works in the following way: an initial design is randomly drawn from a full factorial design. From the initial design the algorithm will, through an iterative process, exchange alternatives in the initial design with ones from a list of candidate alter-

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[36] A-efficiency is a function of the arithmetic mean of the eigenvalues. D-efficiency is a function of the geometric mean of the eigenvalues and G-efficiency is based on the maximum standard error for prediction over the candidate set. All three of these criteria are convex functions of the eigenvalues of $(X'X)^{-1}$ and hence are usually highly correlated.

[37] Orthogonality is satisfied when the levels of each attribute vary independently of one another. Level balance is satisfied when the levels of each attribute appear with equal frequency. Minimal overlap is satisfied when the alternatives in each choice set have nonoverlapping attribute levels. Utility balance is satisfied when the utilities of alternatives within choice sets are the same (Huber and Zwerina, 1996).

natives until it is not possible to reduce D-error any further. Experts have worked with SAS language in order to obtain, as final output, a design matrix of alternatives determined by the number of choice sets and the number of alternatives in each choice set taking into account orthogonality criteria.[38] It is also common to add in each choice set a non-purchase alternative (blank card); that is, the option to choose none of the rest alternatives ("nothing is important").

Finally, it is important to present attribute levels in a choice set so that none of the attributes become dominant or inferior. Traditional designs, such as orthogonal designs, disregard this aspect and only ensure that we can estimate the effects of the different attributes independently of each other. A D-optimal design considers explicitly the importance of the levels of the attributes and ensures that the alternatives in the choice sets provide more information about the trade-off between the different attributes. However, this requires explicit incorporation of prior information about the respondents' preferences into the design. Thus, a key issue when applying more advanced designs is the need for more prior information. One source of information results from previous studies, but primarily the information is obtained from own focus groups and pilot studies (Carlsson et al, 2002).

Our Experiment

We carried out two different choice designs, one for amoxiciline and the other for statins. Due to the elevated number of combinations, a fractional factorial design seems to be the best solution, thus implying the construction of several choice sets each composed

[38] There arre two modules in SAS for experimental designs. QC devoted to experimental designs and module IML of matricial language. There are several macros such as MKTDES and CHOICEFF. The latter is more appropiate for a choice model experiment because it takes into account a multinomial logit model.

by a limited number of alternatives. As stated before, one of the alternatives in each choice set must be the blank card or the non-purchase option.

We assume the blank card for the throat infection to be "Home remedies", a natural alternative to treat an infection without taking antibiotic and the blank card for high blood cholesterol to be "Soya lecitine", a natural medicine used to reduce and maintain LDL cholesterol. Taking into account the potential number of respondents, we finally construct 50 choice sets each composed by 5 alternatives, being one of them the blank card. Besides that, we undertook two different choice experiments for each active ingredient differing in the utility function form: in the first case, we assume a linear utility function with logarithmic price and in the second one, a linear utility function with quadratic price. In both scenarios, the design matrix is exactly the same.

Once obtained the design matrix, we have to analyze the existence of dominant or inferior alternatives in each choice set. The idea is to eliminate those alternatives in a choice set that are dominant because otherwise there could be a loss of information in the trade-off. In fact, we want utility balance criteria to be satisfied and therefore we need prior information about consumers preferences in pharmaceuticals market. Herebelow, we present the main assumptions about dominance:

- Those drugs (alternatives) in a choice set that are neither prescribed by the physician nor recommended by pharmacist are considered a "bad" if the rest of attributes levels (commercial name, laboratory and price) are equal.

- The alternative formed by levels "generic", "unknown laboratory", "maximum price", "non prescribed" and "non recommended" is also a "bad", that is, assuming individual rationality, none respondent would choose it. In this sense, it is a dominated alternative implying that the rest of alternatives in the same choice set are always superior.

- The attributes combination composed by "brand-name drug" (in the case of amoxiciline, Clamoxyl), "known laboratory", "minimum price", "prescribed" and "recommended" can be considered a "good", that is, it is the best combination and therefore, assuming individual rationality, will always dominate the rest of alternatives whatever the choice set.

- If some alternatives have the same levels of "commercial name", "laboratory" and "price", then we have to look at the "physician prescription" and "pharmacist recommendation" attributes. Therefore, the order of preferences will be: (1) prescribed and recommended, (2) prescribed and non-recommended, (3) non-prescribed but recommended and (4) non-prescribed and non-recommended. The same applies if the price is low and the drug is highly prescribed and recommended.

The application of these dominance criteria aims to avoid the lexicographic preference orderings where only one attribute matters and individuals do not trade. In the case of a lexicographic ordering of goods and characteristics, an individual is not prepared to trade-off and so goods or characteristics cannot be substituted for one another (non-compensatory

decision making). In the case of a lexicographic ordering of a bundle of goods, there are no other bundles to which it is indifferent (Scott, 2002).

Finally, we impose some additional conditions for the construction of choice sets: (i) at least one drug (alternative) must be a generic version, (ii) at least one drug (alternative) must be prescribed by the physician and (iii) at least one drug (alternative) must be recommended by pharmacist (Appendix 2.B).

2.4.4 Collection of Data

The experiment was conducted by the author with the help of students.[39] It is essential to ensure that respondents understand the context, are motivated to cooperate and are able to participate in an informed manner. The context should be as realistic as possible in order to encourage realistic and truthful responses (but not to bias the answers).

The interview consists of two parts: firstly individuals are asked about socio demographic characteristics such as age, gender, education level, professional status, income and others (see questions 1-9) and habits of drug purchase (see questions 10-24 in amoxiciline questionnaire and questions 10-28 in cholesterol questionnaire) and afterwards they are asked to rank a set of alternatives according to their preferences for generic or trade-name drugs taking into account different combinations of attributes. They are all close-ended questions with few levels of variation. At the end, respondents are asked about name and address (Appendix 2.C). This information about respondents will serve as control variables

[39] We selected students from Pompeu Fabra University in Barcelona and Carlos III University in Madrid.

and will also allow to segment the demand according to socio-economic characteristics and drug purchase habits.

In order to rank alternatives, a realistic scenario must be defined. For the amoxiciline experiment, respondents have to imagine a situation in which they have a throat infection and, consequently, go to the primary care doctor. In this case, the physician prescribes an antibiotic, in particular, amoxiciline, and afterwards patient has the option to throw the prescription away and prepare a natural remedy at home (blank card) or the option to buy a chemical drug (the rest of the alternatives in the choice set).[40] Each alternative in the choice set represents a drug that can be either a generic or a trade-name drug, prescribed or not prescribed, recommended or not recommended, etc. For the statins experiment, respondents have to imagine a situation in which physician diagnoses high blood cholesterol and consequently prescribes one type of statins. The patient has the option to take a natural medicine (blank card) or the option to buy one of the chemical drug represented in the choice set.

In order to carry out both experiments-amoxiciline and statins-, we have to select two different subsamples, one formed by general population and the other by persons with high blood cholesterol. Notwithstanding, both subsamples are asked to rank the alternatives for amoxiciline and statins.The interviews took place in primary health care centers, chemist's shops, hospitals or other inward and outward locations mainly in the cities of Madrid and Barcelona (Spain).

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[40] Under this scenario, patient noncompliance could appear.

Summary Statistics

The study recruited a total sample of 439 adults from 20 to 65 years old. From those, 315 belong to general population and 124 have high blood cholesterol; the latter were mainly found in hospitals and primary health care centers. According to a review of choice modelling experiments, the ratio between the number of individuals surveyed (439) and the number of attributes estimated (5 plus blank card) moves around the average (Table 2.10).

Title of the paper	Journal	# individuals	# attributes	Estimation method
"Predicting Consumer Preferences for Fresh Salmon: the Influence of Safety Inspection and Production Method Attributes" (Holland and Wessels)	Agricultural and Resource Economics Review (1998)	756 (mail survey)	3 attributes (main effects and interaction effects)	Rank ordered logit
"Measuring willingness-to-pay for risk reduction: an application of conjoint analysis" (Telser and Zweifel)	Health Economics (2002)	500 (face-to-face survey)	4 attributes (main effects)	Random effects probi
"Using conjoint analysis to assess women's preferences for miscarriage management" (Ryan and Hughes)	Health Economics (1997)	196 (mail survey)	5 attributes	Simple probit model
"Choice Modelling Approaches:a superior alternative for environmental valuation?" (Hanley et al)	Journal of Economic Surveys (2001)	267 (mail survey)	8 attributes	Conditional logit mod
"An application of a Product Positioning Model to Pharmaceutical Products" (Green and Krieger)	Marketing Science	356 (mail survey)	9 attributes	Conjoint analysis
"Assessing the Potential Demand for Electric Cars" (Beggs et al)	Journal of Econometrics (1981)	200 (survey)	9 attributes	Rank ordered logit
"Conjoint Analysis of Price Premiums for Hotel Amenities" (Goldberg et al)	Journal of Business (1984)	180 (face-to-face interviews)	43 attributes	Conjoint analysis
"Residential Broadbrand Subscription Demand: an Econometric Analysis of Australian Choice Experiment Data" (Madden and Simpson)	Applied Economics (1997)	598 (face-to-face interviews)	13 attributes	Conditional logit mod
"Cellular Telephones in the Israeli Market: the Demand, the Choice of Provider and Potential Revenues" (Tishler et al)	Applied Economics (2001)	1000 (face-to-face interviews)	16 attributes	Conditional logit mod
"Customers' Choice Among Retail Energy Suppliers: the Willingness-to-Pay for Service Attributes" (Train et al)	EPRI document (2000)	1205 (phone-mail-phone format)	40 attributes	Rank ordered logit

Table 2.10. Review of Choice Modelling Experiments

General population subsample is representative of the Spanish population with respect to gender and age. According to statistics, Spanish population from 20 to 65 years old is formed by a 50% male and a 50% female. Those percentages with respect to age are: 38% people from 20-34 years old, 26% from 35-44, 22% from 45-54 and 11% from 55-65

years old.[41] This slightly differs from the structure of our subsample (Table 2.11). We have a higher proportion of women due to the fact that they use to be the one in charge of going to the chemist's shop and buying the drugs.

We do not have much information about details of the prevalence of cholesterol among the Spanish population, however we know that high blood cholesterol affects more to older and male people than younger and female. This trend is also reflected in our sample.

[41] Source: National Statistics Institute (Instituto Nacional de Estadística, INE), www.ine.es.

Summary Statistics for Explanatory Variables

Variable name	Full sample (n=439)	General population (n=315)	High blood cholesterol population (n=124)
Socio-economic Characteristics			
Sex	439	315	124
Male	41%	37%	52%
Female	59%	63%	48%
Age	436	313	123
20-34	31%	42%	5%
35-44	23%	26%	14%
45-54	27%	21%	40%
55-65	19%	11%	41%
Level of Education	438	315	123
None	3%	1%	6%
Primary	26%	21%	40%
Secondary	22%	20%	27%
University	49%	57%	28%
Professional Status	439	315	124
By his/her own	24%	25%	20%
Employed	48%	50%	40%
Unemployed	8%	8%	6%
Housewife	16%	12%	27%
Others*	5%	4%	6%
Family Head	438	315	123
Yes	45%	43%	50%
No	55%	57%	50%
Children	439	315	124
Yes	62%	55%	80%
No	38%	45%	20%
Household Net Income	407	289	118
< 3000 €/month	79%	76%	86%
> 3000 €/month	21%	24%	14%
Health Care Habits			
Private Insurance	439	315	124
Yes	32%	34%	26%
No	68%	66%	74%
Household Drug Expenditure	435	311	124
< 30 €/month	85%	90%	72%
> 30 €/month	15%	10%	28%
Laboratory Identification	438	315	123
Yes	32%	33%	31%
No	68%	67%	69%
Chemist's Loyalty	437	314	123
Yes	68%	64%	79%
No	32%	36%	21%
Generic Drugs			
Generic Knowledge	439	315	124
Yes	86%	88%	81%
No	14%	12%	19%
Generic Purchase	439	315	124
Yes	46%	46%	44%
No	54%	54%	56%
Region of Residence	438	315	123
Catalonia	84%	87%	76%
Rest of Spain	16%	13%	24%
Interview Location	439	315	121
Primary health care center	14%	12%	21%
Hospital	13%	2%	37%
Chemist's shop	11%	13%	5%
Others**	62%	73%	37%

* Others include students, retired and disabled individuals.

