UNIVERSITÀ DEGLI STUDI DI VERONA

DIPARTIMENTO DI SCIENZE ECONOMICHE

Sede di Verona

Corso di Laurea Magistrale in Economics

Optimal ticket pricing in the sport industry. The case of the Italian Serie A

Relatore
Ch.mo Prof. Angelo Zago

Laureando
Federico Silvestri, VR403236

Anno Accademico 2016/17

Table of Contents

Figures and Tables

INTRODUCTION

Football[1] represents much more than a rolling ball. The raising media interest and increasing global visibility of European football have crucially shaped an actual industry, which in the last decade has been fueled by a growing foreign investment (UEFA, 2017). While team success was due to owners' grants and donations until a decade ago, the Financial Fair Play (FFP) regulations have transformed the framework, in that clubs sporting competitiveness is backed by actual *firms*, who are forced to find income streams to be able to invest on the players market[2] (Drayer et al, 2012).

In such context, the contribution of gate receipts to the overall proceeds is not keeping the pace with the other income channels, such as broadcasting rights and commercial revenues (UEFA, 2017). Nonetheless, the football matches continue to be the crucial product designed by each club. If sport competitions did not take place, there would be nothing to broadcast, sponsors would not gain visibility by means of the association with a club, T-shirts and other merchandizing items would unlikely be sold.

Since matchday attendees represent a core part of such product (Borland and MacDonald, 2003), ticket pricing strategies must be carefully evaluated, given the possible spillovers that they may generate on other revenue sources.

In such framework, Economics could play a crucial role in assisting sport clubs in their complete business-driven transformation, by means of the application of theoretical insights and by borrowing common practices from other industries that share the same issues (see Courty, 2000 and Drayer et al, 2012).

Consistently with such purpose, the objective of this Economics Master thesis is twofold: first, to explore the game tickets market and to understand how football clubs should optimally set game tickets prices, considering that such choice could affect other revenue sources; second, to verify if and how a more flexible and demand-driven pricing scheme may improve the economic results of football clubs, consistently with the overall profits maximization objective.

The latter issue derives from the observation of the price menus offered by several football clubs participating to the Italian top league (Serie A). Figure 0.1 shows the game-tickets pricelists published by Hellas Verona before the starting of the 2017-18 season, on the last page of the brochure presenting the season tickets sale. Two price menus are offered: the first one for matches against "regular" opponents, the second one for events in which the visiting team is one of the most prestigious Italian clubs. The underlying implication is that fifteen matches[3], belonging to the first price category, are considered as homogeneous goods that entail the same

---

[1] With the term "football" this thesis refers to European football, which is commonly known as "soccer" in other parts of the world.

[2] The FFP regulations were introduced in 2009 by the European Union of Football Associations (UEFA) in order to reduce the operating losses that characterized the football industry, where the private spending capabilities of wealthy owners were crucial in determining teams' success. In a nutshell, the main implication of the FFP is that clubs must comply with several economic indicators in order to participate to the European football competitions. The purpose of such indicators is to guarantee the financial health and autonomy of clubs.

[3] The Italian Serie A is composed by twenty football clubs. Every club faces each of the other nineteen participants twice, in a home and an away match. Therefore, nineteen home matches take place in a season, for each club.

tickets demand. Is it so? Was Hellas-Genoa, that took place on a December Monday night, as attractive as the city derby against Chievo Verona, that was scheduled on a warmer March Saturday night? Since the former match exhibited 2,608 game tickets sold, while in the latter case 8,805 occasional attendees showed-up[4], the pricing model of Hellas Verona apparently did not effectively deal with some demand fluctuations that occurred, thus there may be some room for optimizing prices.

However, it is not clear whether an optimization procedure may be worth of being implemented either, since several other issues concerning, for instance, the ticket price sensitivity of attendees should be answered. Furthermore, the concept of "optimal" ticket price is not straightforward, and it crucially depends on several assumptions on the club's objectives and behavior.

Figure 0.1 Hellas Verona Game Tickets Pricing

HELLAS VERONA FC

LISTINI PREZZI BIGLIETTI in €uro

SETTORE	Prevendita	Gara	BIGL. FASCIA ALTA Prevendita	BIGL. FASCIA ALTA Gara
POLTR.ME EST INT	40	45	75	80
POLTR.ME EST RID	25	28	50	55
POLTR.ME EST Under14	2	3	8	10
POLTRONE EST INT	25	28	40	45
POLTRONE EST RID	13	15	30	35
POLTRONE EST Under14	0,5	0	8	10
TRIBUNA SUP. EST INT	20	23	30	35
TRIBUNA SUP. EST RID	13	15	20	23
TRIBUNA SUP. EST Under14	2	3	8	10
CURVA SUD INT	18	20	22	25
CURVA SUD Over60	18	20	22	25
CURVA SUD Under16	18	20	22	25
CURVA SUD Under14	2	3	8	10
POLTR.ME OVEST INT	65	70	85	90
POLTR.ME OVEST RID	40	45	60	65
POLTR.ME OVEST Under14	3	5	8	10
POLTRONE OVEST INT	32	35	50	55
POLTRONE OVEST RID	22	25	35	40
POLTRONE OVEST Under14	2	3	8	10
TRIBUNA SUP. OVEST INT	20	23	30	35
TRIBUNA SUP. OVEST RID	13	15	20	23
TRIBUNA SUP. OVEST Under14	2	3	8	10
PARTERRE EST	10	13	13	15

4 gare

Riduzioni:
Donne: Qualsiasi età
Under 14: Per i nati dopo il 20/08/2003
Under 16: Per i nati dopo il 20/08/2001
Over 60: Per nati prima del 20/08/1958

Listino gare fascia Alta
Per le gare contro Milan, Inter, Juventus e Napoli verranno applicati i prezzi di fascia alta. La società si riserva di variare i prezzi dei due listini durante la stagione sportiva per una o più partite.

Source: www.hellasverona.it/files/campagna_abbonamenti_2017_2018.pdf[5]

Such questions are interesting in that they lie between two different topics of the sport events literature. The first one concern the explanation of an apparently inefficient pricing behavior of sport clubs: if teams are

[4] See Chapter 3 for the data sources.
[5] Retrieved in July 2017.

believed to be monopolist in the game tickets market (see Chapter 2), standard undergraduate microeconomics textbooks suggest that the equilibrium should never lie in the inelastic part of the demand curve. However, as Chapters 2 explains, inelastic pricing is a recurrent result of the empirical sport events literature (see, among the others, Drayer and Rascher, 2013). Several explanations have been proposed by the literature, from the questioning of the profits maximization objective, to the role of complementary goods and the possible existence of network externalities between different groups in a football match (see Budzinski and Satzer, 2011).

On the other hand, several studies concern the introduction in the sport industry of pricing strategies that are commonly exploited by capacity-constrained service firms operating in different markets, such as dynamic ticket pricing. While such possible implementation is surely reasonable, given the existence of common issues and features (see Drayer et al, 2012), a successful adoption should be aware of the factors that drive the optimal pricing decision.

The thesis tries to answer the above questions by examining the football industry and the sport events literature in order to design a (simple) theoretical model of optimal price determination. Moreover, the data collected allow to perform an econometric estimation of the demand for tickets in the Italian Serie A, that can be exploited to quantify the impact of the current pricing strategies adopted and to simulate the effect of a further optimization procedure. The process proposed connects the two lines of debate reported above, in that it is consistent with the supposed pricing objectives of the club, represented by the estimated value of the seasonal elasticity of demand.

Three pillars are crucial in the developing of the method proposed: theoretical modeling, demand prediction and optimal price setting.

The optimal price is theoretically determined by a constrained profit maximization problem, where unmodeled other ticket related revenue sources are included in the objective function; the solving procedure allows to derive an optimal price that is consistent with the inelastic outcome, and that considers the effect of a ticket price increase on the other revenue sources.

Tickets demand is predicted by a panel fixed-effect econometric model, with instrumental variables. The relevant feature of the econometric model is the inclusion of demand factors whose values are available to the football club when ticket prices are usually published.

Eventually, three types of optimal prices are chosen to run the simulations: the tickets revenues maximizing price, which would be chosen by a mono-product monopolist, i.e. by a club that does not consider the effect of attendance on other sources, the optimal fixed price, i.e. a price consistent with the seasonal elasticity level, applied to all matches, and an optimal variable price that restores the category elasticity value in every match[6].

[6] Consider the pricelists of Hellas Verona presented above. The thesis assumes that the management of the club chose the optimal elasticity value on the basis of the average demand in that category; however, within-category demand fluctuations imply deviations from that value at the match-level. The optimal variable price is the one that restores the category-specific elasticity value (see Chapter 2).

While additional expertise, more sophisticated predictive tools and more complete data are likely to remarkably improve the work presented in the next chapters, such thesis displays a route that could be followed by any football club seeking to optimize its pricing structure.

The thesis could be of interest for clubs that may integrate the method with data concerning other revenue sources and the price discrimination strategies, which are not considered here due to data availability[7].

Moreover, although the thesis focuses on the outcomes concerning the game tickets market, the work performed sheds some lights on the relation between attendance and other related revenues, thus generating some inputs for possible research works exploring such related topic.

The thesis is composed by four chapters.

Chapter 1 examines the European football industry, especially focusing on the different revenue sources of professional football clubs and on the concept of the "sport demand". The resulting discussion allows to base some hypothesis on the relationship between stadium attendance and other revenue sources.

Chapter 2 exploits the above discussion to design a simple theoretical model that is consistent with the inelastic pricing result found by the empirical literature. Moreover, the main pricing strategies, which sport clubs borrow from capacity-constrained service firms belonging to other industries, are examined and discussed.

Chapter 3 presents the econometric model that allows to derive a tickets demand equation, by predicting the potential demand and estimating the ticket price sensitivity.

Chapter 4 connects the previous two sections in order to evaluate the consistency of the estimates with the theoretical framework, to run the simulations of interest and to discuss the results.

Finally, the conclusion summarizes the whole work, highlights the main limitations and suggests some other research paths that could be followed to continue the work.

[7] Chapter 2 discusses the price discrimination strategies implemented by sport clubs, especially tier pricing, bundling and market segmentation. The lack of publicly available data concerning sales for each price category of the menu is a common limitation in the sport events literature (Drayer and Rascher, 2013).

Chapter 1

THE FOOTBALL INDUSTRY

1.1 Introduction: the economic profile of European professional football

Football is among the most popular sports in the world. Amid the fifty most attended global sports events or leagues, twenty-nine are related to football; twenty-one took place in Europe, and sixteen of them concerned football[8]. In Italy, 1,353,866 people are registered members of the Federazione Italiana Gioco Calcio (FIGC), and 19.8% of Italian boys in the 5-16 age bracket are registered football players[9]. This chapter provides a review of the relevant data regarding the European football industry. After a broad analysis on aggregate revenues, costs and profits, the examination focuses on the various revenue sources of a typical football club, especially on the one related to the matchday activity. The investigation is first run at the European level, focusing on the Italian Serie A in comparison with the other top leagues (English Premier League, German Bundesliga, Spanish La Liga, French Ligue1), and eventually the top-clubs' data are evaluated. The last part of the chapter focuses on the demand for football and on the role of attendance as a driver of the other revenue sources.

The football industry revenues at the European level have grown by 595% in the last twenty years, at a growing rate[10], especially in the last decade. Table 1.1 shows revenues, costs and profits data of the five European top national leagues. Focusing on revenues, it is possible to notice the massive growth of the last six years (which typically coincide with two "TV cycles", see next paragraph): proceeds grew by an average of 47%, with a certain degree of variability (e.g. +81.9% in England, +24.9% in Italy). Such outcome implies different revenue levels among the top European national leagues, with the English Premier League that is way ahead the others, and overcome only by the NFL (American football) and MLB (American baseball) among all the sport competitions of the world[11].

[8] (UEFA, 2017), pp.40-41
[9] (AREL, FIGC, Pwc, 2017), p.28
[10] (UEFA, 2017), p.66
[11] (AREL, FIGC, Pwc, 2017), p.46. Considering average revenue per club, among the top 10 sport competitions there are the main American ones (related to American football, baseball, basketball and ice hockey) and the main European football leagues (English Premier League, German Bundesliga, Spanish La Liga, Italian Serie A, French Ligue1).

Table 1.1: Revenues, Costs and Profits. Country-level, top-tier leagues data (2015)

	Revenues		Wages		Operating Costs		Net Profits/Losses		
Country	Club Avg	Avg six-year growth rate	Club Avg	W/Revenues	Club Avg	O.Costs/ Revenues	Club Avg	# Teams with net profits	#Teams with net losses
England	220.3	81.9%	134.5	61%	49.8	23%	4.4	13	7
Germany	134.5	55.6%	69.5	52%	50.9	38%	4.1	11	7
Spain	102.4	36.6%	61.9	60%	33.4	33%	3.2	14	6
Italy	95.2	24.9%	65.5	69%	31.4	33%	-14.6	7	13
France	70.9	35.6%	47.9	68%	22.9	32%	-3.2	9	11

Source: (UEFA, 2017) and Arel, Pwc, FIGC (2017). Figures are in €millions.

As shown in Table 1.1, the Italian Serie A is falling behind the other top European leagues. The result has been replicated on the pitch, especially at the beginning of the second decade of the new century, when Italy was relegated to the fourth place of the UEFA Ranking for clubs, threatened by France and Portugal, and only recently recovered the third position.

Table 1.2 displays fundamental figures of the top European clubs, contained in UEFA (2017), which reports data of the top twenty teams for each variable. It shows that five out of the ten top teams for recurrent revenues (i.e. excluding capital gains on player trading) belong to the English Premier League, and Juventus, at the tenth place, is the only Italian club. With aggregate revenues of the European football industry being €16.9 billion in 2015[12], the proceeds of the twenty top teams represent the 40% of the industry.

Table 1.2: Top 20 teams by Recurrent Revenues: Wages, Operating Costs, Profits&Losses (2015)

			Wages			Operating costs		Profits/Losses		
Club	Country	Revenues	Wages	W/Revenues	Multiple of League Average	O.Costs	O.Costs/Revenues	Operating P/L	Net P/L	KPMG's Enterprise Value
Real Madrid	SPA	578	289	50%	4.7	199	34%	90	42	2,895
Barcelona	SPA	561	340	61%	5.5	162	29%	58		2,688
Manchester United	ENG	521	266	51%	2	111	21%	143	-22	3,004
Paris Saint-Germain	FRA	484	255	53%	5.3	109	23%	120		948
Bayern Munchen	GER	474	236	50%	3.4	186	39%	52	24	2,367
Manchester City	ENG	461	276	60%	2.1	121	26%	64		1,909
Arsenal	ENG	449	250	56%	1.9	118	26%	80	24	1,882
Chelsea	ENG	413	284	69%	2.1	122	30%		-30	1,524
Liverpool	ENG	388	216	56%	1.6	86	22%	86	75	1,260
Juventus	ITA	325	198	61%	3	67	21%	59		1,158
Borussia Dortmund	GER	281	118	42%	1.7	124	44%	38		917
Tottenham Hotspur	ENG	258	141	55%	1	70	27%	47		978
Schalke 04	GER	219	111	51%	1.6	95	43%		23	663
Milan	ITA	217	164	76%	2.5	86	40%	-48	-89	504
Zenit St. Petersburg	RUS	196	113	58%	3.2	No data (Out of Top 20)		57	26	
Wolfsburg	GER	191	120	63%	1.7	No data (Out of Top 20)				
Roma	ITA	181	137	76%	2.1	62	34%	-17	-41	433
Bayer Leverkusen	GER	176	No data (Out of Top 20)			55	31%	32		
Internazionale	ITA	172	120	70%	1.8	65	38%		-140	407
Atletico Madrid	SPA	165	No data (Out of Top 20)			No data (Out of Top 20)				771

Source: UEFA (2017) and KPMG (2017). Figures are in €million

12 (UEFA, 2017), p.66

At the same time, wages, which represent 62% of the net costs of European clubs, have grown by seven times in the last twenty years, absorbing the 65% of the revenues growth. The predominant position of English football is such that clubs ranked below the ninth position in the English Premier League can afford higher wages than teams classified between the fifth and eighth place in all the other leagues[13]. The German Bundesliga, the Spanish La Liga and the Italian Serie A shows similar figures in absolute value, but the incidence of wages on revenues is much lower in the former.