** Others include inward and outward locations, for example, the airport, a gym, a restaurant or bar and a park or the street respectively.

Table 2.11. Summary Statistics

Other relevant socio-economic characteristics of our sample are: 1) 49% of the total sample have university studies, 2) 48% of them are employed, 3) although there is a 7% of missing data, nearly 80% of the respondents declare to earn a net household income inferior to 3.000 euros/month.

Nearly 70% of respondents do not have private insurance and just 15% declares to spend more than 30 euros per month in drugs and medicines. A 32% states to take into account the name of the laboratory when buying a drug while the 68% declares to buy drugs always in the same chemist's shop. 86% of the respondents states to be aware of the existence of generic drugs and, from the full sample, only a 46% declares to have bought once a generic drug.

2.5 Results

As explained before, the attributes that influence the drug purchase decision are: (i) price, (ii) commercial name, (iii) laboratory reputation, (iv) physician prescription and (v) pharmacist recommendation. Price parameter will give an idea about elasticity and will also allow us to calculate willingness to pay (WTP). The attributes "commercial name" and "laboratory reputation" are both associated to **brand loyalty** while "physician prescription" and "pharmacist recommendation" are measures of **supplier inducement**. We also include the blank card or outside option in order to get consistency with economic theory. The general utility function to be estimated has the following form:

$$\begin{aligned} U_{ij} = {} & \alpha_i BRAND_j + \beta_i LAB_j + \gamma_i PRICE_j \\ & + \delta_i PHYSICIAN_j + \eta_i PHARMA_j + \theta_i BLANK_j + \varepsilon_{ij} \end{aligned} \tag{2.61}$$

where:

- BRAND is a dummy variable equal to 1 if the "commercial name" takes the level GENERIC and 0 otherwise.
- LAB is also a dummy variable equal to 1 if the "laboratory reputation" takes the level UNKNOWN and 0 otherwise.
- PRICE is a continuous variable that takes three different values for each experiment.
- PHYSICIAN is a dummy variable equal to 1 if the "physician prescription" takes the level YES and 0 otherwise
- PHARMA is a dummy variable equal to 1 if the "pharmacist recommendation" takes the level YES and 0 otherwise.
- BLANK is a dummy variable equal to 1 if the alternative is the blank card (home remedies or soya lecitine) and 0 if the alternative is a chemical drug.

As shown in Table 2.9, the variable BRAND differs across experiments. In the case of amoxiciline, "commercial name" takes three different levels -Clamoxyl, Ardine and Generic- and therefore it must be decomposed in the utility function as follows:

$$U_{ij} = \alpha_i GENERIC_j + \mu_i ARDINE_j + \beta_i LAB_j + \gamma_i PRICE_j + \delta_i PHYSICIAN_j + \eta_i PHARMA_j + \theta_i BLANK_j + \varepsilon_{ij} \quad (2.62)$$

where:

- GENERIC is a dummy variable equal to 1 if the "commercial name" takes the level GENERIC and 0 otherwise.

- ARDINE is a dummy variable equal to 1 if the "commercial name" takes the level ARDINE and 0 otherwise.

We drop Clamoxyl because it is the most prevalent level and, therefore, both variables are measured with respect to it.

The estimated coefficients can be interpreted as the marginal utility derived from each attribute. In the case of PRICE, marginal utility can be easily interpreted. For those dummy variables 0-1, marginal utilities are interpreted as the difference in utility from 0 to 1. For example, the LAB coefficient represents the disutility of purchasing a drug produced by an unkown laboratory with respect to a well-known. Once the parameter estimates have been obtained, a WTP compensating variation welfare measure that conforms to demand theory can be derived for each attribute using the formula below if the utility function is linear:[42]

$$WTP = -\frac{A}{\hat{\gamma}} \tag{2.63}$$

where A is equal to any non-price estimated coefficient and γ is price parameter. .

Socio-economic variables can be included along with choice set attributes, but since they are constant across choice occasions for any given individual (for example, sex and age is the same for each choice they make), they can only be entered as interaction terms. This is the reason why we firstly present the main effects estimated models -both for amoxiciline and statins- and afterwards, we present the *demand clustering exercise*, in which

[42] WTP = Market price + consumer's surplus

we calculate the main effects model for those segments that have different behavior with respect to drug purchasing. We identify demand clusters according to socio-demographic variables and drug purchase habits.

2.5.1 "Main Effects" Model

We use the *rank-ordered* or *exploded logit* to estimate utility function. As stated before, the rank-ordered logit is a generalization of McFadden's conditional logit since each of the terms in the probability product has the form of a conditional logit. In our experiment, each respondent should fully rank a set of five alternatives. First, we ask them to choose the most-preferred one; then, to choose the most preferred card among the rest of alternatives and so on.[43]

We also undertake several likelihood ratio (LR) tests in order to identify the best model specification. In particular, we contrast the unrestricted model with linear and quadratic (logarithm) price with the restricted one with linear price and, according to the results, we can accept the restricted model in all cases ($\chi^2(1) < 3\ 84$). There is no doubt about the specification of the rest of attributes.

Table 2.12 displays the results of the "main effects" model for the amoxiciline experiment. All parameters are significantly different from zero. Note also that all of them have the expected signs. In particular, GENERIC and ARDINE parameters are both negative, which indicates a noteworthy loyalty to Clamoxyl among population. Remember

[43] We estimate the rank-ordered logit model using the command **elogit** (exploded logit) from STATA.However, we also estimate each of the main effects models using a generalization of the **clogit** (conditional logit) command of STATA. That is, we replicate the results of the elogit with an extensive form of clogit, taking into account four orderings and four different choice sets. **elogit** is an ADO file proposed by Jeroen Weesie.

that Clamoxyl is the incumbent and more popular brand. LAB parameter is negative, as expected, which implies preference for a well-reputated laboratory producer instead of an unknown one. PRICE parameter is very small being an evidence of low price elasticity. The two parameters associated with supplier inducement exert a strong influence in the drug purchasing process. PHYSICIAN prescription is the most dominant factor in the decision among commercial drugs and PHARMA is also a powerful attribute. This pattern is also reflected in the WTP values; individuals should be paid more than 9 euros in order to switch from Clamoxyl to the corresponding generic version and more than 6 euros to switch from Clamoxyl to Ardine. On the other hand, they are ready to pay more than 24 euros for a favourable physician prescription and more than 7 euros for a favourable pharmacist recommendation.

Variable	Coef.	Std. Error	P>|z|	WTP
GENERIC	-0.37**	0.07	0.00	9.63
ARDINE	-0.25**	0.09	0.01	6.63
LAB	-0.10*	0.06	0.08	2.73
PRICE	-0.04**	0.00	0.00	1.00
PHYSICIAN	0.95**	0.07	0.00	-24.65
PHARMA	0.29**	0.06	0.00	-7.50
BLANK	-1.45**	0.11	0.00	37.67
Number of Observations	6118			
Log likelihood	-1778.11			
Pseudo R2	0.1501			

** significant at 1%

* significant at 10%

Table 2.12. Amoxiciline Main Effects Model (full sample)

Table 2.13 displays the results of the "main effects" model for the statins experiment. In this case, all coefficients are significantly different from zero except for the parameter associated with the commercial name, GENERIC. This is an expected result considering the fact that we use the full sample to estimate the coefficients. The full sample is composed

of 70% general population and 30% people with high blood cholesterol. General population can not recognize any brand-name drug for cholesterol and we also realize that people with high blood cholesterol often forget the commercial name of the capsules they take every day. Therefore, it is not rare to get nul brand loyalty. One point to remark is the fact that LAB parameter is more statistically significant than in the amoxiciline experiment. One possible explanation is that when individuals can not recognize the commercial brand they give more importance to the producer. Therefore, there exists a kind of brand loyalty. As expected, the signs for PHYSICIAN and PHARMA are positive; notwithstanding if we compare these parameters with the ones obtained in the amoxiciline experiment, we realize that when people are asked about a chronic disease they value physician prescription and pharmacist recommendation even more. In this case, they are willing to pay substantially more for experts advice.

Variable	Coef.	Std. Error	P>|z|	WTP
GENERIC	0.01	0.06	0.84	n.a.
LAB	-0.19*	0.06	0.00	5.97
PRICE	-0.03*	0.00	0.00	1.00
PHYSICIAN	1.35*	0.07	0.00	-43.28
PHARMACIST	0.44*	0.06	0.00	-14.06
BLANK	-1.23*	0.11	0.00	39.46
Number of Observations	6118			
Log Likelihood	-1711.54			
Pseudo R2	0.1819			

* significant at 1%

Table 2.13. Statins Main Effects Model (full sample)

We are now in position to give an idea about the importance of supplier inducement and brand loyalty in the drug purchasing process. We find that both exert a relevant influence, however, when individuals face a chronic disease, the higher is the dominance of the

expert inducement and the lower the influence of brand loyalty. Furthermore, in front of a chronic disease, individuals get more price inelastic.

2.5.2 Interaction Models: Demand Segmentation

As stated before, if we want to include socio-economic variables in the estimation model, we have to use *interactions* with choice attributes. Using those interactions, we are able to explore demand segmentation (clustering). In order to identify significant clusters, we proceed as follows: we conduct likelihood ratio tests and we only accept those restricted models in which the interactions of a socio-economic variable with all the choice attributes are accepted. In those cases, we estimate several different models, one for each demand segment (i.e. if sex is significant, we estimate a model for male and another for female).

The first interaction we analyze is the characteristic of having or not high blood cholesterol, however we can not find significant evidence that those individuals with a cardiovascular risk factor exhibit drug purchase habits different than the rest of population. Afterwards, we check other segmentations using socio-economic characteristics such as sex, age, income, education level and others. We can only accept the restricted models for age and education level.

Now, we estimate the main-effects model for each AGE (20-34 years old, 35-44 years old, 45-54 years old and 55-65 years old):

$$U_{ij} = \alpha_i GENERIC_j * AGE + \mu_i ARDINE_j * AGE + \beta_i LAB_j * AGE + \gamma_i PRICE_j * AGE + \delta_i PHYSICIAN_j * AGE + \eta_i PHARMA_j * AGE + \theta_i BLANK_j * AGE + \varepsilon_{ij} \quad (2.64)$$

Table 2.14 shows that the old firmly trust incumbent brands and doctor's prescription; on the contrary, the youngest are easily influenced by pharmacist's recommendation and, despite not being loyal to incumbent brands, they value laboratory reputation. People from 55 to 65 years old are also more price inelastic probably because they value health more than youngest.