This is mirrored by the club-level figures (Table 1.2): the top ten clubs by wages are the same top ten clubs by recurrent revenues, and they display wages-revenues ratios between 50-70%. Such teams, whose players wage policies are often considered as unsustainable by the media, exhibit the lowest ratios: salaries are backed by a solid recurrent revenue structure. When it comes to Italian clubs, Juventus payroll appears much more sustainable than the one of the others (Roma, Internazionale, Milan): the current Italian champions displays a wages/revenues ratio of 61% (in line with the European top clubs), while the other prestigious Italian teams, whose payroll is much lower, exhibit a ratio of more than 70%. A glance at the wages as multiples of league average demonstrate the equality of the English Premier League: the high wages of the six English clubs appearing in table 1.2 are at most the double of the national top-tier average; on the other hand, it is quite clear why Bayern München, Juventus, Paris Saint Germain and Barcelona/Real Madrid dominated the last editions of their national tournaments, with the only exception being Atletico Madrid. The above teams can afford salaries that are at least three times the average of their league. If player wages are considered a proxy for the sporting value of a team, the economic power of such clubs translates into a competitive advantage on the pitch.

As it is often reported by the media (e.g. the well-known Neymar deal[14]), transfer fees have constantly increased in the last years, reaching astonishing levels. However, the average incidence of net transfer costs (the result of profits/losses from player trading, amortization and other transfer-related income/costs) on operating revenues has not grown at all: the average figure was 2.6% in 2015, the lowest level in the 2009-2015 period[15]. This is somehow consistent with the view according to which, if assets value represents their ability to generate revenues, the increasing player transfer fees are reflecting the growing proceeds that are expected to be produced in the industry, since players are the core of the football entertainment product.

Other operating costs represents the 32% of the aggregate outlays (see Table 1.1 for league-specific figures), and their incidence on revenues has slightly decreased in the last years[16]. Such broad category is related to facilities ownership (amortization/depreciation) and/or costs (maintenance, rent)[17], administrative costs, outlays necessary to run the matchday and commercial businesses (matchday expenses, merchandizing costs, marketing…)[18]. German top-tier teams are the ones with the highest other operating costs; the figure is

[13] (UEFA, 2017), p.88, 93

[14] In the summer of 2017, Paris Saint German bought the playing rights of the Brazilian football player Neymar from Barcelona, for the current world-record fee of €220 million.

[15] (UEFA, 2017), p.99

[16] (UEFA, 2017), pp.88, 101

[17] The stadium ownership (see paragraph 1.3) crucially affects such operational cost breakdown: stadium property implies high amortization costs but prevent the club to pay annual rental fees for the arena. The same consideration applies to training facilities.

[18] Merchandizing costs highly depend on the type of contract stipulated with technical sponsors (see paragraph 1.4)

similar to the one related to English clubs, though the incidence on revenues is much lower for the latter. Club-level figures confirm this state of affairs: German teams spend higher shares of their revenues on operating costs other than wages.

The analysis of the operating profits shows the positive impact of the FFP regulations on clubs' underlying profitability. Until 2011, the football industry was characterized by operating *losses* of about two-three hundreds of millions; from the introduction of the FFP, the losses immediately decreased, and the fiscal years 2014-15 were characterized by operating profits of around seven hundred million: as a result, the FFP regulations cut net losses by 81%[19]. However, Table 1.1 shows that in each league there are still many clubs that experience bottom-line losses. Italian teams are especially experiencing remarkable losses, in comparison with their peers belonging to the other top-tier leagues, and two of the top ones (Internazionale and Roma) have been under the so-called "settlement agreement" procedure[20].

Club-level data confirm the improvement of the operational profitability: most of the top-teams by revenues report substantial operational profits. Bottom-line profits, on the other hand, are more variable and, according to UEFA (2017), they highly depend on capital gains on players sale[21].

It is possible to summarize all these figures with the enterprise value estimated by the consulting firm KPMG[22]: most valued teams are the ones that report higher revenues, with high-but-sustainable wages, which allow them to boost revenues by winning competitions, and positive operational profits. On the other hand, prestigious teams such as Milan and Internazionale, despite their winning history, are remarkably less-valued.

1.2 Revenue sources of a professional football club

The key recurrent revenue sources of a professional football club can be divided in three main groups: broadcasting rights, commercial revenues (i.e. deriving from merchandising activity and sponsorship) and those related to the matchday activity (gate revenues, concessions sold inside the stadium, hospitality services... see next paragraph). Capital gains on players trading are another crucial revenue source: the production or scouting of young talents and their future sale represents a vital part of the business for many small clubs in the top leagues, and for top clubs in less prestigious national leagues. However, such revenues are technically considered as "windfall gains".

Broadcasting rights are sold by the football league (e.g. Serie A) to domestic and international broadcasters; they represent the right to broadcast live matches or their highlights on tv, radio, web, usually for three years. The amount of money that medias are willing to pay to secure the rights has continued to grow, and football leagues have sought to make their product more appealing, e.g. by scheduling matches on different

[19] (UEFA, 2017), pp.107-108

[20] If a football club does not comply with the FFP regulations, the settlement agreement procedure starts: UEFA inflicts sanctions and the two parties agree on a plan to conform with the FFP indicators.

[21] See, for instance, the Pogba deal: in the summer of 2016 Juventus sold Paul Pogba, whose balance sheet value was almost zero, to Manchester United for more than €100million. In other words, the capital gain represented about a quarter of Juventus's recurrent revenues.

[22] See KPMG (2017)

moments of the weekend, or at times such that they can be broadcasted at prime-time in other parts of the world. UEFA (2017) shows that national broadcasting rights have exploded in the top leagues: since 2009 to the current season they increased by 188% in England, 156% in Spain, 55% in Italy, 173% in Germany[23].

Table 1.3 displays the revenue mix of top-tiers national leagues. English clubs are benefiting of an extraordinary advantage in terms of broadcasting rights, due to the appeal of the English Premier League. Serie A is at the second place, with Bundesliga and La Liga that are catching-up. Italian and English clubs share the dependence of their revenues on broadcasting rights, which represent more than half of them (if UEFA broadcasting rights are included, see below).

Table 1.3: Revenue mix. Country-level, top-tier leagues data (2015).

Country	Broadcasting*		Commercial		Gate Receipts	
	Club Avg	%Revenues	Club Avg	%Revenues	Club Avg	%Revenues
England	108	49%	64.8	29%	35.9	16%
Germany	36.1	27%	55.7	41%	26.4	20%
Spain	36.7	36%	28.1	27%	20.9	20%
Italy	47.7	50%	19.3	20%	10.2	11%
France	24.9	35%	27.3	38%	8.4	12%

Source: (UEFA, 2017). Figures are in €millions.

**Excluding UEFA rights. Such exclusion is among the reasons why the percentage shares do not sum up to 100%. Other revenues including several items such as donations and grants are also excluded.*

An important issue concerning such rights is their distribution among teams belonging to the league. Such problem is a constant source of harsh debate among clubs, given the amount of money at stake.

The English mechanism is probably the most equal in the top European Leagues: 50% of the rights are distributed equally, 25% on the basis of how many times a club's match is live-broadcasted[24], and the remaining 25% on the league position at the end of the championship.

According to the Italian mechanism, 40% of the revenues are distributed equally, 30% on the basis of an estimated possible number of supporters, and 30% depend on the current and past sporting performances[25].

The Spanish La Liga has started to collectively sell the rights from the 2015-16 campaign, reforming a system were clubs sold them individually[26] (with a huge advantage for the top teams, Real Madrid and Barcelona).

UEFA (2017) figures are not surprising given what was discussed above: Barcelona and Real Madrid are the two teams that in 2015 (i.e. before the reform) were receiving the highest amount of broadcasting rights, almost

[23] (UEFA, 2017), p.73

[24] In England, less than 50% of matches are broadcasted live. See http://www.calcioefinanza.it/2016/05/24/ripartizione-diritti-tv-premier-league-2015-2016/

[25] However, the distribution scheme has been reformed recently. See http://www.calcioefinanza.it/2017/10/30/diritti-tv-nuova-ripartizione-serie-a-riforma-lotti/

[26] See https://www.tifosobilanciato.it/2016/04/20/diritti-tv-in-europa-valori-e-criteri-delle-big-5-a-confronto/4/

4 times their league's average. Moreover, seventeen out of the top twenty European clubs for broadcasting revenues are English ones, whose share is distributed in a much more uniform way. The remaining team in the top twenty is Juventus[27].

Another share of the broadcasting rights that a club can receive concerns those teams that qualify for the European competitions (i.e., UEFA Champions League and Europe League). UEFA sells the broadcasting rights for such competitions, and distributes the proceeds on the basis of two factors: annual sporting performance in the competition, and the amount that the relative national broadcaster paid for the right to display the matches on national TV. For instance, after the season 2014-15 Juventus received the highest share of UEFA rights, since it qualified for the final match of the Champions League and benefited from the outstanding fee that the Italian media company Mediaset paid for the 2014-2017 cycle rights[28].

Therefore, broadcasting rights are a source of income that is not directly dependent on the business management of a football club: national rights are sold by the league, and the amount received depends on its overall appeal; UEFA rights depend on sporting performances (qualification to the European competitions and accomplishments in them) and on the sum that a national broadcaster is willing to pay for them. Consequently, Italian and English teams highly depend on a source of income that is not directly related to their own business decisions.

When it comes to commercial revenues, German clubs are on average near to English ones, while Italian teams are behind Spanish but also French ones: such outcome could testify an inability to diversify their business, but it also means that there is room for improvement in the area, given the high popularity of football in Italy. The high weight of commercial revenues on the aggregate figure for German teams may be a consequence of the high operating costs that they report (see Table 1.1).

A glance at the revenue mix in Table 1.3 shows that the management of Spanish and German teams is more equilibrated among the revenue sources. However, focusing on club-level data (Table 1.4), it is clear that the richest English teams have a remarkable commercial structure, which allow them to rely on strong channels of income even in periods characterized by disappointing performances on the pitch[29]. When it comes to Italian teams, it seems that Juventus managed to reach the top European clubs mainly because of its dominium at the national level and the satisfactory international performances, since its commercial revenues are far from the ones of the other top clubs; the same holds for the matchday revenues. Milan, instead, despite the disappointing achievements at the end of the Berlusconi era, could rely on commercial revenues almost equal to Juventus's ones. On the other hand, broadcasting rights are dramatically crucial for Roma and relevant for Internazionale.

[27] (UEFA, 2017), p.75
[28] (UEFA, 2017), p.77
[29] E.g.: Manchester United is performing poorly in the UEFA Champions League since the 2013-14 campaign, but it has always showed high revenues and strong spending capabilities on the players market.

1.3 Matchday-related revenues

Matchday related revenues are the proceeds that *directly* derive from the organization of sport events (i.e. matches) inside the stadium. Tables 1.3 and 1.4 show that such revenue source usually displays the lower weight in teams' proceeds, though not negligible[30].

Italian and French clubs receive remarkably less gate receipts in comparison with the other top-countries peers. Club-level data confirm the country-level ones: matchday revenues of Italian teams are remarkably lower than the others. Although Juventus runs its matchday business in a quite efficient way (see below), the revenues accrued are at least half of the ones of the other top teams.

Since the thesis focuses on this revenue stream, it is worth to better explain how it works, and to observe deeper data.

Table 1.4: Top 20 teams by Recurrent Revenues: Revenue-mix (2016)

Club	Country	Broadcasting		Commercial		Matchday	
		2016	%Revenues	2016	%Revenues	2016	%Revenues
Real Madrid	SPA	227.7	37%	263.4	42%	129	21%
Barcelona	SPA	202.7	33%	296.1	48%	121.4	19%
Manchester United	ENG	187.7	27%	363.8	53%	137.5	20%
Paris Saint-Germain	FRA	123.1	24%	305.3	58%	92.5	18%
Bayern Munchen	GER	147.6	25%	342.6	58%	101.8	17%
Manchester City	ENG	215.8	41%	238.9	46%	70.2	13%
Arsenal	ENG	192	41%	142.9	30%	133.6	29%
Chelsea	ENG	191.1	43%	163.1	36%	93.2	21%
Liverpool	ENG	168.1	42%	159.8	39%	75.9	19%
Juventus	ITA	195.7	57%	101.7	30%	43.7	13%
Borussia Dortmund	GER	82.6	29%	140.2	49%	61.1	22%
Tottenham Hotspur	ENG	147.6	53%	77.5	28%	54.6	19%
Schalke 04	GER	75	33%	98.3	44%	51.2	23%
Milan	ITA	88	41%	100.8	47%	25.9	12%
Zenit St. Petersburg	RUS	40.4	21%	145.8	74%	10.3	5%
West Ham United	ENG	115.9	60%	40.4	21%	36	19%
Roma	ITA	154	71%	35.8	16%	28.4	13%
Leicester	ENG	126.6	74%	30.1	17%	15.4	9%
Internazionale	ITA	98.6	55%	54.9	31%	25.7	14%
Atletico Madrid	SPA	139.4	61%	53.2	23%	36	16%

Source: Deloitte UK (2017). Data are in €millions.

[30] Note that Table 1.3 separates Gate Receipts from all the other proceeds deriving from the matchday activity, which are probably included in the commercial share.

In the last fifteen years, several European football clubs have progressively started to buy or build their stadiums, which became part of their balance sheets as a crucial asset. However, as UEFA (2017) reports, stadium ownership is not the rule: in 2015, 69% of the European stadia where not privately owned. Nevertheless, the state of affairs was rather variable among the top leagues: in the English Premier League, seventeen out of twenty clubs directly or indirectly[31] owned a stadium; in the Spanish La Liga, fourteen out of twenty; in the German Bundesliga, seven out of eighteen[32]. In the Italian Serie A, Juventus and Atalanta hold their private stadium (the latter purchased it from Bergamo's municipality in summer 2017), Sassuolo indirectly owns it, and Udinese benefits of a ninety-nine years concession; therefore, only four out of twenty Serie A clubs own a stadium, with several other projects ongoing but still at the beginning phase.

Clubs that do not own an arena usually rent it from a public body (often a municipality) and retain all the matchday revenues. According to Andrea Sartori, Head of Global Sports at the well-known consultancy firm KPMG, the main advantages of stadium ownership are the possibility to build an arena that is dimensioned with the potential customer base of the club and suitable for viewing a football match, and to easily intervene with structural renovations to meet the needs of the potential business strategies (e.g. physical separation of sectors in order to implement price discrimination, creation of a hospitality area for the corporate market, internal merchandizing shops and restaurants, club's museum. . .).

According to Sartori, the building of an arena is not characterized by economies of scale: the bigger the arena, the higher the per-seat cost, because of factors as the necessity to create larger infrastructures around the stadium (parking areas, roads), the higher depth of the foundations of the building, the larger dimension of the roof. The Juventus Stadium, for instance, presented a quite low per-seat cost, since it was built on the same area of the former arena, i.e. new nearby infrastructures were not required.
On the other hand, per-seat revenues are decreasing with the capacity: the more the seats, the lower the average price that has to be charged to fill the stadium. Therefore, calibrating the optimal capacity is a crucial issue when planning the building of a private arena. Specifically, the size should be consistent with the pricing strategy of the football club. In Germany, big arenas are filled by a pricing policy characterized by low prices; in England, smaller stadiums were built in order to be consistent with more expensive tickets.
Eventually, the uncertainty about future sport performances, which may drive demand, renders the choice of the optimal capacity harder: for instance, if Juventus had foreseen the rather successful sport cycle of the current decade, its stadium may have been slightly larger[33].

According to AREL, FIGC, Pwc (2017), out of sixteen Serie A stadiums in 2015-16[34], five were equipped with an athletic track (that reduces the visibility of the pitch), five did not contain an hospitality area, seven did not exhibit sale points for commercial activities, fifteen lacked of an artificial turf (which preserves

[31] i.e. by other party within the group, or publicly hold with a long-term finance lease.
[32] (UEFA, 2017), p.121
[33] The contents of this section were taken by Sartori's interventions on the TV Program Sky Football Benchmark. The two episodes at stake are retrievable at:
- Stadia Development https://www.youtube.com/watch?v=GwbLsv2C-w4&t=4s
- Stadia Landscape https://www.youtube.com/watch?v=KvL4A-UdNAU

[34] Genoa, Milan, Rome and Verona exhibited two clubs in Serie A, which rented the same stadium. Juventus and Torino belong to the same city, but they play in different arenas.

the quality of the pitch in the case of adverse weather conditions), and 74% of the seats were not roof-covered; moreover, the average age of Italian stadia was sixty-nine years, with an average capacity much superior to the average attendance (see below)[35]. Further analysis should be conducted, but the public ownership of the majority of Italian stadia may play a role on such conditions that are not perfectly suitable for exploiting the matchday revenue source.