Amoxiciline	20-34 years old		35-44 years old		45-54 years old		55-65 years old	
Variable	Coef.	Std.Error	Coef.	Std.Error	Coef.	Std.Error	Coef.	Std.Error
GENERIC	-0.18	0.13	-0.50***	0.15	-0.37***	0.14	-0.48***	0.16
ARDINE	-0.33**	0.17	-0.36*	0.20	-0.09	0.19	-0.21	0.22
LAB	-0.20*	0.11	-0.03	0.12	-0.01	0.12	-0.19	0.14
PRICE	-0.05***	0.01	-0.04***	0.01	-0.04***	0.01	-0.02***	0.01
PHYSICIAN	0.73***	0.12	0.88***	0.14	1.07***	0.13	1.27***	0.16
PHARMA	0.34***	0.11	0.15	0.13	0.32***	0.12	0.32**	0.14
BLANK	-1.66***	0.20	-1.67***	0.24	-1.11***	0.22	-1.43***	0.26
Number of Observations	1904		1372		1610		1190	
Log Likelihood	-549.39		-399.43		-471.09		-330.96	
Pseudo R2	0.1562		0.1486		0.1443		0.1867	

*** significant at 1%
** significant at 5%
* significant at 10%

Table 2.14. Age Clustering

Table 2.15 shows that high-educated people (secondary and university studies) value Clamoxyl less than low-educated people and laboratory reputation more than low-educated people. Furthermore, high-educated people value pharmacist's recommendation more than low-educated people.

$$U_{ij} = \alpha_i GENERIC_j * EDU + \mu_i ARDINE_j * EDU + \beta_i LAB_j * EDU + \gamma_i PRICE_j * EDU + \delta_i PHYSICIAN_j * EDU + \eta_i PHARMA_j * EDU + \theta_i BLANK_j * EDU + \varepsilon_{ij} \quad (2.65)$$

Amoxiciline	Low-educated		High-educated	
Variable	Coef.	Std. Error	Coef.	Std. Error
GENERIC	-0.54***	0.13	-0.29***	0.08
ARDINE	-0.31*	0.18	-0.24**	0.11
LAB	-0.07	0.11	-0.13*	0.07
PRICE	-0.04***	0.01	-0.04***	0.00
PHYSICIAN	0.93***	0.12	0.96***	0.08
PHARMA	0.12	0.12	0.38***	0.07
BLANK	-1.38***	0.21	-1.48***	0.13
Number of Observations	1750		4354	
Log Likelihood	-518.3		-1250.06	
Pseudo R2	0.1339		0.1604	

*** significant at 1%

** significant at 5%

* significant at 10%

Table 2.15. Education Clustering

One of the most significant results is the segmentation between those respondents with high switching costs, that is, those that have never tested a generic drug and those with low switching costs, that is, those that have bought generic versions at least one. We find that those patients exhibiting high switching costs firmly trust doctor's opinion and are reluctant to switch to other drugs different than the incumbent. On the contrary, those that have already tested and learnt about generics are more easily influenced by pharmacist's recommendation and laboratory reputation.

$$U_{ij} = \alpha_i GENERIC_j * GEN + \mu_i ARDINE_j * GEN + \beta_i LAB_j * GEN + \gamma_i PRICE_j * GEN + \delta_i PHYSICIAN_j * GEN + \eta_i PHARMA_j * GEN + \theta_i BLANK_j * GEN + \varepsilon_{ij} \quad (2.66)$$

Amoxiciline	Have ALREADY Bought Generic Drugs		Have NEVER Bought Generic Drugs	
Variable	Coef.	Std. Error	Coef.	Std. Error
GENERIC	-0.02	0.10	-0.72***	0.10
ARDINE	-0.28**	0.13	-0.25*	0.13
LAB	-0.15*	0.09	-0.06	0.08
PRICE	-0.04***	0.01	-0.04***	0.01
PHYSICIAN	0.79***	0.10	1.14***	0.09
PHARMACIST	0.37***	0.09	0.18**	0.08
BLANK	-1.19***	0.16	-1.75***	0.16
Number of Observations	2786		3332	
Log Likelihood	-827.69		-930.27	
Pseudo R2	0.1312		0.1836	

*** significant at 1%
** significant at 5%
* significant at 10%

Table 2.16. Switching Costs

It seems to be a general behavior pattern: those that are loyal to commercial brand usually value physicians prescription the most and those that are not loyal to brand-name drug value laboratory reputation and pharmacists recommendation. We also check the correlation between those socio-economic variables. Table 2.17 displays that correlation between age and education level is -0.26 and correlation between age and the variable "have bought generics" is -0.01. Under no circumstances, we can conclude that a correlation problem exists among explanatory variables.

Correlations	Age	Education	Generic purchase
Age Rank (from young to old)	1.00		
Education (low-educated=0, high-educated=1)	-0.26	1.00	
Generic purchase (no=0, yes=1)	-0.01	-0.05	1.00

Age	Low-educated	High-educated
20-34 years	13%	87%
35-44 years	30%	70%
45-54 years	32%	68%
55-65 years	49%	51%

Age	ALREADY bought generics	NEVER bought generics
20-34 years	41%	59%
35-44 years	48%	52%
45-54 years	54%	46%
55-65 years	40%	60%

Table 2.17. Correlation Matrix

In this section, we only show the most relevant demand clustering for a research purpose; however, the marketing department of pharmaceutical companies should be inter-

ested in applying a *K-Means Cluster* analysis. In this approach, one uses cluster analysis to group subjects according to some measure of distance, relatedness or similarity between vectors of coefficients. Once clusters or segments are identified, one normally tests whether the segments differ significantly on various segmentation measures of interest.

2.6 Concluding Remarks

Despite the importance of supplier inducement and brand loyalty in the drug purchasing process, little empirical evidence is found about the influence of those factors in the process by which patients decide among commercial drugs at the chemist's. Under the new scenario of easier access to information, patients become more demanding and are even capable to question physician's prescription. Furthermore, new regulation also encourages patients to adopt an active role in the decision between ttrade-name and generic drugs. in this sense, health care systems are transitioning from a physician-directed system to a patient-directed one. Therefore, the new pharmaceutical framework makes interesting the analysis of patients preferences, however the empirical literature on pharmaceuticals demand is very limited and has always been focused on the behavior of either physicians and pharmacists. Furthermore, all of them use revealed preference data to estimate the objective utility function

On the contrary, this paper directly focuses on consumers' preferences using stated preference data obtained from a choice survey. For this purpose, we undertake two different choice modelling experiments -one referring to a common infection and the other to a

chronic disease- with the aim to contrast whether the degree of illness awareness could modify consumers' decision.

The parameters of our utility function are estimated using a *rank ordered logit* - a generalization of McFadden's conditional logit- and will determine the significance of brand loyalty, laboratory reputation and the reliance upon health care experts along the decision-making process

The "main effects" model shows the significant importance of experts' inducement - although physician's prescription is always more reliable than pharmacist's recommendation- and, to what extent, both brand loyalty and laboratory reputation influence the final decision. We also find that, when individuals face a chronic disease, the higher is the dominance of the expert inducement and the lower the influence of brand loyalty. Furthermore, in front of a chronic disease, individuals get more price inelastic.

Using interactions between choice attributes and characteristics of the respondents, I find that age is a relevant variable in the decision between a trade-name and a generic drug at the chemist's. The old firmly trust incumbent brands and doctor's prescription; on the contrary, the youngest are easily influenced by pharmacist's recommendation and, despite not being loyal to incumbent brands, they value laboratory reputation. In addition, those patients exhibiting high switching costs firmly trust doctor's opinion and are reluctant to switch to other drugs different than the incumbent. On the contrary, those that have already tested and learnt about generics are more easily influenced by pharmacist's recommendation and laboratory reputation.

Another significant implication derived from our results has to do with pharmaceuticals public policy, such as the Generic Paradox. Since generic drugs are generally equivalent and priced lower than their trade-name counterparts, they are expected to entail substantial savings for both National Health Systems and final consumers. However, despite a priori advantages of generic drugs, their penetration rate does not catch up the market share of those branded drugs with the same active ingredient. One possible interpretation of this scarcity is the rise of uncertainty among patients. According to our results, both physicians and pharmacists exert an important influence on patients' decision, therefore, they become key agents in the learning process by which consumers accept generic versions as a feasible alternative.

2.A Appendix. Guideline for a Focus Group on Pharmaceutical Drugs

Focus groups consist of discussion sessions in which about eight people are gathered together in order to argue about a topic of interest. The participants are guided by a team leader or moderator who asks questions and helps the group to be involved in a natural and free conversation among themselves. Therefore, focus groups are aimed at encouraging participants to talk with each other rather than answering questions directly to the moderator. Focus groups usually have a narrow purpose which is to collect the perceptions, feelings and opinions of consumers regarding key attributes of a product or service. The topic of a focus group must be carefully predetermined and based on a previous and in-depth analysis about the situation under scrutiny. Once the purpose statement is clearly defined, the process of writing a script starts which consists of constructing a list of questions that move from general to specific. Taking into account this overview, focus groups must also satisfy the following particular conditions (Krueger, 1994):

- Focus groups are typically composed of six to ten people, small enough for everyone to have an opportunity to share insights but large enough to provide a diversity of perceptions.
- Multiple groups with similar participants are needed in order to detect patterns and trends across groups. Intergroup heterogeneity is required.
- Participants in a same group must be reasonable homogenous and have similar background or experience. Intragroup homogeneity is required.

- Focus groups make use of qualitative data. Results are solicited through open-ended and "think back" questions. It is important to avoid dichotomous questions.in order to force participants to talk to each other.

We conducted two different focus groups, each composed of nine people, in order to collect their opinion and perception about the consumption of drugs and the entrance of generic versions into the pharmaceutical market. Although all participants had similar education background, the first group was composed of older people with children while the second group was composed of younger people with no family responsabilities.

1. Opening question: During this session, we are going to discuss about pharmaceutical drugs. Just to start, I would like to know your opinion about the consumption of medicines.[The aim of the above question is to determine whether participants in the discussion group are more or less reluctant to consume chemical drug, their disposal to use domestic and natural remedies and the practice of self-prescription, etc.]

2. What type of drugs could I find in your medicine chest at home?; could you let me know the commercial brand name and the laboratory of any of them?

3. Introductory question: How do you assess the entry of generic drugs in the pharmaceutical market? [The aim is to perceive the level of knowledge of generic drugs and their opinion about the penetration in the market.]

4. In your opinion, which are the main differences/similarities between a branded drug and its generic version?

5. Transition question: What is your opinion about the information provided by the Ministry of Health and other sanitary institutions on generics? [The aim is to notice whether final consumers are aware of the public advertising campaigns funded by the goverment.]

6. How do you perceive the information provided by your physician and/or your pharmacist about generics? Remember last time you visited the doctor, what type of medicines did he/she precribe to you? Remember last time you bought a drug in a chemist's; did the pharmacist advice you to buy a cheaper but equivalent medicine?; have you suggested the substitution of the prescribed drug by a cheaper one?

7. Key questions: In your opinion, what factors influence the final purchase decision between a branded and a generic drug with the same chemical compound? [The aim is they mention all likely attributes and factors that determine the demand for a generic drug, among them price, name of the laboratory, format, prescriptor, dispensor, type of illness, etc.]

8. How do you assess the new regulation that allows pharmacists to substitute the drugs prescribed by the physician for cheaper ones?

9. Imagine that you go to the chemist's with your physician's prescription and the pharmacist gives you the chance to substitute the prescribed drug for a cheaper one; under what conditions are you going to accept the substitution?; what factors would make you refuse the substitution?

10. Ending question: Do you consider we have missed any important issue?

Do not hesitate to contact me if you have additional comments and suggestions. Thanks to all for your collaboration.

2.B Appendix.Contingent Ranking

This appendix displays an example of a choice set used for the contingent ranking experiment. Remember that each choice set is composed of five cards, each representing a drug alternative, and that card number five is always the blank card or outside option. In the case of amoxiciline, the blank card is "home remedies" (remedios caseros).

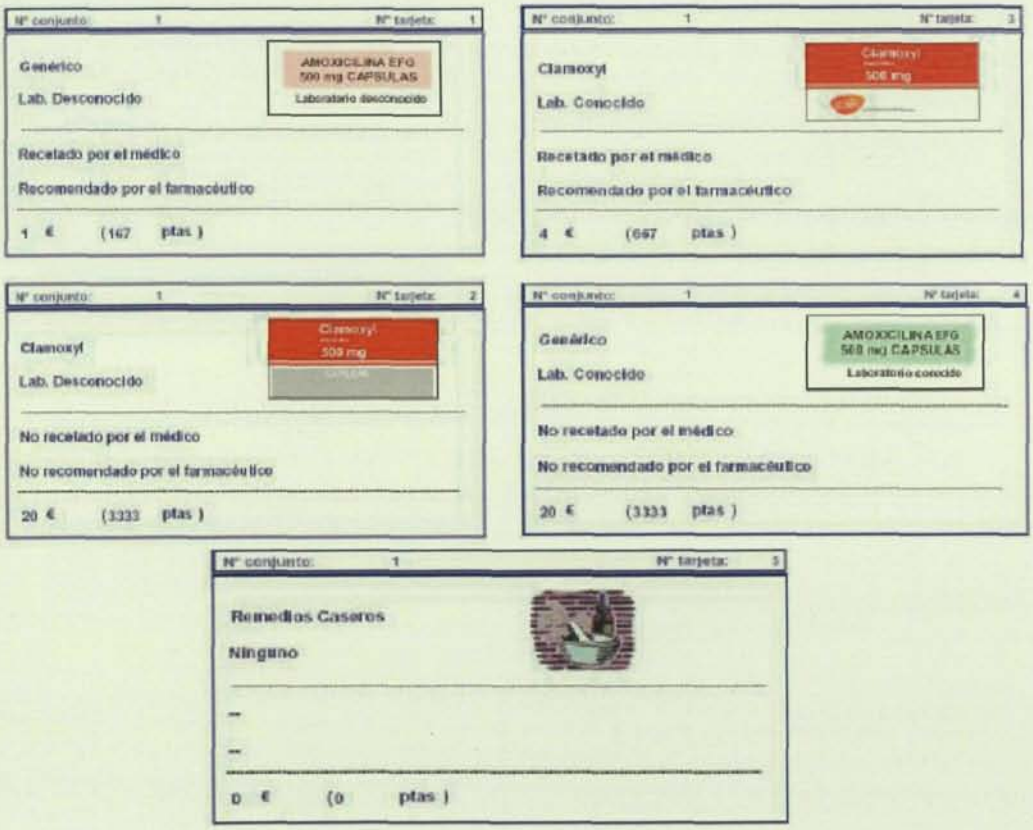

Figure 2.5. An Example of Choice Set

Choice Set Number:
First Choice:
Second Choice:
Third Choice:
Fouth Choice:
Fifth Choice:

2.C Appendix. Questionnaire

Table 2.18 shows the questions included in our questionnaire.

Question	Answer Range
Sex	male, female
Spanish Nationality	yes, no
Age	years
Education Level	none, primary, secondary, university
Professional Level	by my own, employed
Family Head	yes, no
Home size	number
Children	yes, no
Household Net Income	range
Member Social Security	yes, no
Member Mutuality	yes, no
Private Insurance	yes, no
Household Drug Expenditure	range
Generic Knowledge	yes, no
Generic Purchase	yes, no
Physician Generic Prescription	yes, no
Pharmacist Generic Recommendation	yes, no
Laboratory Identification	yes, no
Chemist's Loyalty	yes, no
Personal Identification	name, region of residence
Interview Location	hospital, primary care center, chemist, others

Table 2.18. Questionnaire

Chapter 3
Eliciting Consumers Preferences Using Stated Preference Discrete Choice Models: Contingent Ranking versus Choice Experiment

Abstract

The aim of this paper is twofold: firstly, to undertake a theoretical review about the most recent stated preference techniques used for eliciting consumers preferences and secondly, to compare the results of two different stated preference discrete choice approaches. They differ in the measurement scale for the dependent variable and, therefore, in the estimation method, despite both use a multinomial logit. One of the approaches uses a complete ranking of full-profiles (contingent ranking), that is, individuals must rank a set of alternatives from the most to the least preferred, and the other uses a first-choice rule in which individuals must select the most preferred option from a choice set (choice experiment). From the results we realize how important the measurement scale for the dependent variable becomes and, to what extent, procedure invariance is satisfied.

3.1 Introduction

In the last decades, measuring consumers' preferences for goods and services has been a significant challenge for both academics and practitioners in public and private contexts. People often want to know what other people think. Public officials want to know voters' opinion; marketers want to know consumers' preferences and the general public wants to know what others think about political, social, health and other issues. Individuals' valuation are used for many different purposes, including setting social policies and evaluating the acceptance of a new product in the market.

The aim of this paper is twofold. Firstly, to undertake a theoretical review about the most recent stated preference techniques used for eliciting consumers preferences and, secondly, to empirically compare two stated preference approaches and discuss their main strengths and weaknesses.

Although *revealed preference* data have been traditionally used to estimate consumers' valuation for attributes, *stated preferences* hold important advantages when historical data do not suit the objective function. Notwithstanding, there exist many methods to elicit stated preferences from individuals -contingent valuation, conjoint analysis, discrete choice methods- and recently, a great debate has emerged focusing on the pros and cons of each of them, mainly between conjoint analysis and choice methods.[44]

There is considerable confusion amongst academics and practitioners about what really constitutes the difference between each of the stated preference techniques. Neverthe-

[44] There exists a great confusion about the terminology applied to stated preference techniques. Although the term contingent valuation seems to be commonly accepted by the overwhelming majority, the concepts conjoint analysis and discrete choice methods are extremely confusing and usually receive more than one name.

less, there are very substantial differences among them and a number of these differences matter very considerably in economic valuation and other applications. Although this is not the final aim of the present paper, we intend to clarify differences and similarities to understand the framework of our analysis and we anticipate that the main differences are related to the election of the preference model, the measurement scale for the dependent variable and the estimation method (Section 3.2).

On the other hand, the empirical aim of this paper is to compare the results of two particular stated preference discrete choice model (SPDCM) approaches and assess the validity and reliability of each of them.[45] They differ in the measurement scale for the dependent variable and therefore, in the estimation method, despite both use a multinomial logit (Section 3.3). One of the approaches uses a complete ranking of full-profiles (contingent ranking), that is, individuals must rank a set of alternatives from the most to the least preferred, and the other uses a first-choice rule in which individuals must select the most preferred option from a choice set (choice experiment).[46] From the results we realize how important the measurement scale for the dependent variable becomes and, to what extent, procedure invariance is satisfied; that is, two different measurement methods used to assess the same issue should yield the same outcome. However, this is not always satisfied and inconsistency raises when those different methods yield different results. This inconsistency is called *procedure preference reversal* (Section 3.4).

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[45] The term SPDCM was firstly used by J. Louviere.

[46] The terms Contingent Ranking and Choice Experiment are borrowed from the environmental literature, one of the more advanced fields in those techniques.

This paper is organized as follows. Section 3.2 describes the most recent stated preference techniques developed in public and private fields. Section 3.3 revises the SPDCM approaches focusing on the contingent ranking and the choice experiment. Section 3.4 displays the results derived from the two approaches and finally Section 3.5 concludes.

3.2 Stated Preference Techniques

Measuring consumers preferences will allow us to quantify the individuals' economic valuation or willingness-to-pay (WTP) for public and private initiatives. In this sense, economic valuation techniques are not only valuable as a policy decision-making tool but also as a marketing research technique. In the former case, we refer to the social valuation of a public initiative such as the construction of a dam or a new environmental program; however, these techniques are also widely used as a marketing research tool because they allow to understand what it is about a product or service that drives customers' interest and influences their final purchase decision.

Consumers preferences can be elicited using either revealed or stated preference data. For this purpose, stated preference data can offer some advantages with respect to revealed preference data. One of the main differences between them is the data origin and collection method; revealed preference data are obtained from the past behavior of consumers while stated preference data are collected through surveys (Chapter 2).

In the last few years, a range of stated preference techniques have been developed for eliciting consumers preferences and measuring WTP for goods and services. All these techniques involve asking respondents to consider one or more hypothetical options and to

express their preferences for them through surveys. However, aside from this general commonality, there are significant analytical differences between stated preference techniques -contingent valuation, conjoint analysis and choice modelling- although it is not always evident to understand what constitutes the difference. That leads to a great confusion about the classification and each field of study -environmental, transport or health economics-, and even each author, refers to each of the techniques with different names.

What seems to be the most general and widely accepted classification of stated preference techniques is that between *contingent valuation (CV)* and what we label *multi-attribute valuation techniques (MAV);* that is, between contingent valuation and both conjoint analysis and choice modelling approaches (Figure 3.6).[47]

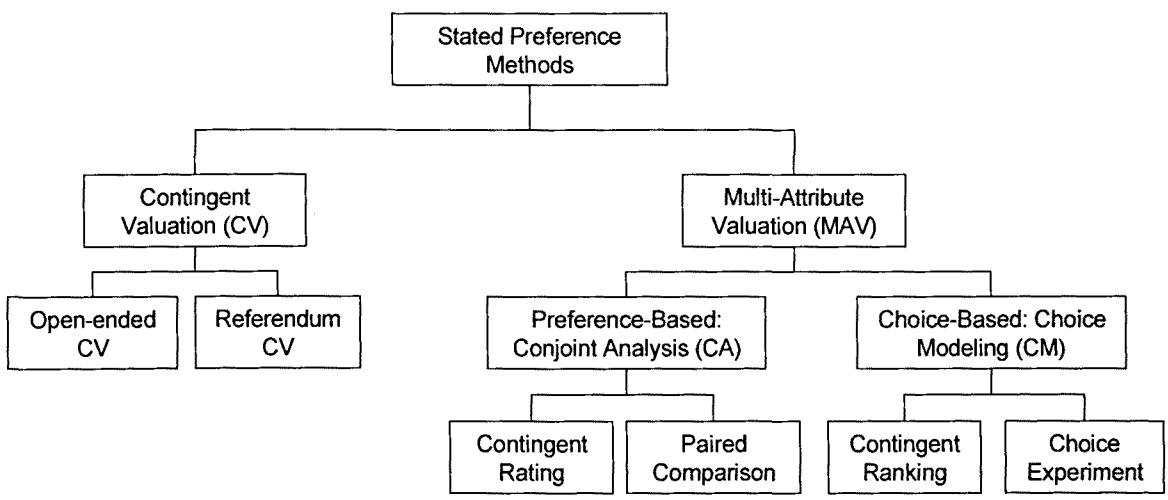

Figure 3.6. The Family of Stated Preference Methods

Contingent valuation is a direct survey approach able to estimate consumers' preferences. By means of an appropriately designed questionnaire, a hypothetical market is described where the good or service in question can be traded. This contingent market

[47] In the most recent environmental literature, Bateman et al (2002) uses the concept of choice modelling instead of multi-attribute valuation (MAV) techniques. However, we adopt this new term in order to distinguish between preference-based and choice-based approaches.

defines the good itself, the context in which it would be provided and the way it would be financed. Respondents are then asked to express their maximum willingness to pay or minimum willingness to accept for a hypothetical change in the level of provision of the good. Theoretically, contingent valuation is well rooted in welfare economics, namely in the neo-classical concept of economic value based on individual utility maximization. This assumes that stated WTP amounts are related to respondents' underlying preferences in a consistent manner (Hanley et al, 2001). This technique derives its name from the fact that the value estimates are *contingent* on a hypothetical scenario that is presented to respondents for valuing.

The choice of elicitation formats for willingness to pay questions in contingent valuation surveys has passed already through a number of distinct stages (Hanley et al, 2001). The original form of contingent valuation constitutes an open ended question, in which respondents are asked to state their willingness to pay (or accept compensation) for a specified change or improvement. The **open-ended CV** method is now rarely used because it has been found to be vulnerable to a range of biases, for example, respondents find open-ended questions too difficult to answer because they are not accustomed to pay for non-market goods and services. Respondents may have a preference for one alternative over the other but do not know their maximum willingness to pay for a good (CIE, 2001). Ordinary Least Squares regression is employed for the estimation under the open-ended CV version.

Owing to the problems of eliciting values using an open-ended question, most CV studies are now undertaken using the **referendum or dichotomous** choice elicitation. The preference data generated using this method is encoded in binary forms, as respondents

are only given the option of answering yes or no, what implies the adoption of a random utility function. In this case, the coefficients values are obtained through the estimation of a binary logit model using the maximum likelihood procedure. After receiving the endorsement of the NOAA experts panel in 1993 (Arrow et al, 1993), the use of dichotomous choice questions substantially increased, particularly in US applications.[48] However, an increasing number of empirical studies revealed that dichotomous choice results seemed to be significantly larger than open-ended values, possibly due to "yeah saying" (Hanley et al, 2001).[49]

Therefore, both approaches appear to have some limitations for estimating values. Firstly, only one attribute or scenario can be presented to a sample of respondents for valuation. Secondly, it is a poor method for estimating consumer values because respondents are unlikely to provide an accurate response when presented with a hypothetical scenario. A third potential weakness of CV is that it may induce some respondents to behave strategically, particularly when public goods are involved.