Once the stadium is built or rented, football clubs operate in the matchday market by selling a fixed capacity. Matchday revenues mainly arise from the corporate market (i.e. companies rent hospitality areas for their employees/clients), gate receipts and the so-called ancillary revenues (i.e. consumption occurred inside the stadium, especially food and beverages, but also parking and merchandizing, if sale points exist). Putting aside the former revenue stream, the latter depend on the sale of tickets, which are essentially rights of attending the match *and* to consume inside the stadium. The latter aspect is crucial in the determination of the optimal ticket price (see Chapter 2).

In running the matchday business, the football club incurs in high fixed costs: the rent of the stadium or its amortization cost and maintenance. The payroll of the staff needed to organize a football match is on the borderline between being a fixed or variable cost: a staff base is needed to open the stadium; more employees are occasionally hired if demand is predicted to be high. The marginal cost of one ticket (i.e. of admitting an additional attendee) is negligible[36].

A ticket is a highly perishable item, since it becomes valueless when the match is over: hence, every empty seat is money left on the table. Therefore, variables like the load-factor, i.e. the share of capacity used, and the *per-seat* revenues are crucial in analyzing the matchday revenue stream.

Table 1.5: Matchday figures by country (2015-16)

Country	Avg Attendance	Avg Capacity	Avg Load Factor	Avg Ticket Price	IndexUva*	Avg Gate Revenues	Avg per-seat Revenue
England	36,461	38,155	96%	52.2	54%	1,903,264	49.88
Germany	43,327	47,029	92%	35.5	40%	1,538,109	32.71
Spain	28,568	38,864	74%	41.2	54%	1,177,002	30.29
Italy	22,280	39,608	56%	24.9	36%	554,772	14.01
France	20,896	31,208	67%	19.9	25%	415,830	13.32

Source: Elaboration of data contained in AREL, FIGC, Pwc (2017).

*Incidence of average ticket price over average daily wage 2015

[35] (AREL, FIGC, Pwc, 2017), p.52

[36] The ticketing academic literature often assumes that such marginal cost is zero (see Chapter 2).

Table 1.5 allows to compare the top leagues on the basis of what has been discussed above. German stadiums are the largest, and they allow Bundesliga's clubs to exhibit the highest average attendance, with a high load-factor. English teams almost exhibit an average sell-out, although the average ticket price is the highest. Italian stadia are similar in size to the Spanish ones, but they are less exploited, since the load-factor is the lowest among the top divisions. Such result occurs despite a lower ticket price than in England, Germany and Spain. All these figures translate in a per-seat revenue of almost €50 in England, and only €14 in Italy. Therefore, data suggest that Italian stadia are over-dimensioned for an apparent weak demand.
Such result is generalized among Italian teams, with Juventus being the only exception. Table 1.6 displays per club data starting from the season 2014-15 to the first half of the 2017-18. The Italian champions are the only team that exploits most of its capacity, apart from Spal, a small club that is participating to Serie A for the first time after decades. All the other participants exhibit a load-factor below 80%, and sixteen of them never experienced a sellout.

.

1.4 Demand for football and the relationship between revenue sources

After the above discussion of the revenue sources of a typical football club, it is possible to examine who demands football and what drives such demand. First, however, it should be clear what kind of product the football clubs are selling.
The key issue is that football clubs cannot "produce" individually. The football product is, as Villar and Guerrero (2009) point out, the result of two teams opposing in a single match, and *n* other teams participating to a competition. Therefore, demand for football crucially depends on the matchday contenders; furthermore, the meaning and importance of the same match depends on what is at stake, i.e. the relative competition: for instance, whatever the demand for football is, clearly it will be higher for a Champions League final between Juventus and Real Madrid, than for a summer friendly match between the same teams. Consequently, clubs should be interested in the growth of the competition to which they participate, and thus, paradoxically, to the growth of their opponents[37].

[37] See the Louis-Schmelling paradox in Villar and Guerrero (2009).

Table 1.6: Capacity utilization, Serie A clubs (2014-15 to 2017-18, first half).

Club	Home Matches	Avg Attendance	Capacity	Avg Load Factor	# Sell-outs
Atalanta	63	16,480	24,276	68%	0
Benevento	10	12,341	16,867	73%	1
Bologna	48	20,482	36,462	56%	0
Cagliari	47	12,294	15,919	77%	8
Carpi	19	8,969	21,092	43%	0
Cesena	19	16,236	23,860	68%	2
Chievo	66	11,928	31,045	38%	0
Crotone	26	9,834	16,640	59%	0
Empoli	57	9,392	16,284	58%	0
Fiorentina	66	27,861	46,366	60%	0
Frosinone	19	7,288	9,680	75%	1
Genoa	66	21,080	36,599	58%	0
Hellas	48	18,705	31,045	60%	0
Inter	67	45,273	80,018	57%	5
Juventus	67	39,241	41,475	95%	35
Lazio	65	25,967	70,634	37%	0
Milan	66	40,175	80,018	50%	5
Napoli	66	37,119	60,240	62%	0
Palermo	55	16,303	36,349	45%	0
Parma	19	11,978	22,352	54%	0
Pescara	19	13,566	20,476	66%	3
Roma	67	36,226	70,634	51%	0
Sampdoria	67	21,041	36,599	57%	0
Sassuolo	66	12,187	21,584	56%	4
Spal	9	11,456	13,020	88%	2
Torino	65	18,467	27,958	66%	0
Udinese	67	14,652	21,570	68%	4
TOTAL	1319	22,599	39,727	57%	70

Source: Our elaboration

Attendance data: http://www.stadiapostcards.com

Capacity data: https://www.transfermarkt.it/

Borland and Macdonald (2003) distinguish between a *direct* and a *derived* demand for sport. The former is the demand to attend live events. With the concept of derived demand, instead, direct consumers "*become part of a product that is consumed by other consumers*"[38]. Such other consumers use football as an input of production and can be broadly classified as: broadcasters, sponsors, i.e. companies that exploit football as an input for their marketing campaigns, or for directly selling merchandize (*technical sponsors*)[39], bookmakers and media that do not broadcast, e.g. newspapers that fill the sport pages with football-related contents. Since football clubs cannot seize any proceeds from bookmakers and other media, they should concentrate on the first three subjects and on what they are really demanding.

According to Borland and Macdonald (2003), attendees derive utility from a mix of two factors: the affinity with a specific club (based on geographical or emotional connection) and the quality of the contest. The weight of such factors depends on the type of fan. Giulianotti (2002) classifies four types of attendees (supporters, fans, followers, flaneurs) in a sort of matrix, reported in Figure 1.1: the vertical axes (cool/hot) describes the intensity of the identification and solidarity with the club, while the horizontal one (traditional, consumer) defines the kind of relation sought by the attendee. Supporters and fans feel a stronger affiliation with the club, though of a different kind: the former is more traditional, cultural, popular, while the latter is more market-centered. The most important corollary is that supporters, which represent a strong and durable attendees base and create a warm atmosphere inside the stadium, sometimes do not tolerate to be treated as mere customers, since they feel their passion been exploited for profit reasons. Nufer and Fisher (2013), report the example of the "Kein Zwanni fur nen Steher" (twenty Euros for standing – no way) campaign: Borussia Dortmund core supporters boycotted the match against their historical rivals of Schalke 04 when the club increased ticket prices by 50% to benefit from the strong demand.

The relation with the other types of attendees, instead, is more similar to a firm-customer one, and they may be more interested in the quality of the performance they attend. Consequently, a football club should carefully segment its attendees base while developing business strategies in the matchday market (see Chapter 2).

Broadcasters are media companies (televisions, radios, websites) that purchase the rights to transmit live matches or the post-game highlights. They exploit football as an input to produce programs in order to attract customers (in the case, for instance, of Pay TVs) or advertisers. They are interested in broadcasting a popular show capable of attracting viewers: therefore, they are concerned with the popularity of football and the quality of the single match and of the competition.

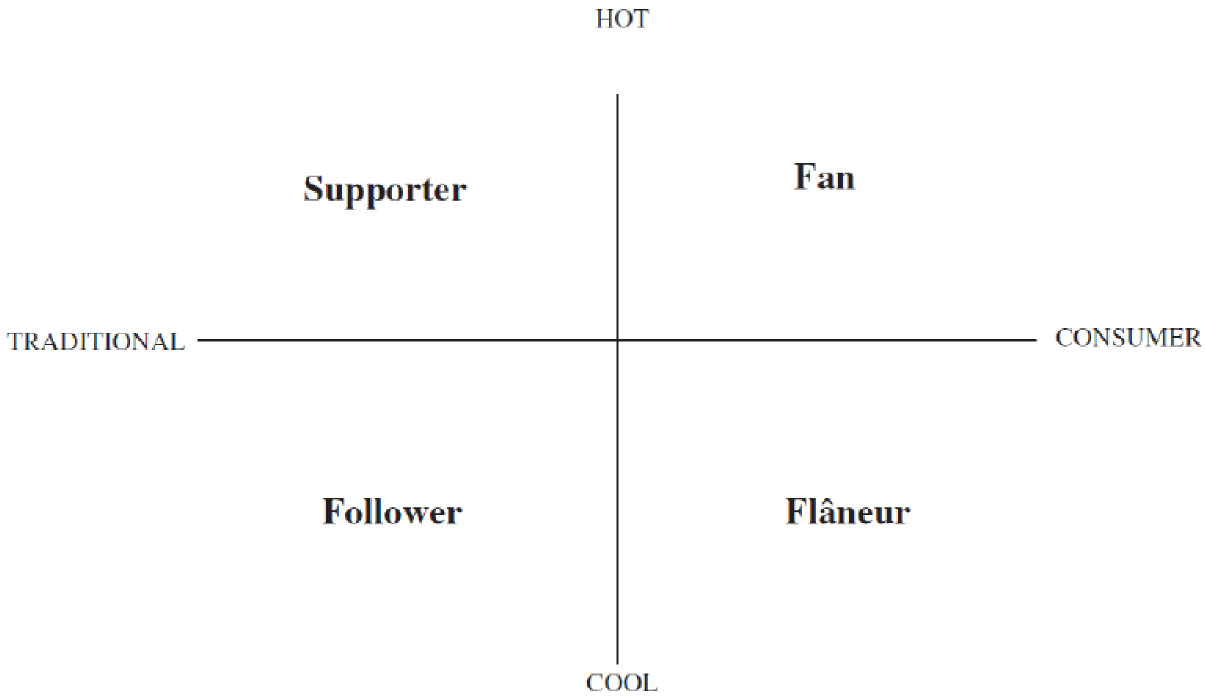
---

[38] Borland and Macdonald (2003), p.478

[39] Football teams usually stipulate two kinds of contracts with technical sponsors (e.g. Nike, Adidas):

- In the first case, sponsors pay a relevant fix fee and grab most of the proceeds deriving from the sale of technical merchandizing;
- In the second case, the fixed fee is negligible, and the technical sponsors basically act as suppliers, from which clubs buy and sell technical merchandizing.

Figure 1.1: Giulianotti's matrix



Source: Giulianotti (2002)

Sponsors are companies, belonging to several types of industry[40] that purchase advertisement space or audio messages within the stadium or on players' uniforms, as part of their marketing strategies. The purpose of their affiliation with a football club is to improve their visibility, to link their brand to the team and, possibly, to involve players in commercial initiatives. Technical sponsors, instead, are on the borderline between being actual sponsors or suppliers. Sponsors are mainly interested in reaching the maximum number of potential customers within the arena or through the media, depending on the type of advertisement they purchase. Moreover, they may also be concerned in the sporting performance of the team, in order to be linked with a successful club (see Borland and Macdonald, 2003, and Budzinski and Satzer, 2011).

Késenne (2006) affirms that non-gate revenues are positively correlated with stadium attendance and football clubs consider such factor in their ticket pricing strategy: a reduction of ticket prices may increase tickets demand, with a positive effect on the other income streams. The remaining part of the chapter thus tries to explain such claim, analyzing the relationship between attendance and advertisement, sponsorship, broadcasting rights and merchandizing[41].

Budzinski and Satzer (2011) formalize such conclusion by exploiting the theory of multisided platforms[42]. A company represents a platform if it can connect two different customer groups; such connection

[40] See AREL, FIGC, Pwc (2017), pp.48-49
[41] Except for broadcasting rights, all the other sources are included in the broad category of commercial revenues.
[42] Such type of market structure has been defined in several ways: multi-sided/two-sided markets/platforms

generates positive externalities ("network effects") from at least one group (say, group A) to the other (group B)[43]: therefore, the participation of group A to the platform benefits group B.
According to Rochet and Tirole (2006), *"a market is two-sided if the platform can affect the volume of transactions by charging more to one side of the market and reducing the price paid by the other side"*[44].
Consequently, the platform may take advantage of its role by decreasing the price of joining the platform for group A (so that to increase its participation), and raising the one paid by group B: the augmented participation of group A creates a positive externality that increases the willingness to pay of group B.
Budzinski and Satzer (2011) provide the example of a newspaper, that links advertisers and readers (two customer groups). By reducing the cover price, the publishing house can increase the number of potential viewers of an advertisement page, creating spillovers to the advertisers. Consequently, the latter will be willing to pay more for commercial space.

The same authors affirm that in the framework of a football match, attendance may generate positive externalities to both sponsors and broadcasters.
A higher attendance implies an augmented amount of potential advertisement viewers (or listeners) inside the stadium. Moreover, attendance may be considered as a lower bound of the number of people interested in the team, to which the sponsor links its brand. Therefore, attendees generate a positive externality to sponsors. When it comes to the opposite direction, it can be argued that, if visual advertisement does not interfere the pitch view, and audio advertisement is concentrated in the halftime, publicity announcements do not generate remarkable negative externalities for the attendees: a low and moderate level of advertisement does not affect fans. On the other hand, if sponsoring contracts augment the clubs' capability to purchase talent (i.e. better players), sponsors may generate a positive externality to fans.

Furthermore, a higher attendance enriches the atmosphere within the stadium, improving the "football product" that is bought by broadcasters. Therefore, attendance may generate a positive effect on broadcasters, even if it decreases the potential media audience. Quantitative works concerning English and Spanish football[45] confirms such claim: broadcasting has a negative effect on attendance, but the latter has a positive feedback on TV audience. However, applying the theory of multisided markets when a group is composed by broadcasters is quite problematic. Football clubs, indeed, directly sell their tickets, but the broadcasting rights are collectively sold by the league. Therefore, in the framework of multisided platforms, only a ticket price reduction policy agreed by *several* teams in the league may boost broadcasters' willingness to pay.
A potential link between attendance and broadcasting revenues can be derived from the fact that an increased number of stadium spectators may boost the home field advantage and, consequently, positively affect sporting

[43] According to Filistrucchi et al (2012), a platform does not need network effects in both directions to be considered multi-sided.
[44] (Rochet & Tirole, 2006), p.2
[45] See Buraimo (2008), Buraimo and Simmons (2009), which model both attendance and TV audience; moreover, Caruso et al (2017) model TV audience for the Italian Serie A with two alternative specifications that found, in the first case, no effect on audience, while in the second case an increase of attendance positively affect TV demand.

performance. As a result, a low-ticket pricing policy may increase the share of broadcasting rights that is distributed on the basis of the club's final position in the league[46].