Partly as a response to these problems, valuation practitioners are increasingly developing an interest in alternative stated preference formats such as *multi-attribute valuation (MAV) methods* which includes conjoint analysis and choice modelling. The main difference between contingent valuation and multi-attribute valuation is that the former analyzes one attribute of the product at a time while the latter explores more than one attribute simultaneously. This may not be a limitation for CV if the objective of the study is to estimate

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[48] The National Oceanic and Atmospheric Administration (NOAA) organized a panel of experts headed by Robert Solow and Kenneth Arrow.

[49] The phenomenon of yeah saying appears when respondents accept to say "yes" and pay the specified amount to avoid the embarrassing position of having to say "no".

values for a one-dimensional attribute. However, it is an inefficient method of value estimation if multiple attributes are involved and we are interested in the values attached to each of them and trade offs between them. For this reason, contingent valuation is mainly used to contrast different policies while conjoint analysis and choice methods are more focused on marketing due to the decomposition of products into attributes.

Multi-attribute valuation techniques is a family of survey-based methodologies for modelling preferences for goods, where goods are described in terms of their attributes and the levels that these take.[50] Respondents are presented with various alternative descriptions of a good, differentiated by their attributes and levels and are asked to rank the various alternatives, to rate them or to choose their most preferred. By including price/cost as one of the attributes of the good, WTP can be indirectly recovered from people's rankings, ratings or choices. Attribute valuation approaches allow a more direct route to the valuation of the characteristics or attributes of a good and of marginal changes in these characteristics. Contingent valuation can, of course, be used to value such changes, but the number of scenarios that can be considered is limited. There will be a presumption, therefore, that multi-attribute valuation approaches will be preferred over contingent valuation approaches in contexts where it is important to value several attributes.

Some advantages of multi-attribute valuation methods that solve the drawbacks of contingent valuation are: (i) the only way that a CV study can estimate these attributes is to design different valuation scenarios for each attribute level, however, this is very costly.

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[50] The conceptual microeconomic framework for multiattribute valuation lies in Lancaster's characteristics theory of value which assumes that consumers' utilities for goods can be decomposed into utilities for composing characteristics.

Multi-attribute methods, because they look at more than two alternatives, provide a natural way to do this; (ii) since multi-attributes designs are based on the attribute theory of value, they are much easier to pool with cost models or hedonic price models than CV; (iii) multi-attribute designs can reduce the extreme multicollinearity problems because attribute levels are usually designed as orthogonal and (iv) multi-attribute methods may avoid some of the response difficulties that appear in CV (Bateman et al, 2002).

3.2.1 Multi-Attribute Valuation

Two different types of multi-attribute techniques have been suggested: (i) *preference-based approaches* which require the individual to rate or rank each alternative product and (ii) *choice-based approaches* which make the consumer to choose one among several alternative products. The former is a research technique in which customers are asked to evaluate a series of hypothetical and real products, defined in terms of their features. The latter differs in that consumers are asked to view a series of competing products and select one or, in some cases, more than one. In this regard, choice-based approaches are based on a more realistic task that consumers perform every day, the task of choosing a product from among a group of competitors while preference-based approaches do not require respondents to make a commitment to select a particular option. This is one of the reasons to state that choice-based approaches are better or at least more preferred than preference-based approaches.

Choice-based approaches originate from the economics discipline and have been widely used for valuing a diverse range of goods and services. On the contrary, preference-

based approaches have their origins in the marketing literature and it is mainly focused on gaining an insight about consumers preferences rather than to estimate economic values (Louviere, 1988). The growing acceptance of choice-based approaches among marketing research practitioners is primarily due to the belief that obtaining preferences by having respondents choose a single preferred stimuli from among a set of stimuli is more realistic and thus a better method of approaching actual decision processes.

Generally speaking, preference-based approaches are labelled with the global term **conjoint analysis** while choice-based approaches receive the name of **choice modelling.**[51] One of the main differences between them is the form of the utility function: preference-based approaches use a deterministic utility function while choice-based approaches use the random utility function where the stochastic component includes all unidentified factors that impact choices. In the deterministic case, the utility function is assumed to be related to individual's ratings via a transformation function ϕ :

$$U_{ij} = \phi[V_{ij}(X_{ij})] \tag{3.67}$$

that can take the following shapes: (i) vector model (linear), (ii) ideal point model (linear plus quadratic) and (iii) part-worth function model (piecewise model). The vector model estimates the fewest parameters by assuming the potentially restrictive linear functional form, whereas the part-worth model estimates the largest number of parameters because it permits the most general functional form. The ideal point model is between these two extremes (Green and Srinivasan, 1978, 1990).[52] These data are typically analyzed using

[51] Choice Modelling is also called Stated Preference Discrete Choice Model (SPDCM).

[52] In the vector model, the preference u_j can be represented as the projection of the stimulus point x_{jp} on the vector w_p in the t-dimensional attribute space:

ordinary least squares (OLS) regression techniques which imply a strong assumption about the cardinality of the ratings scale (Bateman et al, 2002).

On the contrary, choice-based approaches use the random utility function that represents the integrated behavioral theory of decision-making and choice behavior and is composed by a deterministic V_{ij} and a stochastic component ε_{ij}:

$$U_{ij} = V_{ij}(X_{ij}) + \varepsilon_{ij} \tag{3.68}$$

The Random Utility Theory (RUT) leads to families of discrete choice models that describe the behavior of individual choice probabilities in response to changes in attributes and/or factors that measure differences across individuals. The most commonly used estimation method is the maximum likelihood.

Individual preferences can be elicited by asking respondents to rank the options presented to them, to score them or to choose their most preferred. These different ways of measuring preferences correspond to different variants of conjoint analysis and choice modelling. There are four main variants according to the measurement scale for the dependent variable: *contingent rating*, *paired comparison*, *choice experiments* and *contingent ranking* (Figure 3.7).

$u_j = \sum_{p=1}^{t} w_p x_{jp}$

The ideal-point model posits that the preference is negatively related to the squared weighted distance d_j^2 of the location x_{jp} of the stimuli or alternative from the individual's ideal point x_p :

$d_j^2 = \sum_{p=1}^{t} w_p (y_{jp} - x_p)^2$

The part-worth model permits the most general functional form: $u_j = \sum_{p=1}^{t} f_p(x_{jp})$

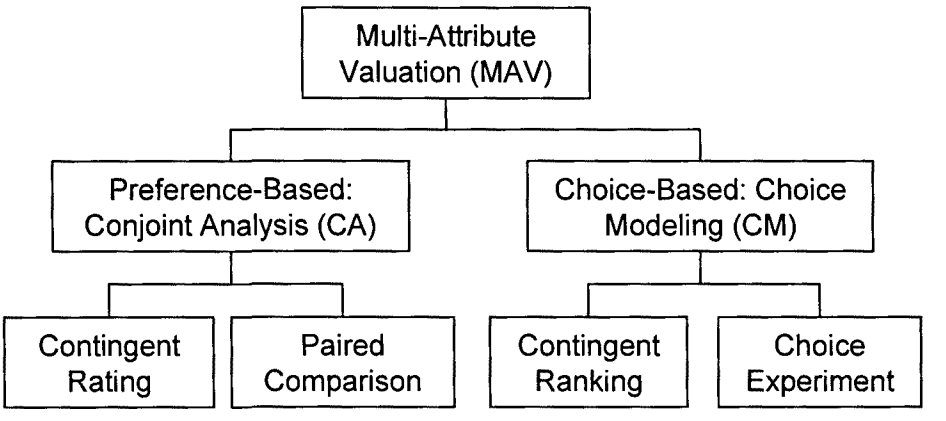

Figure 3.7. Preference-based versus Choice-based Approaches

These techniques differ in the quality of information they generate, in their degree of complexity and also in their ability to produce WTP estimates that can be shown to be consistent with the usual measures of welfare (Bateman et al, 2002).

Both *contingent rating* and *paired comparison* belong to the family of conjoint analysis what implies the use of a deterministic utility function and the ordinary least squares as estimation procedure. Notwithstanding, these two variants differ in the measurement scale for the dependent variable.

In a *contingent rating* exercise, respondents are presented with a number of scenarios one at a time and are asked to rate each one individually on a semantic or numeric scale. This variant does not, therefore, involve a direct comparison of alternative choices. Ratings must be transformed into a utility scale. The indirect utility function is assumed to be related to individual's ratings via a transformation function. These data are typically analyzed using OLS regression techniques which implies a strong assumption about the cardinality of the ratings scale. These assumptions relate either to the cardinality of rating scales or to the implicit assumption of comparability of ratings across individuals: both

are inconsistent with consumer theory. Hence, contingent rating exercises do not produce welfare consistent value estimates.

In a *paired comparison* exercise, respondents are asked to choose their preferred alternative out of a set of two choices and to indicate the strength of their preference in a numeric or semantic scale. This approach combines elements of choice experiment (choosing the most preferred alternative) and rating exercises (rating the strength of preference). Also in this case, utility function is estimated using ordinary least squares.

On the other hand, *choice experiment* and *contingent ranking* belong to the family of choice modelling what implies the use of a random utility function and the maximum likelihood as estimation procedure.

In a *choice experiment*, respondents are presented with a series of alternatives and are asked to choose their most preferred option. A baseline alternative, corresponding to the status quo, is usually included in each choice set. Choice experiments give welfare consistent estimates for four reasons. First, they force the respondents to trade-off changes in attribute levels against the cost of making these changes. Second, the respondents can opt for the status quo. Third, we can represent the econometric technique used in a way which is exactly parallel to the theory of rational and probabilistic choice. Fourth, we can derive estimates of compensating and equivalent surplus. In this case, we estimate a McFadden's conditional logit model using the maximum likelihood procedure.

In a *contingent ranking* experiment, respondents are required to rank a set of alternative options from most to least preferred. Each alternative is characterized by a number of attributes, which are offered at different levels across options. Respondents are then

asked to rank the options according to their preferences. In order to interpret the results in a welfare economic terms, one of the options must always be in the individual's currently feasible choice set. This is because, if a status quo is not included in the choice set, respondents are effectively being forced to choose one of the alternatives presented, which they may not desire at all. Ranking data provides more statistical information than choice experiments, which leads to tighter confidence intervals around the parameter estimates. We estimate a rank ordered or an exploded logit model using the maximum likelihood procedure.

As a summary, we build a decision tree that indicates the most appropriate state preference approach according to the sequential decisions about number of attributes, elicitation format (preference-based versus choice-based) and measurement scale (Figure 3.8). The contingent valuation variants can also be included in this decision tree as long as the *open ended CV* belongs to the preference-based family and the *referendum CV* belongs to the choice-based family.