When it comes to merchandizing revenues, it is not possible to apply the theory of multisided markets, since the group of merchandizing buyers probably overlaps with the attendees one (Budzinski and Satzer, 2011). However, it is possible to affirm that increasing attendance by reducing prices may enlarge the customer base of merchandizing products and therefore have a positive impact on commercial revenues. Church and Ware (2000) provide, in a different setting, the example of the Rolling Stones' concerts: despite the long queues at the box offices, ticket prices were kept rather low, considering the excess demand described by fans queueing for days and nights. A possible explanation is that low prices attracted customers with a low willingness to pay for tickets, and a high one for merchandizing products. The example illustrated by Church and Ware (2000) is related to a sell-out setting, where the merchandizing products are sold during the event. However, the idea may be extended to settings where capacity is not totally used (lower ticket pricing attracts more potential customers in both the matchday and merchandizing markets) and products are also sold outside the event: high prices may render football as an "elitist" sport, and drift apart potential fans that may represent additional merchandizing customers. This is particularly reasonable in an industry where, as Borland and Macdonald (2003) report, habit is an important determinant of demand.

1.5 Concluding remarks

Chapter 1 has provided an overview of the football industry, especially of the relevant revenue sources of a typical football club. Broadcasting and commercial proceeds capture higher shares of total revenues: this is a common fact concerning clubs across the different national leagues. However, the matchday source represents a key driver of the revenue structure, since it may positively affect the other income streams.

Therefore, given the higher and growing importance of broadcasting and commercial revenues in football clubs' profit and loss account, it should be noted that teams have an incentive to reduce ticket prices to boost attendance, in order to increase the proceeds originated by the other sources of income. The consideration of the interdependence of the different revenue channels, and especially of the matchday source with the others, provides valuable insights to explain how football teams set the ticket price, which will be exploited in the next chapter.

[46] In this setting, such win maximization policy may also boost commercial revenues, if a positive correlation with sporting performance is believed/empirically tested.

Chapter 2

TICKET PRICING IN THE FOOTBALL INDUSTRY

2.1 Introduction: ticket pricing issues

Tickets represent a particular good that is sold by different industries, especially the entertainment (concerts, theatre plays, cinema, sport events...) and transportation ones. Such industries exploit tickets as a tool to sell the right to attend an event or to travel.
Several issues arise from the utilization of tickets, common to both type of industries that exhibit similar features, entailing a set of pricing strategies that can be implemented to maximize profits with the same purpose: "*selling the right seat to the right individual at the right time*"[47]. Pascal Courty (2000 and 2015) provides two literature reviews about ticket pricing in the entertainment industries, describing issues and strategies, and how the latter borrow from several topics of the economic theory. This introductory paragraph draws upon his work.

Whichever is the pricing strategy implemented, a company selling tickets should bear in mind that it is not selling homogeneous goods: although every ticket gives the right, say, to attend the event, it allows the buyer to do so in different ways, e.g. from different positions in the venue, by seating or by standing. Such outcome derives from the physical structure of the event venue/transportation mean, but can be stressed by the firm that applies tier pricing (see paragraph 2.3.1). Moreover, companies should consider the role of complementary goods that are on sale at the event, since each ticket sold represent a potential additional customer in the venue. Such consideration creates the incentive to reduce prices in order to increase the quantity of tickets sold (if the capacity constraint does not bind) to boost the so-called ancillary revenues (see Rascher et al., 2007, and Drayer et al, 2012).

As it was anticipated in Chapter 1, most of the companies in these industries operate with a fixed capacity[48]. Consequently, unused capacity may ensue when demand is weak, while an excess demand may occur when it is strong. Furthermore, tickets are non-storable and thus highly perishable goods, since their

[47] Courty (2015), p.1
[48] This is not always the case. In the circumstance of a single event (e.g. a concerts tour with a single date in a given city) the company may choose a venue with a capacity that is optimal given the predicted demand. Football teams, however, play their home games in the same stadium that they own/rent.

value is zero after the event/journey. Two implications arise: first, every unsold ticket is money left on the table, and the company has a potential incentive to sell it at an extremely low price when the event/journey is approaching (Drayer et al, 2012), since the marginal cost of a ticket is negligible; second, firms cannot store unsold tickets to deal with periods of high-demand, as it can happen with other goods.

Therefore, any ticket pricing strategy should borrow insights from the peak-load pricing theory (Courty, 2000): variation of demand cannot be matched by the fixed supply; hence price is the variable that companies should exploit to optimize their behavior. Keeping the price constant may lead to inefficient outcomes, while theory suggests reducing it when demand is weak and raising it when demand is strong.

Another feature of the ticket-based industries is the uncertainty of demand, mostly because of the time lag between the starting of the tickets sale and the occurrence of the event/journey. Courty (2000) specifies that demand is uncertain from an aggregate and individual point of view.

Aggregate demand uncertainty arises as conditions that may affect demand are not predictable in advance (e.g. weather for outdoor events, what is at stake in end-of-season league sport matches); individual demand uncertainty results from the fact that some buyers are not aware in advance of their possibility to attend the event (e.g. businessmen).

Such uncertainty is among the reasons that drive the existence, in some cases, of secondary markets for capacity constrained events, which are boosted by a general tendency of underpricing tickets in the primary market. Brokers and scalpers operate, legally or not, on secondary markets by buying early and re-selling at a profit, because tickets value increases and the advance buyers may not be the consumers with the highest willingness to pay. The longer the time lag, the higher the aggregate and individual uncertainty and the greater the incentive to operate in secondary markets.

The existence and the size of secondary markets reflect the inefficiency of the ticket pricing strategies on primary ones, since companies lose the opportunity to seize the consumer surplus captured by brokers (see Drayer et al, 2012). The presence of online secondary markets gives firms the possibility to measure how much additional profit they could obtain with a more suitable strategy that accounts for demand uncertainty: companies may permit and control resales (that allow to reduce no-shows, which affect ancillary revenues) or apply dynamic pricing strategies (see paragraph 2.5).

In the Italian football, clubs have the opportunity to prevent secondary ticketing: tickets are indeed nominative and thus personal by law, and the enforcement of such rule at the gates[49] should prevent the resale of tickets; however, clubs often give attendees the opportunity to change the name on the ticket before the match, therefore implicitly allowing the possibility to resale it. However, since resales are not controlled by a club specific platform, secondary markets arise. The FIFA World Cup 2006 represents a successful instance of resale deterrence, since tickets could be resold at the purchase price through an official website managed by FIFA itself (see Eichhorn and Sahm, 2010).

[49] Stewards are required to check the identity of the attendees by controlling the correspondence of the ticket to the right holder by means of an ID card.

When it comes to the entertainment industries, an additional ticketing related issue is the fairness perception of customers, which can react negatively to some sophisticated pricing strategies. This is particularly true for such industries (live concerts, sports) where customers value the sense of affiliation that they feel towards the performer (singer, sport club)[50]. Therefore, an entertainment company should implement pricing strategies in a careful fashion, since customers may feel to be exploited.

After such review of the typical ticketing issues, the chapter describes the main related pricing strategies that are (or can be) applied in the football industry. Before, however, the analysis will start from an evaluation of how football clubs set their optimal ticket price, drawing upon the conclusion of the previous chapter.

The main ticket pricing strategies that can be combined in the sport industry are applications of the concept of price discrimination. Tier Pricing arises from the possibility to divide the capacity in several sectors with different valuable characteristics (e.g. seat location in a theatre, seat class in a train…). Bundling can be implemented by those companies that organize several events at different dates (like sport clubs). Market segmentation arises from the ability of the company to identify customer groups with different willingness to pay and to price them differently.

Variable ticket pricing and dynamic ticket pricing can be labeled as demand-based approaches to pricing. Variable ticket pricing seeks to identify the variables that affect sales, and sets the price according to the fluctuating predicted demand; the result is that prices will fluctuate with such variables at each event. Dynamic ticket pricing makes a further step, setting different prices for the same event, depending on demand and supply conditions at the purchasing date.

2.2 Optimal price level

The sport events literature models the pricing choice of a sport club starting from two crucial assumptions. First, since sport clubs are endowed with a strong market power, they are considered as regional monopolists[51]. Market power arises mainly because of the fan loyalty that characterizes sport attendance and the limited concentration of top-league clubs in the same territory[52].

Second, the marginal cost of selling an additional ticket is assumed to be zero. Since capacity is fixed and built well before the event, short-run marginal costs are negligible. In such framework, revenue maximization coincides with profit maximization[53].

---

[50] See the supporters' section of the Giulianotti's matrix in the previous chapter.

[51] see Coates and Humpreys (2007), Marburger (1997), Késenne (2006), Eichhorn and Sahm (2010)

[52] Some cities host more than a professional club for the same sport; however, since the rivalry among such clubs is rather strong, the concept of fan loyalty may be more intense in that setting.

[53] See Marburger (1997), Krautmann and Berri (2007), Rascher et al (2007). Einav and Orbach (2007) also assume zero marginal costs for the cinema industry.

On the basis of such assumptions, it is possible to derive the optimal price and the related tickets sold. Suppose that a football club is a monopolist that faces a linear demand curve for tickets:

$$q_t = a + bp_t$$

Where $b < 0$, $a > 0$; q_t and p_t represent the quantity of tickets sold and the relative price respectively. Assuming variable costs equal to zero, the profit function for tickets will be:

$$\pi_t = q_t \cdot p_t - F$$

Where F represents the fixed costs.
The football club will choose the ticket price in order to maximize profits, subject to the capacity constraint.

$$\max_{p_t} q_t \cdot p_t - F$$
$$s.t. \, q_t \leq C$$

Taking the Lagrangian function, plugging the demand curve and deriving the first order conditions:

$$L = q_t \cdot p_t - F + \lambda \cdot (C - q_t) = ap_t + bp_t{}^2 - F + \lambda \cdot (C - a - bp_t)$$

$$\frac{\partial L}{\partial p_t} = 0 \rightarrow \; a + 2bp_t - \lambda b = 0 \qquad (1.1)$$

$$\frac{\partial L}{\partial \lambda} = 0 \rightarrow \; C - a - bp_t = 0 \qquad (1.2)$$

Adding the condition allowing for the possibility of a non-binding capacity constraint and the sign of the multiplier:

$$\lambda(C - a - bp_t) = 0 \qquad (1.3)$$

$$\lambda \geq 0 \qquad (1.4)$$

Note that the Lagrange multiplier λ represents the marginal revenues deriving from relaxing the capacity constraint, i.e. of adding one seat to the stadium (Coates and Humpreys, 2007).
Such constrained optimization problem presents two sets of solutions, depending on the Lagrange multiplier λ being either equal or different from zero.

Consider the case where λ=0.

In such occasion, the capacity constraint is not binding. If lambda is zero, it means that adding one seat to the capacity conveys no revenues to the football club. This is straightforward, considered that a non-binding capacity constraint means that some tickets are unsold.

In this case, the optimal price can be derived from (1.1):

$$p_t^{MP} = -\frac{a}{2b}$$

Where *MP* stands for "Mono-product". Plugging such price in the demand curve, it follows that $q_t^{MP} = \frac{a}{2}$.

At this point, it is interesting to derive the elasticity of demand corresponding to such price-quantity combination:

$$\varepsilon_t^{MP} = \frac{\partial q_t}{\partial p_t} \cdot \frac{p_t}{q_t} = b \cdot \frac{p_t^{MP}}{q_t^{MP}} = -1$$

If the football club is considered as a monopolist facing a linear demand curve, with marginal costs equal to zero, it will set a price such that the elasticity of demand is, in absolute value, equal to 1.

Now move to the case where $\lambda \neq 0$. In such occasion, the capacity constraint is binding, which imply that the tickets sold equal capacity:

$$q_t^{MP} = C$$

A positive lambda (from (1.4)) means that the marginal revenue from adding one seat is greater than zero: if there is excess demand, adding a seat implies the sale of additional tickets, and thus more revenues for the club[54].

The optimal price can thus be derived by (1.2):

$$p_t^{MP} = \frac{C-a}{b}$$

Note that the numerator is negative: since *a* represents the demand when the price is zero, it will be surely higher than the capacity, given the binding constraint.

The related elasticity of demand will thus equal:

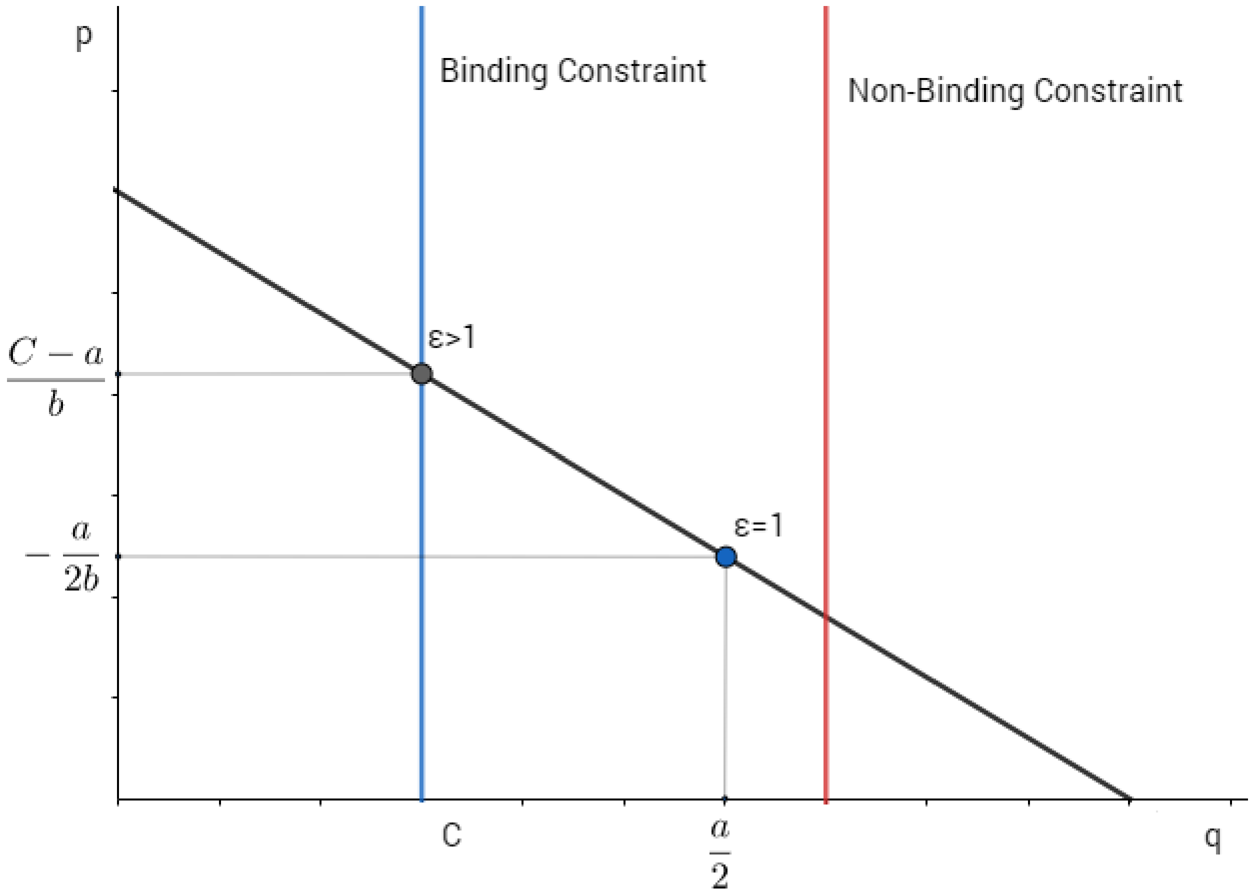
$$\varepsilon_t^{MP} = b \cdot \frac{\frac{C-a}{b}}{C} = \frac{C-a}{C}$$

[54] As it will be explained below, a binding constraint implies elastic pricing: therefore, in such part of the demand curve marginal revenues are positive.

Such elasticity can potentially be higher or lower than one. However, a binding constraint implies that the first solution (corresponding to a unitary elasticity) is not reachable: consequently, capacity will be lower than demand, and the firm will thus set a higher price. Therefore, the club will set the price in the elastic part of the demand curve (see figure 2.1).

However, numerous empirical works in the sport events literature report an elasticity of demand that is below 1[55]. The outcome is persistent among sports, geographic areas and time. Such result seems inconsistent with the profit maximizing behavior of a monopolist, which, theoretically, should never price in the inelastic part of the demand curve.

Figure 2.1: Optimal ticket price for a mono-product monopolist



Source: Our elaboration

Several possible explanations arise from the literature, sharing the idea that inelastic pricing may be caused by either non-optimal behavior or a different objective function.

[55] See Krautmann and Berri (2007) and Fort (2006) for a review of such works.