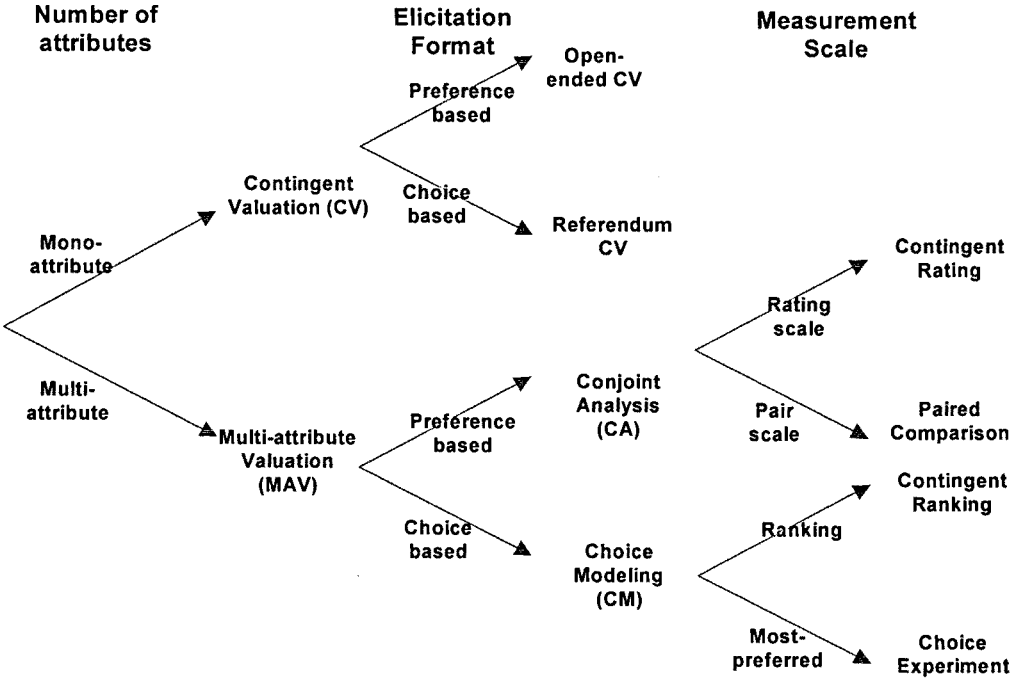

Figure 3.8. Stated Preference Method Decision Tree

The assumptions about the number of attributes, the elicitation format and the measurement scale determine the model specification and the estimation procedure for each of the variants (Table 3.19). As stated before, the specification model for the preference-based approaches is the linear regression model and the estimation procedure is the ordinary least squares (OLS). On the other hand, the specification model of the choice-based approaches is the multinomial logit model and the estimation procedure is the maximum likelihood (MLE). In particular, and due to the differences in the measurement scale, the model specification for the choice experiments is the McFadden's conditional logit while the model specification for the contingent ranking is the rank ordered logit or exploded logit of Beggs et al (1981).

	Utility Model	Elicitation Format	Measurement Scale	Model Specification	Estimation Method	Welfare Consistent Estimates
Contingent Valuation (CV)	Open-ended CV: deterministic Referendum CV: stochastic	Open-ended CV: preference-based Referendum CV: choice-based	Open-ended CV: WTP in monetary units Referendum CV: yes, no	Linear Regression Model	OLS	YES
Contingent Rating	Deterministic	Preference-based	Score alternative scenarios on a scale of 1-10	Linear Regression Model	OLS	Doubtful
Paired Comparison	Deterministic	Preference-based	Score pairs of scenarios on similar scale	Linear Regression Model	OLS	Doubtful
Choice Experiments	Random Utility	Choice-based	The most-preferred between two or more alternatives	Conditional Logit Model	Maximum Likelihood	YES if non purchase option is included
Contingent Ranking	Random Utility	Choice-based	Rank a series of alternatives from most to least preferred	Rank Ordered Logit	Maximum Likelihood	YES if non purchase option is included

Table 3.19. Characteristics of Stated Preference Approaches

Contingent valuation and choice experiments can both generate results that are consistent with welfare theory. Contingent ranking can also generate welfare theory-consistent results, if do-nothing is included as an option so that the respondents are not forced to rank other options. On the other hand, contingent rating is not widely used in economic valuation mainly due to dubious assumptions that need to be made in order to transform ratings into utilities notwithstanding, due to its simplicity, conjoint analysis variants have been high-frequently used in marketing fields.

3.2.2 Stated Preference Techniques in Health Economics

Stated preference techniques have recently been used to estimate utilities instead of the more traditional approach of revealed preferences. Actually, interest in the use of stated preference theory and methods has increased dramatically in environmental and health eco-

nomics since the mid-1990's, as academics and practitioners make use of developments in transport economics and marketing. Because of their characteristics, contingent valuation has been traditionally used to obtain the monetary value of a change described as a result of a hypothetical or actual policy; on the contrary, conjoint analysis and choice modelling approaches have been traditionally used to better understand consumers' preferences and choice behavior and therefore they are more usually applied for marketing purposes.

Until few years ago, contingent valuation techniques -open ended and referendum- have been the most common approaches employed in health economics to assess utility from various health care interventions or contrast health policy initiatives. However, due to the important drawbacks of contingent valuation variants, multi-attribute valuation approaches, such as conjoint analysis and choice modelling, have been recently adopted in health economics experiments in order to obtain more detailed information about the monetary value of consumers for more than one attribute at a time. In particular, contingent valuation was born in the environmental field and it was applied to health economics for first time by Acton (1973) with the aim to value the benefits of a medical treatment. Some international reviews about the application of contingent valuation approaches in health economics are provided by Diener et al (1999) and Olsen and Smith (2001). Among those, we can point out the work of O'Brien et al (1995) where they assess the economic value of a new antidepressant or Davey et al (1998) where the authors undertake an economic value of insulin lispro versus neutral insulin therapy.

The use of multi-attribute valuation (MAV) approaches constitutes an alternative way to assess utilities however, to date, the application of those methods in the area of health

economics has been limited. In the USA, it has been used by non-economists to examine what factors are important to patients in the provision of primary health care systems, to establish consumers preferences for rural primary health care facilities, to identify what factors are important to consumers in choosing a hospital and to establish consumers preferences for dental services. In the UK, it has been used by health economists to establish the monetary value of time spent on NHS waiting lists, to examine the trade-offs that individuals make between the location of clinic and waiting time in the provision of orthodontic services, to look at the value of assisted reproductive techniques and to assess preferences in the doctor-patient relationship (Ryan and Hughes, 1997). Although multi-attribute valuation methods have been widely used in several fields of economics as well as marketing research, it has only recently become more widely used in health care research. Some recent studies are Ryan and Hughes (1997), Telser and Zweifel (2002), Hall et al (2002).

The majority of examples shown in Table 3.20 actually uses choice modelling approaches, or what is also called stated preference discrete choice models (SPDCM), instead of conjoint analysis approaches. In some cases, this latter term is incorrectly labelled conjoint analysis; this is what happens in Telser and Zweifel (2002) and Ryan and Hughes (1997) papers that use the term "conjoint analysis" but in fact they are using a SPDCM approach.

	Title of the paper	Journal	Approach
COTINGENT VALUATION	"Evaluating Public Programs to Save Lifes: the Case of Heart Attacks" (J.P. Acton)	Santa Monica: RAND Report (1973)	Open-ended Contingent Valuation
	"Health Care Contingent Valuation Studies: a Review and Classification of the Literature" (Diener)	Health Economics (1998)	Contingent Valuation
	"Theory versus Practice: a Review of Willigness-to-Pay in Health and Health Care" (Olsen and Smith)	Health Economics (2001)	Contingent Valuation
	"Economic Evaluation of Insulin Lipsro versus Neutral (regular) Insulin Therapy using a WTP Approach" (Davey et al)	PharmaEconomics (1998)	Open-ended Contingent Valuation
	"Assessing the Economic Value of a New Antidepressant: a WTP Approach" (O'Brien et al)	PharmaEconomics (1998)	Open-ended Contingent Valuation
MULTI-ATTRIBUTE VALUATION	"Measuring willingness-to-pay for risk reduction: an application of conjoint analysis" (Telser and Zweifel)	Health Economics (2002)	Choice modelling
	"Using conjoint analysis to assess women's preferences for miscarriage management" (Ryan and Hughes)	Health Economics (1997)	Choice modelling
	"An application of a Product Positioning Model to Pharmaceutical Products" (Green and Krieger)	Marketing Science	Conjoint analysis
	"Using Stated Preference Discrete Choice Modelling to Evaluate the Introduction of Varicella Vaccination" (Hall et al)	Health Economics (in press) 2002	Choice modelling

Table 3.20. Review of Stated Preference Experiments in Health Economics

In a recent white paper by Louviere (2000) entitled "Why Stated Preference Discrete Choice Modelling is NOT Conjoint Analysis (and What SPDCM is)", the author defines, compares and discusses two paradigms that are being increasingly applied in health economics and show why one of these approaches -conjoint analysis- generally is inappropriate for economic valuation and should be applied with caution.

3.3 Choice Experiment versus Contingent Ranking

As previously explained, there exist two variants of choice modelling: the choice experiment and the contingent ranking. They mainly differ in the measurement scale for the dependent variable because the former implies the choice of the most preferred option rel-

ative to the remaining while the latter implies a complete ranking of options from most to least preferred (true ordinal scale). In the choice experiment, respondents are usually asked to perform a sequence of such choices (true nominal scale).

The measurement scale determines the multinomial logit to estimate, that is, choice experiment derives a *conditional logit model* (McFadden, 1973) while contingent ranking determines a *rank ordered or exploded logit* (Beggs et al, 1981; Hausman and Ruud, 1987; Chapman and Staelin, 1982). Consequently, the likelihood function in both cases is different. Both of them assume a random utility function and the only difference is that ranked data allows considerably more information from a given survey than from simply the most preferred alternative.

Let's derive McFadden's conditional logit. Suppose that individual i chooses alternative j^* from a choice set C_i If rational choice behavior is assumed, individual preference implies that $U_{ij^*} \geqslant U_{ij}$ for $j = 1\ J$. Because the utility function is partly stochastic, the probability of this event occurring may be written as:

$$P_{ij^*} = \Pr(U_{ij^*} \geqslant U_{ij}) = \Pr(\varepsilon_{ij} - \varepsilon_{ij^*} \leqslant X_{ij^*}\beta_j - X_{ij}\beta_j) \tag{3.69}$$

where P_{ij^*} is the probability that decision maker i chooses alternative j^*. If the stochastic error terms are assumed to be i.i.d. according to the extreme value type I distribution (also called double exponential or Gumbel):

$$\Pr(\varepsilon_{ij} \leqslant t) = \exp[-\exp(-t)] \tag{3.70}$$

one can show that the choice probabilities have the following form (McFadden, 1973):

$$P_{ij^*} = \frac{\exp(X_{ij^*}\beta_j)}{\sum_{j=1}^{J} \exp(X_{ij}\beta_j)} \tag{3.71}$$

This particular parametric form of the stochastic utility model is often called the multinomial (or conditional) logit model because it is the multiple choice generalization of the binary logit model. The most commonly used estimation method is the maximum likelihood. Suppose a random sample of individuals and for each individual we observe the choice actually made and the values of attributes associated to each of the alternatives. The likelihood function used to estimate the utility parameters is:

$$Li = \prod_{j=1}^{J} \frac{\exp(X_{ij^*}\beta_j)}{\sum_{j=1}^{J} \exp(X_{ij}\beta_j)} \tag{3.72}$$

The aggregated likelihood function is:

$$L = \prod_{i=1}^{N} \prod_{j=1}^{J} \frac{\exp(X_{ij^*}\beta_j)}{\sum_{j=1}^{J} \exp(X_{ij}\beta_j)} \tag{3.73}$$

Therefore, the above is the maximum likelihood function to be estimated in the case of a choice experiment where the dependent variable measures the most preferred option with respect to the remaining alternatives. If respondents make sequential or repeated choices, we assume independence between observations or elections.

For the contingent ranking, we use an extension of McFadden's conditional logit regression model. In the economics literature, the generalization was proposed by Beggs et al (1981) and further developed by Hausman and Ruud (1987) under the name of *rank-ordered logit model.* The model was independently formulated by marketing researchers (Chapman and Staelin, 1982) who called it the exploded logit model. They developed a

procedure to enhance the estimation of the parameters of the stochastic utility model by exploiting the additional information contained in preference rank ordering of choice set alternatives. This enhacement is achieved by exploiting the additional information contained in preference ranking of alternatives. Particular attention is focused on the incremental contribution of using the additional information contained in the preference rank ordering rather than just employing knowledge of the most preferred option. This estimation methodology can be extended if the researcher has available a complete rank ordering of all alternatives in the decision makers' choice sets.