Drayer and Rascher (2013) cite the possibility that clubs' owners are not *profit* maximizers but *win* maximizers instead. If a positive correlation between attendance and home field advantage is demonstrated, owners may underprice tickets in order to increase the former and boost sport performances. However, it may also be argued that, in modern football, a profit oriented approach to the management of the club is related to on-field success: Chapter 1 showed that the most successful teams are those with the best economic fundamentals.
A more sophisticated approach suggests the role of habits in attendance, reported by the literature reviews contained in Krautmann and Berri (2007) and Fort (2006). According to such clue, clubs maximize long-run profits by underpricing tickets, thus attracting more attendees that may become loyal fans. Loyalty should create a habitual behavior that may boost future demand (and future prices).
Krautmann and Berri (2007) also report a public choice explanation, which points out the potential arrangements between politicians and teams' owners: the former may give support, say, for public funding of stadiums building, while the latter may accept to underprice tickets, given the usual popularity of sport entertainment.

The most cited explanation for inelastic pricing, that has also been tested empirically, is the consideration of sport clubs as multiproduct monopolists. Marburger (1997) explains inelastic pricing for performance goods (e.g. theatre, movies, sporting events), by highlighting the fact that tickets give the right to attend an event and to *consume* in the event venue. Whether attendees include concession prices in ticket purchasing decisions or not, such choices are crucial in creating the concession market, and thus the stream of ancillary revenues. The empirical results presented in its paper confirm such hypothesis. The same approach is recalled by Fort (2006) and Rascher et al (2007). Coates and Humphreys (2007) and Krautmann and Berri (2007) test such results; the latter, especially, estimates that tickets in the main American sports leagues are 20-50% lower than the mono-product optimal price, depending on the kind of sport considered (baseball exhibits greater discounts).
Such point of view is consistent with the hypothesis presented at the end of Chapter 1, according to which attendance is positively correlated with other revenue streams, especially matchday ancillary and commercial ones. The latter are not contemplated in the works cited above, though mentioned by Drayer and Rascher (2013) and consistent with the theory of multisided markets discussed in the previous chapter.

The consideration of the club as a multiproduct monopolist allows to modify the objective function presented above[56]:

$$\pi = (q_t \cdot p_t - F) + R_C(q_t) + R_{SM}(q_t) + R_B - E$$

The following unmodeled terms have been added:

[56] Marburger (1997) presents a similar model to explain inelastic pricing; however, the author does not consider capacity constraints, and only includes concession revenues; Coates and Humphreys (2007) include capacity constraints and limit their analysis to tickets and concession revenues, although the conclusions are similar. Moreover, they assume that concession prices enter the ticket demand function, and vice-versa.

- $R_C(q_t)$: represents concession revenues, which directly depend on the quantity of tickets sold; consequently, they negatively depend on ticket price:

$$\frac{\partial R_C}{\partial q_t} > 0; \frac{\partial R_C}{\partial p_t} < 0$$

- $R_{SM}(q_t)$: represents commercial revenues (deriving from sponsorship and merchandizing), which negatively depend on ticket price for the same reason:

$$\frac{\partial R_{SM}}{\partial q_t} > 0; \frac{\partial R_{SM}}{\partial p_t} < 0$$

- R_B: represents broadcasting revenues, which are assumed to be independent on the quantity of tickets sold, since they are negotiated and traded by the sport league:

$$\frac{\partial R_B}{\partial q_t} = 0; \frac{\partial R_B}{\partial p_t} = 0$$

- E: represents the club's expenditures related to other divisions, which are assumed as independent on the quantity of tickets sold[57]:

$$\frac{\partial E}{\partial q_t} = 0; \frac{\partial E}{\partial p_t} = 0$$

It is therefore possible to re-state the profit maximization problem where, for conciseness reasons, concession and commercial revenues are grouped in $R_O(q_t)$, i.e. other tickets-dependent revenues[58].

$$\max_{p_t} (q_t \cdot p_t - F) + R_O(q_t) + R_B - E$$
$$s.t. q_t \leq C$$

As before, we build the Lagrangian function, plug the demand curve and derive the first-order conditions:

$$L = q_t \cdot p_t - F + R_O(q_t) + R_B - E + \lambda \cdot (C - q_t) = a \cdot p_t + bp_t^2 - F + R_O(q_t) + R_B - E + \lambda \cdot (C - a - bp_t)$$

[57] If we believe that an increase of the quantity of tickets sold boosts the demand for sponsors, concessions and merchandizing, it may be that variable costs related to the last two items increase. Here we assume that other costs do not increase, for simplicity, but further research should evaluate such aspect.
[58] Note that we are assuming *separability* of the different revenues sources in the profit function.

$\frac{\partial L}{\partial p_t} = 0 \rightarrow\ a + 2bp_t + R_O{}' - \lambda b = 0$ (2.1)

$\frac{\partial L}{\partial \lambda} = 0 \rightarrow\ C - a - bp_t = 0$ (2.2)

Where $R_O{}'$ is the (negative) variation of other revenues after a price increase: $R_O' = \frac{\partial R_O}{\partial p_t} < 0$

The other conditions related to the constraint and the Lagrangian multiplier are unchanged:

$\lambda(C - a - bp_t) = 0$ (2.3)

$\lambda \geq 0$ (2.4)

The constrained optimization problem presents, again, two sets of solutions, depending on the multiplier lambda.

If $\lambda = 0$, we can derive the optimal price from (2.1):

$$p_t{}^* = -\frac{a +\ R_O{}'}{2b}$$

Since $R_O{}'$ is negative, the price set by a multiproduct club with no binding constraint is lower than in the mono-product case[59]:

$$p_t^{MP} - p_t{}^* = \frac{R_O{}'}{2b}$$

The price reduction that a multiproduct monopolist applies depends:

- Positively on the effect of a ticket price increase on other revenues, in absolute value; therefore, the model suggests that the clubs that underprice tickets the most should be the teams that exhibit a stronger correlation between attendance and other revenues;
- Negatively on the marginal effect of ticket price on ticket demand (b): the higher the ticket price sensitivity, in absolute value, the lower the price reduction necessary to attract more attendees;

Consequently, we expect that tickets sold will be higher, and elasticity lower than in the previous case.

Plugging the price in the demand curve:

$$q_t{}^* = \frac{a -\ R_O{}'}{2}$$

[59] Note that if $R_O{}'$was larger than a in absolute value (i.e. very large), the price charged would be negative: other revenues would be so important that the club would pay fans to attend the event.

$$q_t{}^* - q_t^{MP} = -\frac{R_O{}'}{2}$$

The higher $R_O{}'$, the higher the increase of the amount of tickets sold.

The elasticity of demand will thus be:

$$\varepsilon_t^* = \frac{\partial q_t}{\partial p_t} \cdot \frac{p_t}{q_t} = b \cdot \frac{p_t}{q_t} = -\frac{a + R_O{}'}{a - R_O{}'}$$

Which, in absolute value, will be lower than one.

$$|\varepsilon_t^{MP}| - |\varepsilon_t{}^*| = \frac{-2R_O{}'}{a - R_O{}'} > 0$$

The reduction of the point elasticity will depend:

- Positively on the absolute value of $R_O{}'$: the stronger the effect of a ticket price increase on other revenues, the higher the elasticity reduction;
- Negatively on a: the bigger the potential market, the lower the elasticity reduction needed to attract the optimal number of attendees; consequently, the model suggests that clubs/matches with a bigger potential market should exhibit an elasticity level that is nearer to unity.

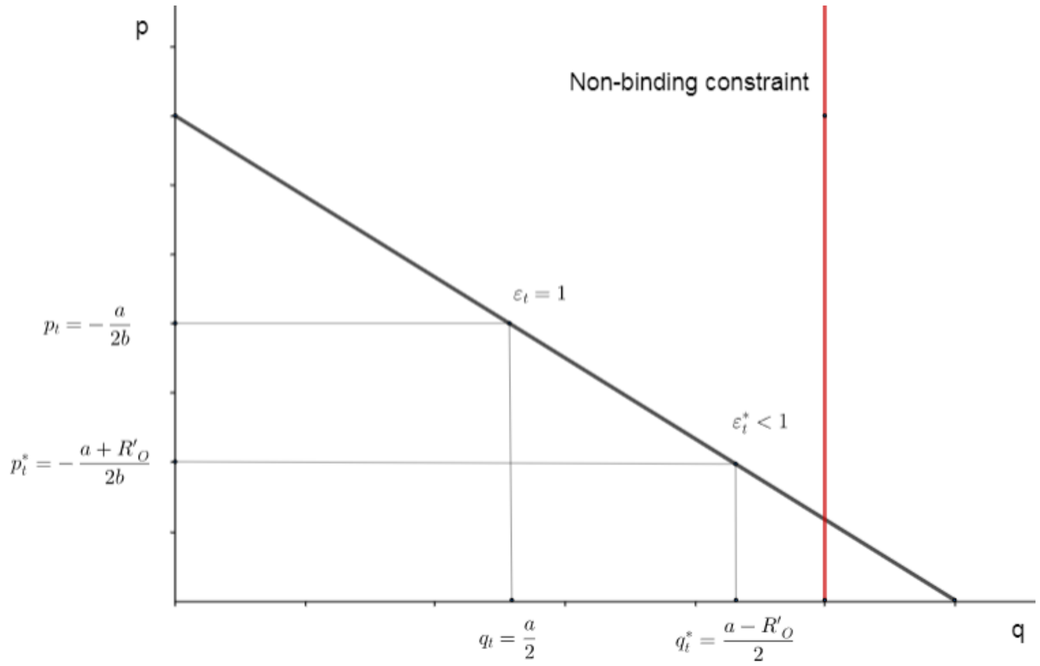
The analysis of profit maximization of a multi-product monopolist allows to state three propositions:

Proposition 1: the higher the price reduction/quantity increase (from the mono-product optimal level) and the distance of the optimal elasticity from unity, the stronger the effect of a ticket price increase on other revenues.

Proposition 2: the higher the ticket price sensitivity, the lower the optimal price reduction from the mono-product level.

Proposition 3: the larger the potential demand, the lower the elasticity reduction (from unity level) needed to attract the optimal number of attendees.

Figure 2.2: Optimal ticket price: mono-product vs multi-product monopolist (non-binding constraint)



Source: Our elaboration

If $\lambda \geq 0$, the result is the same of the mono-product case: clubs set the highest price that is compatible with the arena sellout[60]. Such price will be thus higher than the optimal one with a non-binding constraint. Consequently, if the constraint binds, elasticity will be higher in absolute value: inelastic, unit elastic and elastic pricing are all consistent with revenue maximization.

Such outcome allows to state an additional proposition:

Proposition 4: If the capacity constraint does not bind, elastic pricing is not consistent with revenue maximization.

Therefore, the consideration of the sport club as a multiproduct monopolist entails, if capacity constraints are not binding (i.e. typical case in the Italian football, with Juventus as the only exception), inelastic pricing. If the capacity constraint binds, the club sets the highest price that is compatible with the sell-out. In the mono-product case, such result entailed elastic pricing by construction. In the multi-product setting, we only know that the point elasticity will be higher than in the no-binding case: both elastic and inelastic pricing are consistent.

[60] It could be argued that clubs may in any case underprice tickets to generate a persistent excess demand, in order to boost the interest of more fans and, consequently, sponsors. If that was true, inelastic pricing would be more likely to arise in the sellout case as well.

Can the sport club do better? Given the market power endowment that teams have, several price discrimination strategies may be applied to boost revenues. According to Drayer and Rascher (2013) *"effective price setting can be easily and inexpensively changed and can result in dramatic increases in profitability"*[61].
The next paragraphs will explore such price techniques that football clubs apply.

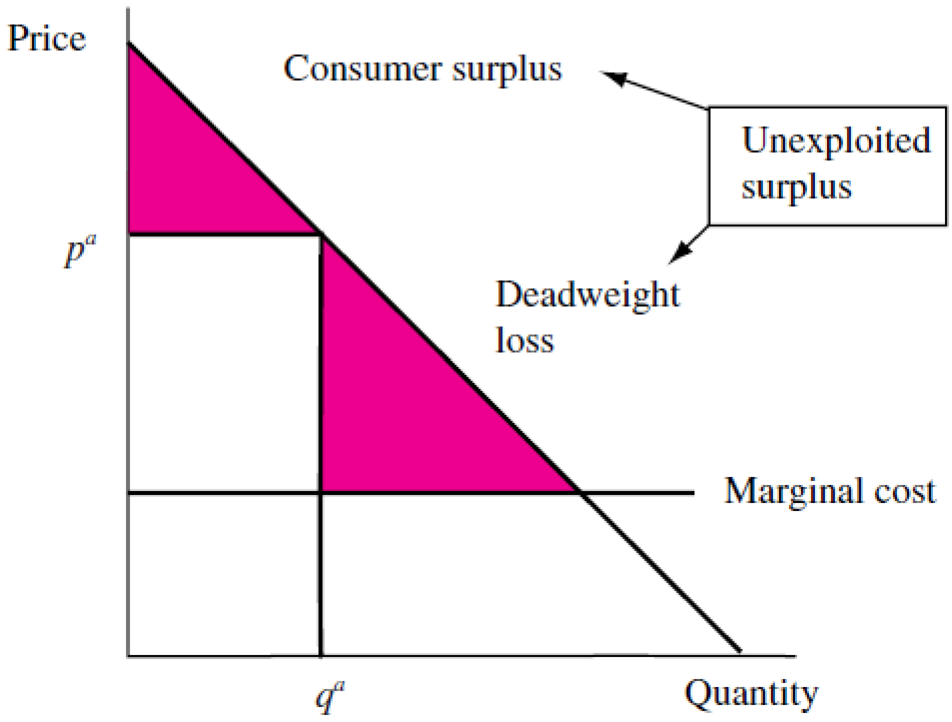
2.3 Price discrimination

The last paragraph showed how a football club sets the monopoly price, given the market power that it is endowed with. However, such pricing decision is not the most profitable one, since it entails an amount of surplus that is not (and could be) exploited. Figure 2.3 displays the intuition. In such setting, only a few attendees (theoretically, only the last one) buy tickets at a price that is equal to their willingness to pay. Football clubs may increase profits by extracting more surplus from fans that are willing to pay more. Moreover, if the capacity constraint is not binding, the club is leaving empty seats unsold, with potential attendees willing to pay something more than the extremely low marginal cost, though less than the price set by the team. Such deadweight loss represents money left on the table for the club. The outcome arises because, if the club wanted to sell an additional ticket to the marginal attendee, it would reduce the price paid by all the others, thus decreasing overall revenues.

Price discrimination techniques allow the monopolist to increase its profits by extracting a part of such unexploited surplus by, broadly speaking, charging different ticket prices to different consumers (see Church and Ware, 2000).
This is possible because different types of consumers exist in every market, with different willingness to pay for the good. However, consumers do not reveal their personal valuation: therefore, the monopolist should implement techniques with the purpose to identify the type of customers and encourage them to pay a price that is nearer to their willingness to pay.
Second-degree price discrimination is characterized by the implementation of techniques aimed at inducing consumers to reveal their type, in a way that allows additional surplus to be extracted. In such setting, the monopolist is not able to distinguish among the several types of consumers, therefore it offers a menu of prices, quantities and/or qualities such that the latter self-select: high willingness to pay ones will choose to pay more. Football clubs employ two main kinds of second-degree discrimination techniques: quality discrimination and bundling.

[61] Drayer and Rascher (2013), p.123

Figure 2.3: Motivation for price discrimination: unexploited surplus



Source: Church and Ware (2000), p.157

Third-degree price discrimination techniques are instead implemented when a company manages to identify specific groups with different willingness to pay. Such groups are characterized by features that are likely to affect demand. Market segmentation is the typical example of third-degree discrimination: the firm identifies different markets (i.e. groups) and sets different prices in each of them; specifically, lower prices will be set in the market characterized by a more elastic demand. A crucial requirement for the implementation of such techniques is the impossibility for customers to change group (i.e. to arbitrage): for such reason, groups are often identified on the basis of strict and easily checkable characteristics (e.g. gender, age).