To exploit the rank ordering information, one must relate ranking behavior to choice behavior. The theoretical justification for relating ranking behavior to choice behavior is provided by a proof reported by Luce and Suppes in 1965. The Luce and Suppes *Ranking Choice Theorem* states that for any rank ordered preference we have:

$$\Pr(a\,b\,c\quad) = \Pr(a \mid C) \cdot \Pr(b\,c\quad) \tag{3.74}$$

where $Pr(a\,b\,c\quad)$ is the probability of observing the rank order of alternative a being preferred to alternative b being preferred to alternative c and so on and $\Pr(a \mid C)$ is the probability of alternative a being chosen from the set of alternatives $C = \{a\,b\,c\quad\}$. This Ranking Choice Theorem enables the probability of a ranking event, $Pr(a\,b\,c\quad)$ to be decomposed into the product of two probabilities -the probability of a choice event $\Pr(a \mid C)$ and the probability of a subranking event $Pr(b\,c\quad)$ By successively applying this Ranking Choice Theorem to the subranking events, one can derive a probability expression

for the ranking event which is the product of the probabilities of $J-1$ choice events, i.e.

$$\Pr(a\,b\,c\quad) = \Pr(a \mid C) \cdot \Pr(b \mid C - \{a\}) \cdot \Pr(c \mid C - \{a\,b\,\}) \tag{3.75}$$

where $C - \{a\}$ is the set of alternatives excluding alternative a. The above equation is equivalent to saying that the probability of the joint ranking event of J alternatives is composed of J-1 statistically independent choice events.

If one applies the Ranking Choice Theorem to the stochastic utility model, assuming that the alternative index j is now interpreted as a serial preference index, it follows that:

$$\Pr ob(U_{i1} \geqslant U_{i2} \geqslant \quad \geqslant U_{iJ}) = \prod_{j}^{J} \Pr ob(U_{ij^*} \geqslant U_{ij}\, for j \quad = j^*\ J \quad) \tag{3.76}$$

The left side is the joint probability that alternative 1 is preferred to alternative 2 which is preferred to alternative 3 and so on to alternative J-1 which is preferred to alternative J for decision maker i. The right side of equation may be interpreted as the statistical definition of the independence of the events $(U_{i1} \geqslant U_{ij}\, j \quad = 1\ 2\, J \quad)$ $(U_{i2} \geqslant U_{ij}\, j \quad = 2\ 3\, J \quad)$ and so on (Chapter 2).

The aim of this paper is to compare the results obtained from a sequential choice experiment with those obtained from contingent ranking, both consistent with economic theory if the design includes the blank card or outside option. In fact, we want to know if it is possible to replicate a contingent ranking, that is, whether two different measurement scale for the dependent variable (most preferred option versus ranked from most to least preferred) satisfy the procedure invariance or, on the contrary, it appears any inconsistency.

This inconsistency, called *procedure preference reversal*, occurs when different methods for measuring a preference yield different results. A robust finding is that these rever-

sals occur with regularity across a number of different measurement methods, yet no satisfactory explanation of this phenomenon exists. Some authors suggest that the current lack of a satisfactory explanation is due to reliance on the common assumption that alternatives are evaluated independently of each other during choice.

3.3.1 Experimental Design

As stated in Chapter 2, in order to obtain efficient estimates, it is indispensable for the experiment to be designed in a way that minimizes the variances and co-variances matrix of the vector of parameters.This is a *sine qua non* condition to be able to compare the results obtained from a choice experiment (conditional logit) and a contingent ranking (rank ordered logit). For this purpose, we undertake two different experiments that should be applied to the same sample. Hence, we prepare two experimental designs in order to obtain two different database: one with the full ranking of alternatives from most to least preferred and the other with the most preferred options from four different choice sets.

For the *contingent ranking*, we design an experiment composed of 50 choice sets with 5 alternatives each. In this case, we obtain four orderings from each respondent ($J-1=4$). The reasoning behind this decision is that we want ten individuals to rank the same choice set; if we assume a sample of 500 individuals ($50*10=500$), we need a total of 50 choice sets (Chapter 2). On the contrary, for the *choice experiment*, we design an experiment with 200 choice sets with 5 alternatives each and, in this case, we need ($n\ \ 4*10=500$) a total of 200 choice sets. This is due to the fact that we want each respondent to select the most

preferred option from four different choice sets. As a result, we also have four orderings or choices (Appendix 3.A).

Another important issue is that one of the five alternatives in each choice set is always the blank card or outside option ("home remedies"). We include the outside option to get consistency with economic theory.

The cognitive process underlying each of the experiments are slightly different because, in the first case, we assume that each individual must completely rank a choice set of five alternatives from most to least preferred while in the second experiment, each respondent must choose the most preferred option from four different choice sets. Once obtained the design matrix, we have to analyze the existence of dominant or inferior alternatives in each choice set. The aim is to eliminate those alternatives in a choice set that are dominant because, otherwise, there could be a loss of information in the trade-off. In fact, we want utility balance criteria to be satisfied and therefore we need prior information about consumers preferences in pharmaceutical market (Chapter 2). Finally, we impose some additional conditions for the construction of choice sets: (i) at least one drug must be a generic version (in both contingent ranking and choice experiment cases, card or alternative one is always a generic and card four varies from branded and generic), (ii) at least one drug must be prescribed by the physician and (iii) at least one drug must be recommended by the pharmacist. Moreover, in each choice set, card five is always the blank card or outside option (Table 3.21).

		Contingent Ranking					Choice Experiment				
		Card 1	Card 2	Card 3	Card 4	Card 5	Card 1	Card 2	Card 3	Card 4	Card 5
Brand	Generic	100%	0%	0%	40%	0%	100%	0%	0%	51%	0%
	Clamoxyl	0%	87%	77%	26%	0%	0%	82%	68%	25%	0%
	Ardine	0%	13%	23%	34%	0%	0%	18%	32%	23%	0%
	Home remedies	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%
Laboratory	Known	58%	56%	46%	40%	0%	44%	52%	53%	51%	0%
	Unknown	42%	44%	54%	60%	0%	56%	48%	47%	49%	0%
	None	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%
Price	0 €	0%	0%	0%	0%	100%	0%	0%	0%	0%	100%
	1 €	47%	19%	29%	35%	0%	37%	34%	30%	35%	0%
	4 €	25%	31%	40%	30%	0%	30%	30%	38%	34%	0%
	20 €	28%	50%	32%	35%	0%	33%	36%	32%	31%	0%
Physician	Prescribed	66%	51%	46%	37%	0%	54%	51%	50%	45%	0%
	Non-prescribed	34%	49%	54%	63%	100%	46%	49%	50%	55%	100%
Pharma	Recommended	51%	62%	34%	51%	0%	46%	46%	53%	55%	0%
	Non-recommended	49%	38%	66%	49%	100%	54%	54%	47%	45%	100%

Table 3.21. Experimental Design Composition

We apply the same conditions to each of the experiments with the aim to be as similar as possible. If there exist differences between the two methodologies, we want them to be easily identified along the measurement scale or estimation process but not in the experiment design.

We ask respondents to firstly rank the five alternatives of the choice set and then select the most preferred option from four choice sets with five alternatives each. We did this way because, according to our opinion, it is more complicated to rank a group of five alternatives than to select just the most preferred option. We preferred respondents to undertake first the most difficult task and afterwards the less complicated. Obviously, there can also be a component of tiredness (or learning) but, in this experiment, it was even more important to apply both experiments to the same individuals.

3.4 Results

Using the choice experiment and the contingent ranking database, we estimate the objective utility function; in particular, we estimate the "main effects" model with the amoxiciline data. We do not consider interactions with socio economic and drugs purchase habits because we are mainly interested in those attributes that are chosen by respondents through cards. Actually, we want to explore the consequences of two different measurement scales methods on the estimated explanatory variables that compose the utility function.

$$\begin{aligned} U_{ij} = & \alpha_i GENERIC_j + \mu_i ARDINE_j + \beta_i LAB_j + \gamma_i PRICE_j \\ & + \delta_i PHYSICIAN_j + \eta_i PHARMA_j + \theta_i BLANK_j + \varepsilon_{ij} \end{aligned} \tag{3.77}$$

Section 3.4.1 displays the estimated parameters using the choice experiment database and contrasts the consistency along the sequential choices. Section 3.4.2 compares the results of the choice experiment with those derived from the contingent ranking (Chapter 2) and discusses the existence of procedure preference reversal.

3.4.1 Conditional Logit Results

From the choice experiment database, we are able to estimate several conditional logit models taking into account the four sequential choice experiments jointly and/or separatelly. Actually, we can estimate the utility function for each of the choice experiments by separate and analyze the choice pattern along them or we can estimate different models taking into account an additional choice experiment each time. Table 3.22 shows the cumulative choice experiments results, that is, the estimated results taking into account the first choice experiment (1), the first two choice experiments (1+2), the first three choice experiments

(1+2+3), the last two choice experiments (3+4) and, finally, we estimate the model taking into account the four choice experiments (1+2+3+4).

	First choice experiment (1)	The first two choice experiments (1+2)	Third & fourth choice experiments (3+4)	The first three choice experiments (1+2+3)	Four choice experiments (1+2+3+4)
GENERIC	-0.15	-0.15	-0.35***	-0.21***	-0.27***
	(0.14)	(0.10)	(0.09)	(0.08)	(0.07)
ARDINE	-0.49***	-0.25**	-0.35**	-0.32***	-0.32***
	(0.19)	(0.12)	(0.14)	(0.10)	(0.09)
LAB	-0.62***	-0.37***	-0.19**	-0.24***	-0.28***
	(0.12)	(0.09)	(0.09)	(0.07)	(0.06)
PRICE	-0.09***	-0.08***	-0.09***	-0.09***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
PHYSICIAN	1.55***	1.50***	1.90***	1.65***	1.67***
	(0.14)	(0.09)	(0.11)	(0.08)	(0.07)
PHARMA	0.81***	0.75***	0.31***	0.63***	0.53***
	(0.12)	(0.09)	(0.09)	(0.07)	(0.06)
BLANK	0.19	0.20	0.20	0.21*	0.16
	(0.21)	(0.15)	0.15	(0.12)	(0.10)
Number of Observations	2195	4390	4380	6585	8770
Log likelihood	-548.37374	-1131.0881	-1058.4956	-1659.88	-2203.9525
Pseudo R2	0.2239	0.1996	0.2492	0.2169	0.2193

*** significant at 1% ( ) Standard Error

** significant at 5%

* significant at 10%

Table 3.22. Cumulative Choice Experiments

Table 3.22 shows that the estimated results taking into account the four choice experiments (1+2+3+4) are all statistically significant at 1%, except for BLANK, and the absolute value of coefficients increases as the number of sequential choice experiments grows. The pseudo R^2 is better for the last two choice experiments (3+4) than for the first two choice experiments (1+2) what suggests the existence of a **learning process.** It is important to point out that GENERIC parameter is not significant for the first two choice experiments while PHYSICIAN and PHARMA are statistically significant at 1% from the beginning. This could be an evidence that, in a first stage, individuals mainly take into account expert advice as the unique decision-making variable and it is just after a learning process that they realize about the existence of other choice attributes. In this sense, it seems as if supplier inducement becomes more dominant than brand loyalty along the drug purchase

process. As a curiosity we can say that, along the interviews, many people first looked for the prescribed alternatives and then valued the rest of attributes.[53]

Table 3.23 shows the estimated results for each individual choice experiment by separate. In this case, the number of observations for each model is exactly the same.