2.3.1 Second-degree quality discrimination: tier pricing

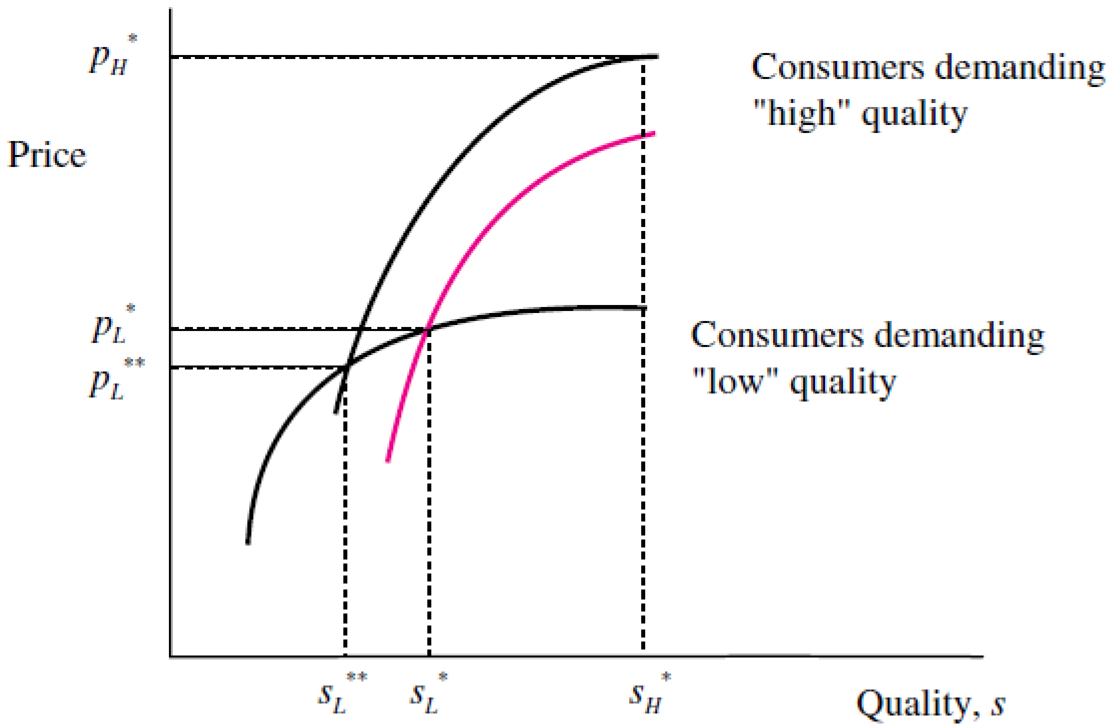
Tier pricing (or "scaling the house"[62]) is a common second-degree price discrimination strategy used in entertainment industries such as theatres, concerts and sport events, that can be connected to the concept of quality discrimination. In such setting, the firm tries to induce customers' self-selection by offering different qualities of the same product; specifically, the main goal is to give consumers with the higher willingness to pay the incentive to choose the high-quality product, thus spending more money.

[62] See Courty (2000)

Figure 2.4 explains how the mechanism works[63]. Since each attendee only buys one ticket, on the horizonal axis we can put the "amount" of quality that she demands. In the graph, rational consumers consider quality as a good, and price as a bad, therefore indifference curves are south-east oriented.

Consider two types of consumers: those demanding high quality (H), and those demanding low quality (L); the first menu of prices-qualities proposed by the firm is $(p_L^*, s_L^*;\ p_H^*, s_H^*)$. With such menu, type H consumers can move to a superior indifference curve by choosing the L price-quality combination, thus decreasing the company's profits. However, the firm can reduce the price and the quality of the L combination, inducing H type consumers to choose the H price-quality bundle. The small profit loss on L customers, which will pay less, is lower than the reduction of revenues that would occur if H-type consumers did not self-select.

Figure 2.4: Quality discrimination



Source: Church and Ware (2000) p.190

In the framework of the live performance industries, quality discrimination is implemented via tier pricing, i.e. charging different prices for different seats inside the event venue. As Leslie (2004) points out, every seat in the venue is characterized by the same (zero) marginal cost. Therefore, differences in prices cannot be explained by differences in costs.

Tier Pricing naturally arises since each seat in the event venue provides a difference experience in terms of view quality and distance; therefore, entertainment companies exploit the physical structure of the venue to

[63] The explanation has been retrieved from Church and Ware (2000), pp. 189-190

implement quality discrimination by grouping seats in different categories. Moreover, price discrimination is stressed by the different quality of the seat itself (leather seats versus less comfortable ones). In some instances, the cheapest tickets are sold in "standing areas", which do not provide a seat, as it happens in the German football[64]. Different quality among seat categories limits their substitution and it helps inducing self-selection through the same mechanism: reducing the quality of cheap seats/sectors makes them less attractive for high willingness to pay customers.

Seat enforcement is a crucial issue for an effective implementation of tier pricing: firms must ensure that attendees do not change sector once they enter the venue (Courty, 2000). If that was possible, any attendee could occupy a high-quality seat, having paid for a low-quality one. However, given the rigid division of sectors in football stadiums, for security reasons, inter-sectors seat enforcement is not hard to implement.

A more delicate issue is represented by cross-elasticities. Since different seats represent substitutes, clubs should be aware that every price change of a seat category may induce attendees to switch sector, with the possibility to affect profits if fans move to a cheaper one.

Cross-elasticities may be either positive or negative. Since seat categories are substitutes, a price increase in a given area may positively affect the tickets sold in the other sectors. However, as Leslie (2004) argues, cross-elasticities may be negative in a capacity constrained framework.

Consider a seat category, *c*, that is sold-out. In such case, an attendee *A* willing to purchase a *c* ticket, may buy instead a ticket in another (say, more expensive) sector *e*. After a price increase in *c* (such that *c* is still cheaper than *e*) some consumers may decide not to buy the ticket, leaving their seat free for attendee *A*, which will pay less by moving to the preferred cheapest sector *c*. Consequently, cross-elasticity for sector *e* and price *c* may result negative, and the firm profits may be negative affected after a price increase in the cheapest sector. Therefore, it should be noticed that the implementation of quality discrimination is a rather delicate issue, since every price change may induce not straightforward customer behaviors.

Table 2.1 shows the pricing strategies of the Serie A 2017-18 teams. When it comes to tier pricing, the number of seat categories is quite variable among clubs, 6-7 on average. Internazionale, Milan and Juventus exhibit the highest number of tiers, while Chievo the lowest, joined by a couple of other teams with only four tiers. The cheapest tickets of a Serie A club costs on average €23. Juventus and Internazionale sell the most expensive tickets, surprisingly followed by Crotone and Spal; Hellas Verona[65], Bologna, Cagliari and Fiorentina sell the cheapest ones.

[64] See Nufer and Fisher (2013). In the Italian football, there are sectors (the so-called *"curve"*) that are *de facto* standing areas, given the lack of intra-sector seat enforcement.

[65] The cheapest sector for Hellas Verona's matches (Parterre seats) is rather small; the second cheapest one's price is in line with the other "economical" teams cited.

Table 2.1: Pricing Strategies in the Italian Serie A (2017-18, first half of the season)

Club	Seat Categories	Avg Miminum Price	Avg Maximum Price	Max/Min Ratio	Segments	Season Ticket Price	Season Ticket Discount	%Capacity sold via season tickets	Price categories (VTP)
Atalanta	7	25	219.5	8.78	O65, U14, W, D	9.47	62%	58%	2
Benevento	6	24.54	150	6.11	U10	16.67	32%	46%	1
Bologna	5	16.63	100.9	6.07	O60, U18, UNI, W	11.58	30%	37%	3
Cagliari	5	19.18	72.27	3.77	O65, U18, U12, W, D	10.53	45%	52%	>3
Chievo	3	26.36	83.18	3.16	O60, U26, U18, W	9.47	64%	23%	3
Crotone	5	27.72	99.09	3.57	O65, U14	15.79	43%	44%	2
Fiorentina	8	19	90	4.74	U21, U14	13.16	31%	37%	>3
Genoa	4	24	96	4.00	U16	12.78	47%	48%	2
Hellas	7	11.09	72.27	6.52	O60, U16, U14, W	8.42	24%	37%	2
Internazionale	19	30	156.81	5.23	U18, UNI, Family	12.37	59%	N.A.	>3
Juventus	10	35.45	120	3.39	U18, U16, W, D	28.42	20%	71%	>3
Lazio	4	20	79	3.95	U16, D	13.68	32%	N.A.	3
Milan	12	22	140	6.36	O65, U16	10.78	51%	N.A.	>3
Napoli	5	18.44	61	3.31	Family	18.42	0%	N.A.	>3
Roma	6	23.92	83	3.47	O65, U14, W	15.53	35%	30%	>3
Sampdoria	4	22.78	87.37	3.84	O65, U18, W	9.44	59%	45%	2
Sassuolo	7	25.5	94.5	3.71	O65, U30, U16, W, S, D	8.95	65%	24%	3
Spal	6	27.36	101.36	3.70	O65, U16, W, D	18.61	32%	62%	2
Torino	4	20.5	67	3.27	U16	11.05	46%	44%	>3
Udinese	4	22.27	50.9	2.29	O65, U18, W, D, UNI	12.11	46%	47%	>3
Average	6.55	23.087	101.2075	4.46		13.36	41%	44%	

Source: Our elaboration of data retrieved from Clubs' official websites. %Capacity sold via season tickets computed after season ticket holders (http://www.stadiapostcards.com/) and capacity (https://www.transfermarkt.it/) data.

Note: Prices refer to full fare tickets.

Segments: U=Under, O=Over, W=Women, UNI=University students.

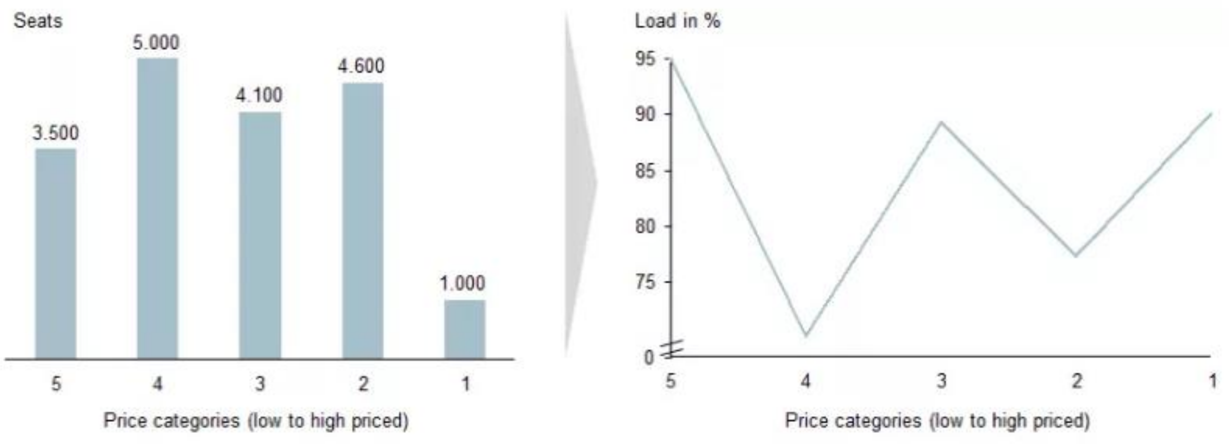
Season ticket price: per-game quota of a full-fare ticket for the cheapest sector.

Season ticket discount refers to the season ticket price in comparison with the average minimum price.

The German pricing consultancy firm Smart Pricer claims that the stadium layout is a crucial driver of revenues in a ticket-based industry. They reveal that in most cases clubs only focus on the price level of each category per se, without considering the importance of how many seats are sold for a given price category. The amount of tickets available for each category is often simply given by the capacity left after the season tickets sale, and the stadium layout, that should be efficiently modified every season (if not before every game), is left unchanged for years. Another common inefficiency that they claim to find is an inconsistency between the tickets available for a given sector and the load factor corresponding to that sector. Figure 2.5 show a typical distribution of seats per sector, and the matching load factor: the largest sectors are also the emptiest ones in percentage terms[66].

[66] See http://smart-pricer.com/httpsmart-pricer-comblog-3-proven-ways-sports-clubs-can-improve-ticket-sales-e/ . Smart Pricer is a German consultancy firm that is specialized in designing pricing strategies for the cinema, sport, ski industries. Two of the founders come from the airline industry.

Figure 2.5: Inefficient distribution of seats per price category



Source: Smart Pricer (2017)

2.3.2 Second-degree discrimination: bundling (season tickets)

When it comes to the matchday revenue stream, sport clubs can be considered as event firms that sell performances (matches) at different dates. The club may increase profits by bundling them in packages (season tickets), that give the right to attend all the games of the season[67]. Obviously, since the value to the customer of the season ticket is no greater than the sum of the values of all the single-match tickets, the sale of a bundle is meaningful only at a discount.

The consideration of matches as identical goods or differentiated ones, slightly changes the motivation for introducing bundling.

In the first-case, bundling induces fans, which in absence of season tickets would attend only some matches, to watch every game[68], since the per-game price of a season ticket is lower than the matchday price.

In the second circumstance, bundling induces fans, which would attend only the most prestigious fixtures, to attend low-demand ones as well. Such circumstance is an application of the mixed-bundling strategy, analyzed by Adams and Yellen (1976). The authors distinguish the pure bundling strategy, where only bundles are sold, with the mixed bundling one, where consumers can choose between the whole bundle and the single components. Bundles are bought by customers if the surplus derived in this way is higher than the one obtained by purchasing the single preferred components. At the same time, firms can extract surplus, via separate single-components markets, from the customers that value single goods more.

Since such mechanism creates a sort of self-selection among consumers, mixed bundling can be considered a second-degree price discrimination strategy.

The creation of a season ticket market alongside the matchday one can be explained by another factor: a strong and loyal fan base is a valuable asset for every sport club, since it creates the atmosphere inside the

67 Some sport clubs also offer smaller packages of a couple of games, see Courty (2015) and Nufer and Fisher (2013).
68 See bundle-size pricing in Chu, Leslie and Sorensen (2011).

arena that improves the matchday experience. The introduction of season tickets allows to identify those loyal fans that should be treated in a more careful way: season ticket holders are considered long-term customers; for this reason, season tickets prices are less-variable and less responding to demand (see Drayer et al, 2012, and Courty, 2015).

Such argument helps to explain the persistent underpricing (i.e. exaggerated discounts) of season tickets pointed out by Nufer and Fisher (2013): in the 2011/12 German Bundesliga, 55% of the seasonal capacity was sold before the starting of the championship via season tickets; the latter were, for many teams, rationed at a certain level, and long waiting lists could have been diminished by a price increase[69].

Courty (2000) reports another argument for bundles underpricing. Season ticket holders cannot foresee the kind of championship that they are going to attend. Purchasers are worried to lose-out by committing to attend a low-quality campaign: had Hellas Verona fans known in advance that the team would have been relegated in 2015-16 Serie A season, their willingness to pay for the season ticket would have been much lower; on the other hand, in the English Premier League of the same year, Leicester fans would have been willing to pay much more for the season ticket, had they known that they were going to attend the historical league victory of their team; the purchase of a season ticket can thus be considered a risky choice, and a certain degree of risk-aversion can explain such underpricing.

A drawback of bundling is the potential creation of secondary markets if season ticket holders resale their tickets, thus basically behaving as brokers. In the Italian football, such behavior is legally prevented, since season tickets are personal, the attendee's identity is checked at the gates, and teams usually do not allow the transfer of the season ticket to another fan, as it happens for single-match ones. However, the impossibility of reselling the seat creates the issue of no-shows: season ticket holders that are not able to attend a match leave an empty seat, with potential negative effects on ancillary revenues. Consequently, some clubs are creating their own official secondary markets, which allow season ticket holders that cannot attend a specific match to recover the per-game expenditure and the club to re-sell the empty seat at matchday price, thus at a profit. In the case of Juventus, which is the only Italian team that has so far implemented such mechanism[70], fans can use the per-game expenditure recovered to buy merchandizing or as a discount on the following year season ticket[71]. The English club Chelsea, which applies the same type of secondary market system, communicated that 20,518 tickets were exchanged in the 2016/17 season, generating a profit of £101,001, that was destined to charity[72].

Table 2.1 shows the full-fare season tickets per-game prices of the 2017-18 Serie A teams, related to the cheapest sectors, which result to be 41% cheaper than the least expensive matchday tickets in the same tier. Atalanta, Chievo and Sassuolo are the clubs that discount season tickets the most, while Hellas, Juventus and

[69] Nufer and Fisher (2013), p.53. The argument in favor of a price increase can be strengthened by the fact that, in a framework in which sell-outs are business as usual, the purchase of a season ticket implies a guaranteed seat for the whole championship: therefore, the value of the season ticket is not merely the sum of the values of the single-match tickets.

[70] Consider that Juventus is the only Italian team that regularly sells-out its capacity. With unsold capacity, a club would lose out by implementing such mechanism.

[71] http://www.juventus.com/it/tickets/abbonamenti/campagna-abbonamenti-2016-2017//faq/, visited on 05/02/2018

[72] http://www.chelseafc.com/tickets-membership/tickets-home.html#match=none, visited on 20/01/2018.

Napoli the least. The behavior of Napoli is rather odd since there is no incentive to buy a season ticket rather than a sequence of single-match ones, in a stadium that is never sold-out.
With the bundling strategies, Serie A teams sold on average the 44% of their capacity. Juventus, Spal and Atalanta are the clubs that sold the highest share of capacity[73], while Chievo, Sassuolo and Roma the lowest, perhaps because of the exaggerated size of their arenas for their potential demand.

2.3.3 Third-degree discrimination: market segmentation

Football clubs implement market segmentation as a third-degree price discrimination, by identifying specific groups on the basis of characteristics (such as gender and age) that likely affect demand. Such features are easily checkable at the gates, in order to prevent attendees arbitrage. According to Courty (2015), market segmentation is particularly profitable for low-demand games, when increasing the number of tickets sold would imply a massive reduction of all prices. Such strategy allows the firm to increase sales to specific groups that would not attend the event at the reference price.

Table 2.1 displays the market segments identified by the Serie A teams:

- 12 teams set specific fares for older attendees (over 60 or 65);
- every club sets a price reduction for at least a young age group (directly or in the framework of a family offer). The reason of such discount is twofold: young people have lower income; moreover, teenagers' tickets are often paid by parents, thus such reduction can be interpreted as a segmentation towards families;
- 11 teams discount tickets for women: since football generally attracts men more than women, the latter may have a lower willingness to pay;
- 3 teams exhibit reductions for university students, i.e. consumers that may not earn any income despite their age.

Such reductions are often available for specific sectors only. A possible interpretation of such strategy is that clubs try to convene such groups in the same sector, since their components may look for a similar experience. For instance, some teams apply the family offers to a specific sector, since perceived violent acts are considered as a factor that drives households out of arenas. The creation of a family-friendly sector in addition to a targeted price reduction may represent a strategy to attract that specific group.

[73] Juventus is the only Italian team that rationed the number of season tickets on sale, at 29,300.

2.4 Variable ticket pricing

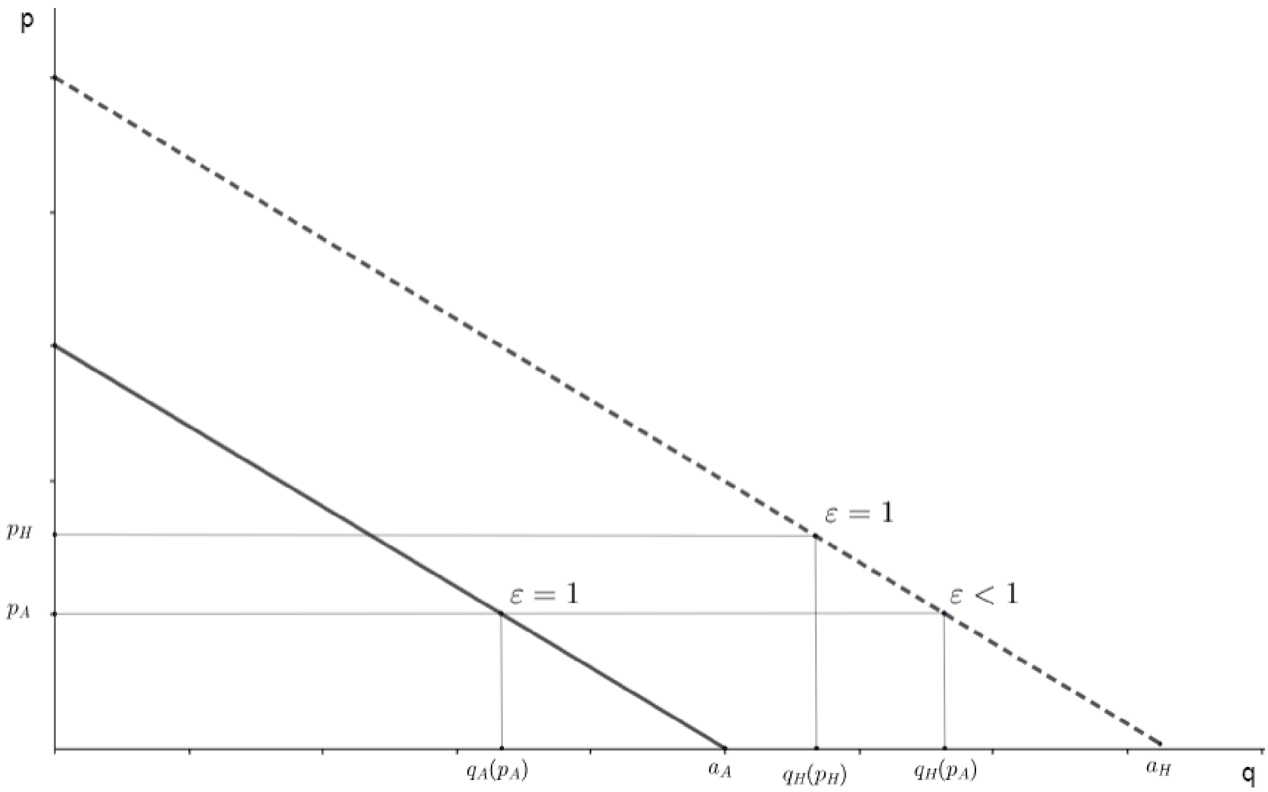
2.4.1 Motivation

The discussion about bundling pointed out the potential consideration of football matches as differentiated goods. Such assumption entails important corollaries when it comes to pricing.

If matches are differentiated goods, demand for tickets will vary among them; given the capacity constraint and the impossibility to store tickets, pricing is the main tool that clubs can exploit to deal with such oscillations. Variable ticket pricing (VTP) is the strategy that deals with demand fluctuations for differentiated events: it allows event organizers to encourage attendance in off-peak situations by reducing price, and to maximize revenues in peak ones by raising it, thus using price as a rationing mechanism (Howard and Crompton, 2004).

The graphical demonstration presented by Rascher et al (2007) clearly shows the motivation for variable ticket pricing (see figure 2.6). We first assume that the monopolist, which operates with zero variable costs and faces the same linear demand curve showed in paragraph 2.2, maximizes ticket revenues (i.e. we do not consider attendance positive spillovers on other revenue sources), without capacity constraints[74].

Figure 2.6: Motivation for Variable Ticket Pricing (mono-product monopolist)



[74] If a quadratic function was used, the revenue gains obtained with the implementation of variable ticket pricing would result even larger. See Rascher et al (2007).

Source: Our elaboration based on Rascher et al (2007), p. 419

If the monopolist sets a fixed price for all matches, it will do so on the basis of an average demand curve, which represents the average tickets sold at every price point. As it was shown in paragraph 2.2, the mono-product monopolist maximizes ticket revenues if it sets a price such that the elasticity of demand equals one in absolute value:

$$p_A = -\frac{a_A}{2b};$$

$$q_A(p_A) = \frac{a_A}{2};$$

$$\varepsilon_A(p_A) = -1$$

where *A* stands for "average demand".
Let us consider a parallel outwards shift of the demand function, which describes a demand increase for a specific match (dotted line in figure 2.6): the new intercept with the horizonal axes is $a_H > a_A$, where *H* stands for "high-demand". If the monopolist sets the fixed price p_A, $q_H(p_A) = a_H - \frac{a_A}{2}$ tickets will be sold. Hence, the elasticity of demand will be lower than one:

$$\varepsilon_H(p_A) = -\frac{a_A}{2a_H - a_A}$$ [75]

Therefore, a club that sets a fixed price does not maximize ticket revenues in high demand matches: the optimal price would be the one that restores the elasticity at unity level:

$$p_H = -\frac{a_H}{2b} > p_A;$$

$$q_H(p_H) = \frac{a_H}{2};$$

$$\varepsilon_H(p_H) = -1$$

[75] The denominator is clearly greater than the numerator.

As a result, when it comes to high demand games, the club maximizes ticket revenues by increasing the ticket price so that elasticity equals 1. The same discussion could be applied to low-demand matches: in such cases, if the team sets the average price, quantity sold will be lower than the average, and elasticity will be higher than one; the club should thus optimally decrease prices to restore the unit elasticity level.

In the setting described in paragraph 2.2, the optimal elasticity level was less than one because of the consideration of a multi-product monopolist that maximize overall revenues and thus of the inclusion of unmodeled "other revenues", decreasing with ticket price, in the objective function. According to Rascher et al (2007), the same mechanism presented above could be applied with any elasticity level, which represents a signal of the pricing strategy of the club: teams should increase (decrease) prices in cases of high(low)-demand games in order to keep the chosen elasticity constant. Therefore, it is possible to state that:

Proposition 5: when demand is stronger (weaker) than the average, prices should be increased (decreased) to restore the optimal average elasticity level[76].

In our setting, such argument is true if the demand parallel shift does not affect the optimal elasticity level. In other words, if:

$$\frac{\partial|\varepsilon^*|}{\partial a} = 0$$

Such condition does not hold, since, assuming that $\frac{\partial R_O'}{\partial a} = 0$ (i.e. the potential demand does not impact on the negative effect of a ticket price increase on other revenues):

$$\frac{\partial|\varepsilon^*|}{\partial a} = \frac{[(a - R_O') - (a + R_O')]}{(a - R_O')^2} > 0$$

Therefore, adjusting prices in order to keep a constant elasticity level is sub-optimal: if the potential demand *(a)* increases, prices should be raised further to increase the elasticity level.

Furthermore, let us verify the assumption that $\frac{\partial R_O'}{\partial a} = 0$, by trying to model the other ticket related revenues, with a simple but meaningful function that is increasing in the quantity of tickets sold at a decreasing rate, i.e. the squared-root of the quantity of tickets sold:

$$R_O = \sqrt{q_t}$$

The effect of a ticket price increase on the other revenues will be:

[76] Such proposition is a corollary of the analysis made by Rascher et al (2007).

$$R'_O = \frac{\partial R_O}{\partial q_t} \cdot \frac{\partial q_t}{\partial p_t} = \frac{1}{2\sqrt{q_t}} \cdot b = \frac{1}{2\sqrt{a + bp_t}} \cdot b$$

The effect of a ticket price increase on other revenues is negative (since b < 0). We now compute the effect of a parallel shift of the demand curve on R'_O:

$$\frac{\partial R'_O}{\partial a} = \frac{-b}{4} \cdot (a + bp_T)^{-\frac{3}{2}} > 0$$

The last equation showed that the negative effect of a ticket price increase on other revenues is decreasing (in absolute value) in the size of the potential demand (a, which represents demand when $p_t = 0$). Since R'_O is what drives the elasticity reduction from the unity level, an increase of a implies a further motivation for adjusting prices upwards, so that the elasticity level is nearer to one.

The implication is that high demand games should be priced such that elasticity is higher than in the average case. Consequently, clubs should not vary price in order to restore the optimal average elasticity level, but they should raise it further, in order to increase elasticity. Therefore, the analysis allows us to state a further motivation for the implementation of variable ticket pricing[77]: when it comes to high-demand events, the monopolist should not only increase prices to restore the average elasticity objective, but it should raise them further to increase the elasticity level.

Moreover, two other elements may support the hypothesis of the efficiency of variable ticket pricing. In the above discussion we only considered, for simplicity, parallel shifts of the demand curve. It could be argued, however, that since high demand games are prestigious events, the related price sensitivity (here captured by the parameter b) could be lower. Such claim represents a further motivation for raising prices in high-demand games. Eventually, capacity constraints were not considered in the analysis. In high-demand games, full capacity utilization may occur. As it was demonstrated in chapter 2.2, such result may imply pricing in the elastic part of the demand curve, therefore with a further price increase.

Therefore, the analysis carried out in paragraph 2.4.1 allows to state that:

Proposition 6: when demand is stronger (weaker) than the average, the optimal elasticity level is nearer to (more distant from) unity: prices should be re-optimized accordingly.

[77] The above analysis is related to a parallel increase of the demand curve; the same reasoning can be applied to parallel decreases (inward shifts) of the demand curve, in the opposite direction.

2.4.2 Implementation

A crucial element for an effective implementation of variable pricing is the ability to correctly predict demand, i.e. to identify the variables that shift the demand curve (Malasavska and Haugon, 2018).
For instance, when it comes to the concerts industry, Courty (2015) reports that prices vary with the city where the event is performed, and the day of the week, if the concert is played several times in the same venue. Malasavska and Haugon (2018) estimate that in the Norwegian Skiing resorts, price should be reduced by 30-35% in weekdays.

The cinema industry represents an interesting and comparable example of the application of variable ticket pricing. Einav and Orbach (2007) discuss the puzzle of uniform pricing in cinemas: multiplex set the same price for all movies. However, some screens are sold-out, others are empty. The natural implication would be the adjustment of prices for different movies. However, while prices in the multiplex industry vary according to day of the week, booking date, season (De Roos and McKenzie, 2014), different movies are priced the same. According to the authors, some demand patterns to correctly adjust prices could be easily identified in the production costs of movies, participation of stars, sequels and critical reviews, which are positively correlated with box-office revenues. Moreover, demand varies with the stages of the movie's screen life: demand diminishes with it, which is longer the more successful the movie is. However, ticket prices do not adjust for such effect.

Drayer et al (2012) report that variable ticket pricing was first introduced in the American sport industry in 1999 by the Colorado Rockies (Major League Baseball, MLB). According to Courty (2015), American professional clubs vary prices on the basis of day of the week, month, holiday, visiting team, seasonal sporting performance, league table position, injuries, historical rivalry, participation of star players… The same work reports that in 2014-15, only two teams out of 30 in the National Hockey League were not implementing variable ticket pricing, which was instead less spread in the National (American) Football League (twenty out of thirty-two)[78].

The last column of Table 2.1 shows that in the current Serie A league[79], 11 out of twenty teams used up to three different ticket pricelists for their internal matches. Table 2.2 focuses on the variable ticket pricing strategies adopted by specific teams in the current season, showing the opponent teams grouped in the same price category. The table shows that within the same price category, the quantity of matchday tickets sold is rather variable, with fluctuations that are on average the 20-25% of the mean. The reason may be that Italian clubs has priced differentiated matches, with a differentiated demand, in the same way. The implication is an inefficient outcome: prices could have been raised in matches with higher demand, and reduced in those with lower demand.

[78] Courty (2015) tables 2-3.
[79] Related data are updated to 26/01/2018, i.e. the 21st stage of the 2017-18 championship. Therefore, each team has played around ten home games.