	First CE (1)	Second CE (2)	Third CE (3)	Fourth CE (4)
Generic vs Clamoxyl	-0.15	-0.21	-0.28**	-0.39**
	(0.14)	(0.14)	(0.14)	(0.13)
Ardine vs Clamoxyl	-0.49***	-0.10	-0.38*	-0.26
	(0.19)	(0.17)	(0.20)	(0.21)
Unknown vs Known Laboratory	-0.62***	-0.13	0.05	-0.42***
	(0.12)	(0.12)	(0.13)	(0.12)
Price	-0.09***	-0.07***	-0.10***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)
Physician Prescription	1.55***	1.45***	2.03***	1.79***
	(0.14)	(0.13)	(0.15)	(0.15)
Pharmacist Recommendation	0.81***	0.66***	0.42***	0.21*
	(0.12)	(0.12)	(0.12)	(0.12)
Blank Card	0.19	0.17	0.37*	0.08
	(0.21)	(0.21)	(0.22)	(0.21)
Number of Observations	2195	2195	2195	2185
Log likelihood	-548.37374	-575.56243	-514.81796	-536.40156
Pseudo R2	0.2239	0.1854	0.2714	0.2373

*** significant at 1% ( ) Standard Error

** significant at 5%

* significant at 10%

Table 3.23. Individual Choice Experiment Estimates

What is valuable to explore is the existence of any *structural change* along the sequential choice experiments; that is, is the choice pattern constant along the choice experiments or there exists **tiredness or a learning effect**?. In order to contrast this hypothesis, we undertake several likelihood ratio tests (Table 3.24):

$$LR = -2[L_{restricted} - L_{unrestricted}] \tag{3.78}$$

[53] We let for future research, the exercise to explore the existence of lexicographic preferences.

where the restricted model is one of the cumulative choice experiments (Table 3.22) and the unrestricted model is the sum of the corresponding individual choice experiments (Table 3.23). In the first test, we compare the first two choice experiments and we realize that, according to the LR test, the choice pattern is similar (H_o accepted); the same happens with the last two choice experiments (3&4).

However, when we contrast the choice pattern along the first three models, we can not accept the null hypothesis any more (H_o accepted). Therefore, the unrestricted model must be accepted because the three individual choice experiments are supposed to give different results. Consequently, the same happened with the four choice experiments taking into account the restricted and unresctricted models. This is an evidence that there exists a structural change after the first two choice experiments possibly due to a learning process or tiredness.

Restricted Model	Unrestricted Model	d.o.f.	Likelihood Ratio	Critical Value	H_0
1+2	1,2	14	14.30	23.68	Accepted
3+4	3,4	14	14.55	23.68	Accepted
1+2+3	1,2,3	21	42.25	32.67	Rejected
1+2+3+4	1,2,3,4	28	57.59	41.38	Rejected

Table 3.24. Likelihood Ratio Tests

One likely explanation for this structural change could be the fact that we estimate the different models taking into account independence across choices, that is, we estimate the models as if each choice is independent from the rest. We suppose independence between observations since choices assumed not to be correlated. Another possibility could be to consider a kind of **Bayesian learning process** whereby individuals update their preferences with respect to experts advice and brand loyalty along the sequential choice experiments.

Under this condition, we should assume that noisy terms are correlated across observations or choices. Nowithstanding, we let this question for further research.

3.4.2 Comparison

In this section, we want to compare the estimated results obtained from using the four choice experiments with the results derived from the full contingent ranking displayed in Chapter 2. If we look at significance level, we realize that contingent ranking parameters are all statistically significant while in the choice experiment all are significant expect for BLANK parameter. As far as we understand, this is a consequence of the main difference between choice experiment and contingent ranking: the measurement scale for dependent variable. Remember that contingent ranking involves the ordering of all alternatives included in the choice set while choice experiment only requires the choice of the most preferred. In the former model, BLANK parameter is significant at 1% what implies that respondents should be paid in order to switch from a chemical drug to the home remedy; in the latter model, the interpretation is that individuals always prefer a chemical compound than the outside option.

Afterwards, we undertake a *mean comparison test* in order to conclude whether the estimated coefficients could be considered equal in absolute value. The sign of the parameters is the expected one in both models, however, the absolute value significantly differs. Confidence interval tests do not accept that the estimators of both models are equal, except for GENERIC and ARDINE parameters because they both enter in the 95% confidence interval. The rest of coefficients are statistically different (Table 3.25).

	Choice Experiment			Full Ranking		
	Coefficients	95% Confidence Interval		Coefficients	95% Confidence Interval	
GENERIC	-0.2656	-0.3973	-0.1339	-0.3706	-0.5094	-0.2317
ARDINE	-0.3248	-0.5069	-0.1428	-0.2549	-0.4387	-0.0711
LAB	-0.2775	-0.3963	-0.1587	-0.1049	-0.2223	0.0126
PRICE	-0.0845	-0.0937	-0.0754	-0.0385	-0.0460	-0.0310
PHYSICIAN	1.6672	1.5292	1.8052	0.9480	0.8187	1.0773
PHARMA	0.5318	0.4139	0.6496	0.2884	0.1688	0.4080
BLANK	0.1554	-0.0502	0.3611	-1.4489	-1.6691	-1.2287

Table 3.25. Four Choice Experiments versus Full Contingent Ranking

This result suggests the existence of *procedure preference reversal*, an inconsistency by which different methods for measuring a preference yield different results. A robust finding is that these reversals occur with regularity across a number of different measurement methods (rating, matching and choice methods), yet no satisfactory explanation of this phenomenon exists. However, we find inconsistency between the measurement scale used in the contingent ranking and the choice experiment, both of them classified as choice methods. From the results we realize how important the measurement scale for the dependent variable becomes and the influence it exerts in the appearance of procedure preference reversal.

3.5 Concluding Remarks

The empirical aim of this paper is to compare the results of two different stated preference discrete choice approaches. They differ in the measurement scale for the dependent variable and, therefore, in the estimation method, despite both use a multinomial logit. One of the approaches uses a complete ranking of full profiles (**contingent ranking**), that is, individuals must rank a set of alternatives from the most to the least preferred, and the other uses a first-choice rule in which individuals must select the most preferred option from a

choice set (**choice experiment**). Our null hypothesis is that *"if two different measurement methods are used to quantify the same thing, they should yield the same outcome"*.

Two common measurement methods, as stated in Section 3.2, are rating scales and choices between alternatives. A desirable property of such measurement devices is that they are consistent in outcome. With rating scales, one item is evaluated at a time and with choices methods, direct comparisons are made between items and one is chosen in preference to the other. A robust finding is that these two methods yield different outcomes. This inconsistency is called *procedure preference reversal* and no satisfactory explanation of this phenomenon exists.

In this paper, we find evidence that preference reversal also raises when comparing two choice methods: a choice experiment and a contingent ranking. In this case, the two measurement methods differ in the measurement scale for the dependent variable because one ask for a complete rank of alternatives while the other implies the choice of the most preferred option.

Usually, this inconsistency is a violation of one of the underlying assumptions of formal choice theory, *independence of alternatives.* Actually, some authors suggest that the current lack of satisfactory explanation is due to reliance on the common assumption that alternatives are evaluated independently of each other in choice methods.

This inconsistency poses a practical problem for the accurate measurement of people's preferences: which measure is the correct one? We let the answer for future research.

3.A Appendix. Choice Experiment

This appendix displays an example of a set used for the choice experiment. Remember that each individual should choose the most preferred option from four different choice sets similar to the one displayed in Figure 3.9.

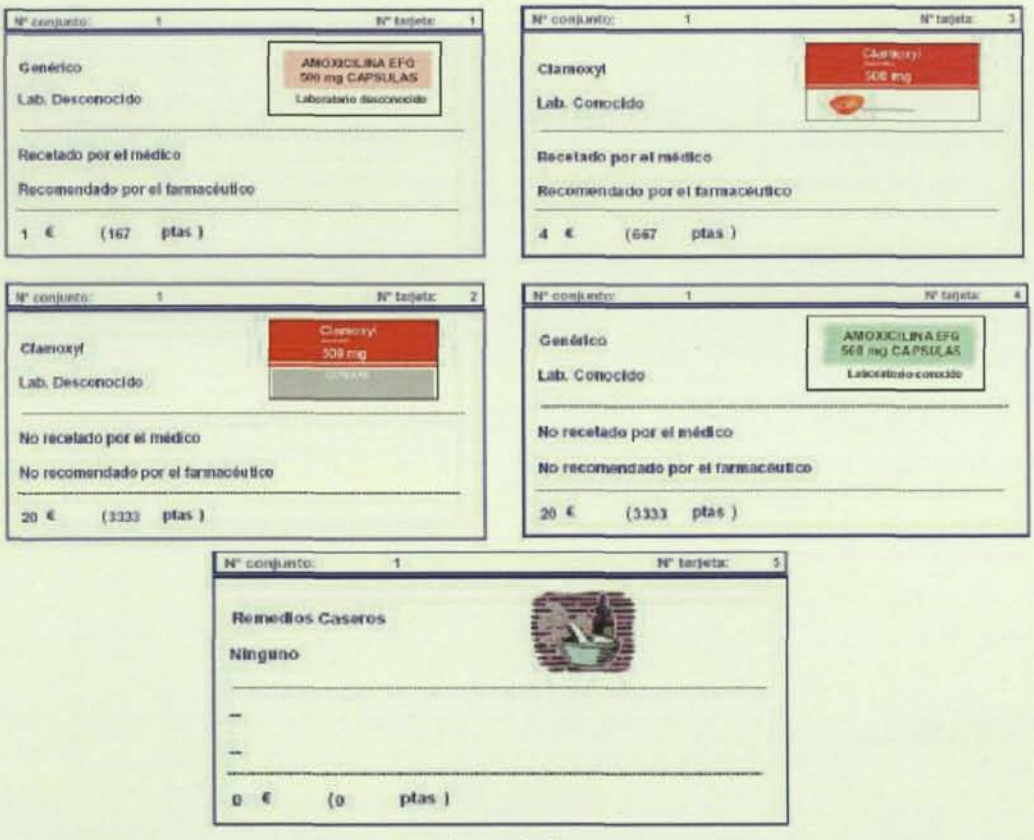

Figure 3.9.

Example:

Choice Set Number: 1
Most Preferred Card:
Choice Set Number: 2
Most Preferred Card:
Choice Set Number: 3
Most Preferred Card:
Choice Set Number: 4
Most Preferred Card:

Chapter 4
Future Research

In this thesis, I analyze the demand for pharmaceutical drugs from different perspectives. The first chapter explores, from a theoretical point of view, the impact of a new reimbursement mechanism, the RP system, on the demand for pharmaceuticals and effective price competition. The second chapter uses a stated preference database with the aim to examine the importance of supplier inducement and brand loyaty in the process by which patients decide among commercial drugs at the chemist's. Finally, the third chapter proceeds to compare two stated preference discrete choice approaches that differ in the measurement scale for the dependent variable.

Under the new scenario of easier access to information, patients become more demanding and are even capable to question physician's prescription. Furthermore, new regulation also encourages patients to adopt an active role in the decision between trade-name and generic drugs. In this sense, health care systems are transitioning from a physician-directed system to a patient-directed one and consumers preferences become an interesting issue of analysis not only for health economists but also for new empirical industrial organization economists.

As far as we know, this is the first empirical work that undertakes a stated preference discrete choice survey to obtain data on consumers preferences. Until now, empirical literature in pharmaceuticals demand has been very limited and always focused on the behavior

of either physicians and pharmacists. Furthermore, all of them use revealed preference data to estimate the objective utility function.

Our study recruited a total sample of 439 adults from 20 to 65 years old. From those, 315 belong to general population and 124 have high blood cholesterol; the latter were mainly found in hospitals and primary health care centers.

After the empirical work developed in Chapter 2, we realize that there exists enough variability for a more in-depth clustering analysis. Moreover, in Chapter 3, we let some questions opened for future research, for example, a satisfactory explanation for the appearence of procedure preference reversal among choice methods. For this purpose, we should better understand the relationship between independence from irrelevant alternatives (IIA) and the cognitive process underlying choice experiment and contingent ranking, if any. Using the same database, I would proceed to estimate our utility function using a random coefficients model and check the existence of lexicographic preferences.

In order to answer which method is the correct one, we should undertake predictions or forecasts and compare those obtained from contingent ranking, choice experiment and random coefficents parameters.

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