Table 2.2: Price categories of selected teams: average tickets sold, average deviations from the category mean (2017-18)

Club	Price Categories	Opponents (1st Category)	AVG Tickets	Average Dev.	AVG Dev %	Opponents (2nd Category)	AVG Tickets	Average Dev.	AVG Dev %	Opponents (3rd Category)	AVG Tickets	Average Dev.	AVG Dev %
Atalanta	2	Rom, Juv, Nap	5,283	366	7%	Sas, Bol, Hel, Spa, Ben, Laz, Cag, Chi, Fio	2,884	480	17%				
Benevento	1	Bol, Tor, Rom, Int, Fio, Laz, Sas, Mil, Spa, Chi, Sam, Cro	4,408	1,918	44%								
Bologna	3	Nap, Int, Juv	12,291	2,342	19%	Tor, Spa, Laz, Sam, Fio, Sas, Gen, Ata	5,605	1,776	32%	Cro, Cag, Udi, Ben	6,228	1,034	17%
Crotone	2	Mil, Int, Nap	5,412	1,068	20%	Hel, Ben, Tor, Fio, Gen, Udi, Chi, Cag, Ata, Spa, Samp	1,668	208	12%				
Fiorentina	3	Mil, Int	12,586	392	3%	Ata, Tor, Rom, Hel	5,682	1,054	19%	Sam, Bol, Udi, Sas, Gen, Ben	8,441	3,102	37%
Hellas	2	Nap, Int, Mil, Juv	12,666	3,887	31%	Fio, Sam, Laz, Ben, Bol, Gen, Cro, Rom, Tor, Chi	4,687	1,517	32%				
Roma	3	Int, Nap, Laz	26,611	6,514	24%	Hel, Udi, Bol, Cag, Sas, Ata, Mil	13,555	3,136	23%	Cro, Samp, Ben, Tor	10,227	1,009	10%
Sampdoria	2	Rom, Mil, Juv	7,214	3,372	47%	Ata, Cro, Chi, Laz, Sas, Spa, Fio, Tor, Hel	2,193	720	33%				
Sassuolo	2	Juv, Mil, Int, Laz	10,241	4,811	47%	Gen, Chi, Udi, Hel, Cro, Tor, Ata, Cag	2,008	531	26%				
Spal	2	Nap, Fio, Laz, Int, Mil	4,379	391	9%	Udi, Cag, Cro, Sas, Gen, Hel, Tor	3,591	640	18%				
AVG					25%				24%				21%

Source: Elaboration of attendance data retrieved from http://www.stadiapostcards.com/.

Price categories were retrieved from the official clubs' websites.

Data refer to the first twenty-six stages of season 2017-18

A glance at the opponents included in the same group shows that grouping was probably made according to the visiting team[80]: top clubs were clustered in the first category, the least prestigious ones in the last class. The demand fluctuations reported in the table may occur for two main reasons: first, grouping on the basis of the visiting team was not made in an efficient way[81]; second, variables other than the opponent may have affected demand, thus grouping on the basis of the away team only was inefficient. If such variables are known when the price decision is made[82], pricing according to them may lead to a more efficient outcome.

Smart Pricer claims that one third of sport games are mispriced, given that prices are often based on the opponents only. It maintains that 44% of demand is driven by external factors, such as team performance, day of the week and evolution of the championship. The consideration of such demand factors can potentially increase matchday ticket revenues by 1-2%[83].

Garcia and Rodriguez (2002) estimate a demand function for the Spanish La Liga matches, finding that several variables, other than those related to the opponent, significantly affect the number of tickets sold: indicators concerning the sport seasonal performance of the home team, weather, day of the week, month, uncertainty of matchday and seasonal outcome.

The next chapter will replicate a similar estimation on the Italian Serie A, trying to identify the main variables that affect demand, and that could lead clubs to price matches more efficiently.

[80] See Chapter 3 for an empirical assessment of such claim.

[81] For instance, in our database, which will be described in chapter 3, matches against Juventus report on average 15,000 tickets sold; matches against Internazionale and Milan sold around 11,000 tickets: therefore, grouping them in the same category appears quite inefficient.

[82] In the Italian football, prices are usually set one-three weeks before the match. Some clubs declare the matchday pricelists of the whole championship when the season tickets sale starts (e.g. Hellas Verona, Crotone, Spal).

[83] http://smart-pricer.com/httpsmart-pricer-comblog-3-proven-ways-sports-clubs-can-improve-ticket-sales-e/

2.5 Dynamic ticket pricing

Dynamic ticket pricing (DTP) is probably the most sophisticated strategy applied in ticket-based industries: it is a combination of demand-based variable pricing, inventory control and price discrimination based on the purchasing date.
Ticket demand may indeed fluctuate during the selling period, since factors affecting the attractiveness of the event may change. Therefore, dynamic ticket pricing may be considered as a variable pricing mechanism that yields different prices for the same event, at different purchasing dates.
Moreover, the monitoring of ticket inventories (and the comparison with past similar sales) allows to evaluate the strength of demand in real time, leading firms to dynamically adjust prices accordingly.
Eventually, the possibility to modify prices during the selling period allows the firm to charge higher prices at the end of it, if late buyers are believed to have a higher willingness to pay (as it happens in the airlines industry).

Dynamic pricing lies in the framework of revenue (or yield) management: a set of different strategies, aimed at maximizing revenues, first adopted by the airlines industry in the last decades of the 20th century.
According to Cross et al (2011) and Nufer and Fisher (2013), revenue management methods arose from the deregulation of the American airlines industry in the late 1970s, which allowed charter airlines to vend tickets for much lower fares than the ones charged by traditional companies.
The first approach to tackle the consequent competition was focused on cost-reduction. However, the firm American Airlines' management realized that they were operating with millions of unsold tickets each year: the company was unable to capitalize on such excess capacity available at a very low marginal cost. Therefore, American Airlines understood that *"they had a* revenue *problem that was more critical than their* cost *problem*"[84]. Consequently, they applied a series of targeted discounts on tickets, with the assistance of large databases, IT infrastructures and skilled analysts to investigate the fluctuating demand patterns of each route (Cross et al, 2011).
Revenue management methods were continuously developed, especially with the subsequent pressure of the low-cost airlines competition, and they soon spread to other companies and industries sharing similar issues, such as hotels, car rental firms, motor carriers and entertainment.

In her seminal paper, Kimes (1989) lists the crucial requirements that a capacity constrained service firm should respect in order to successfully apply revenue management tools, such as DTP:

- **Fixed capacity:** supply cannot be rapidly adapted to excess demand, e.g. planes have a limited number of seats. The same concept applies to rooms for hotels, or vehicles for car rental firms.

[84] Cross et al (2011), p.3

- **Ability to segment markets:** i.e. to identify different types of customers with different needs, for instance price-sensitive and time-sensitive ones; the formers are willing to purchase early if it allows them to save, while the latter are late buyers with a high willingness to pay for the service.
- **Perishable inventory:** if a share of capacity is not exploited in a certain event, such supply immediately expires, creating an opportunity cost.
- **Product sold in advance:** inventory can be sold much before the actual use, giving firms the opportunity to plan the service ahead; at the same time, advance sales entail a trade-off for the sales manager: capacity can be early sold at low prices to time-sensitive customers, or at higher prices to late buyers, thus bearing the risk of leaving capacity unsold if the latter does not appear.
- **Fluctuating (and predictable[85]) demand:** service firms deal with changeable demand patterns, characterized by peaks, implying a possible excess demand, and valleys, entailing a potential unused capacity. For instance, hotels face peak-season/weekends and other periods where demand is much weaker. Shifting demand is a good reason to set different prices, predictability allows to correctly identify such fluctuations.
- **Low marginal sales costs:** providing the service to an additional customer is almost costless, e.g. when an event is already organized and staffed, the cost of selling an additional ticket is practically zero.
- **High marginal capacity change cost:** capacity could be enlarged at a remarkable cost, as it is the case for adding a room in a hotel.

According to Drayer et al (2012), the sport event industry is an appropriate framework for the implementation of revenue management techniques, since it complies with the above requirements:

- sport clubs operate with a fixed capacity, as they play their home games in the same arena; the constraint is even stronger than in other industries, since airlines could put customers on a subsequent flight in the same day, or hotel can accommodate guests in a sister structure in another part of the city (Kimes, 1989);
- the fan base can be segmented in several groups, by gender, age and affiliation with the club (see Giulianotti's matrix in chapter 1); late buyers with higher willingness to pay may also exist;
- tickets are a highly perishable product, since they are valueless after the event;
- the sale period starts well before the occurring of the event, especially in the American sport industry;
- the attractiveness of a match is affected by several variables that renders games different products: if such variables are correctly identified, and their realization occurs before the match, such fluctuating demand can be predicted;
- an additional ticket sold, in a framework characterized by crowds of attendees, does not change the operational costs faced to organize the event;

[85] Predictability of demand was added as a criterion by Kimes et al (1998)

- seats cannot be easily added, for security reasons: capacity enlargements imply huge costs.

When it comes to the sport industry, revenue management tools were first introduced in American baseball. Shapiro and Drayer (2014) claim that the introduction of dynamic ticket pricing in the sports industry arose as a reaction to the development (mainly given by e-commerce technology) of secondary markets, which are completely demand-driven and aim at extracting the highest possible share of the attendees' willingness to pay. The online sale of secondary tickets allowed clubs to understand how much money they were leaving on the table, in an era characterized by a continuous increase of player salaries and other expenses (see Drayer et al, 2012). Moreover, variable ticket pricing was not much effective in the American sport industry[86]. The main reason is that, in the US, the sale of tickets for *all* the league matches usually starts before the beginning of the season. Since variable prices were set months ahead of matches, they were not able to react to demand shifts occurring in the extended selling period (see Shapiro and Drayer, 2012 and 2014).

The San Francisco Giants (MLB) were the first professional sport club to implement dynamic ticket pricing, in 2009. At first, they dynamically priced traditionally low-demanded seats. Given the encouraging results, they extended it to the whole stadium in the following season, reporting a 7% increase of revenues[87]. Other clubs soon followed, first in the MLB and subsequently in the other main US sport leagues: in 2013, 21 out of 30 teams adopted dynamic ticket pricing in the MLB[88]. Qcue, a ticket pricing consulting firm that assisted the Giants with the adoption of DTP, claims that such strategy should increase gate receipts by 30% in high demand-games and 5-10% in regular ones[89].

DTP mechanisms seek to contemporarily maximize attendance and revenues, adjusting prices in real time as a reaction to demand.

When demand is weak, low-prices allow to increase attendance (and, potentially, ancillary revenues) and better exploit the available capacity: ticket *per-spectator* revenues decrease, but *per-seat* ones may increase. According to Nufer and Fisher (2013), such policy helps to build a stronger fan base: the more people attend a match, the better is the matchday experience, which stimulates fans to join another game in the future, thus encouraging habits in attendance. The authors claim that such outcome is particularly favorable for clubs with a low capacity utilization.

On the other hand, DTP allows to increase revenues when a sell-out occurs, since prices better reflect attendees' valuation of tickets, by extracting a larger share of consumer surplus, as it happens in secondary markets. Shapiro and Drayer (2014) estimate two econometric models for the prices on both primary (where DTP was used) and secondary markets of Giants' tickets, finding that the same factors were significant in explaining the two dependent variables. However, the same authors (see Shapiro and Drayer, 2012) found that, despite the introduction of DTP, prices on secondary markets were still higher than those on primary ones: the two markets appear to work in the same direction, but clubs generally charge lower fares than brokers.

---

[86] Rascher et al (2007) estimated that the implementation of variable ticket pricing in the MLB (Major League Baseball) increased ticket revenues by 2.8%

[87] Shapiro and Drayer (2012) p.533

[88] Shapiro and Drayer (2014), p.146

[89] Courty (2015), p.5

While the potential benefits of a DTP system are quite intuitive, its practical implementation is not forthright, as the combination of demand evaluation, inventory control and time discrimination yields not straightforward results. Two papers by Kemper and Breuer (2016a, 2016b) demonstrate such conclusion.

Kemper and Breuer (2016a) try to design a DTP model in order to estimate the potential benefits for the German club Bayern München to move to such a pricing method. The objective of their model is to maximize expected ticket revenues on a finite time horizon, by choosing a different price for each period. The so-called Bellman equation reported below describes the issue from a mathematical point of view:

$$V(c,t) = \max_{p_t}\left\{d_t(p_t) \cdot \left(p_t + V(c-1,t-1)\right) + (1 - d_t(p_t)) \cdot V(c,t-1)\right\}$$ [90]

$V(c,t)$ represents the expected revenues when *c* tickets are still available, and there are *t* periods left to the end of the time horizon; $d_t(p_t)$ is the probability that a ticket is sold, in each period, given the price.

Two boundary conditions accompany the above equation:

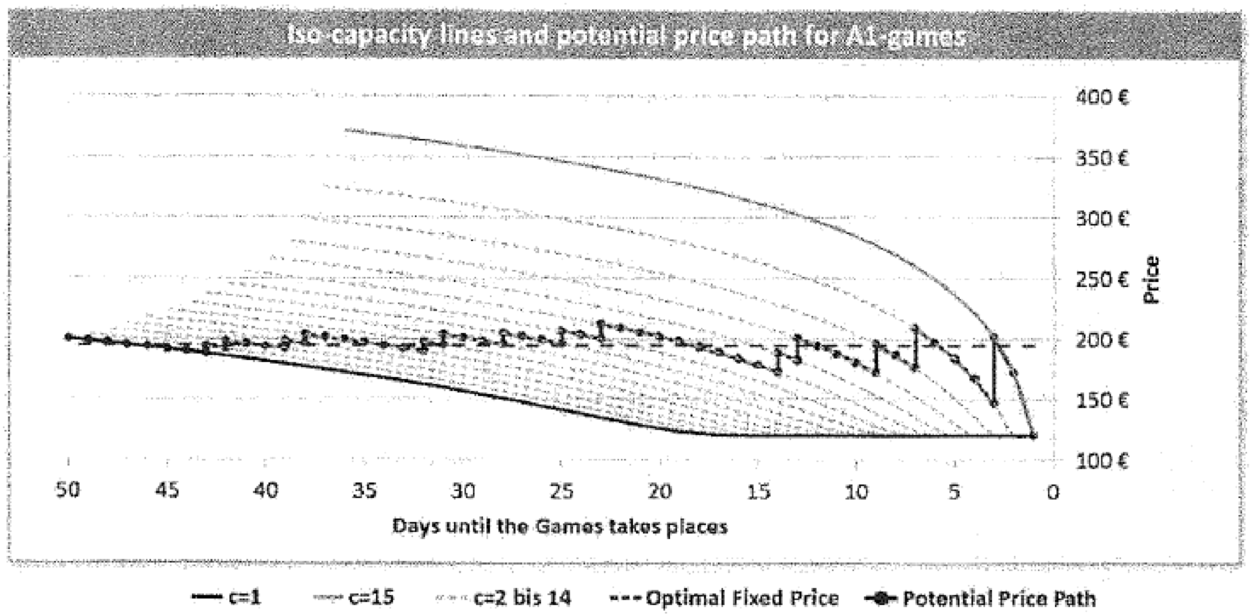
- $V(c,0) = 0$, i.e. when the sale period is over, expected revenues deriving from the unsold tickets are zero;
- $V(0,t) = 0$, i.e. when all tickets are sold, no more revenues can be obtained.

A price is set in every period in order to maximize revenues over the whole remaining time horizon. Expected revenues are the sum of two components. The first one represents the proceeds obtained if a ticket is sold in period *t*: the price of the ticket plus the expected revenues with *c-1* tickets and *t-1* periods remaining; the second one denotes earnings if tickets are not sold in period *t*, i.e. the expected revenues with *c* tickets and *t-1* periods left.

Figure 2.7 graphically shows the mechanism that yields the price path chosen by Kemper and Breuer (2016a) in their estimation. The horizontal axis represents the days remaining before the event, while the vertical ones reports the ticket price; curved lines represent *iso-capacity lines*, i.e. lines along which the amount of tickets left is the same (the bottom curve is the one such that the whole capacity is unsold, while along the top one only one ticket is available). Such curves are downward sloping, i.e. the nearer the event, the lower the price for each available inventory level. Therefore, it appears that the model designed by the authors does not apply time discrimination: for a given inventory level, prices are lower at the end of the sale period. The price path is such that each time a ticket is sold, the price maker moves to the next above iso-capacity curve, thus raising the price.

[90] Kemper and Breuer (2016a), p.7

Figure 2.7: A DTP model with no time-discrimination



Source: Kemper and Breuer (2016a), p.16

Consequently, the revenue-maximizing scenario is the one in which all tickets are sold at the beginning of the sale period, since the iso-capacity lines are downward sloping; moreover, if unsold tickets are available on the matchday, the price collapses to a minimum one.[91] As it was discussed above, such mechanism would allow the team to maximize revenues when demand is strong, since prices are adjusting upwards after every ticket sale.

In such framework, the reaction of a rational customer with perfect information depends on the probability of a sellout:

- If a sellout is likely to occur, attendees weigh the possible gains from delaying the purchase over the potential failure to secure a ticket (McAfee and Te Velde, 2006);
- If a sellout is unlikely to happen (as it is in the current Italian Serie A), the rational behavior is to wait for the last day in order to buy the ticket at the minimum price.

Therefore, in the case of an unlikely sellout, such strategy could not allow to maximize revenues, since rational customers have an incentive to wait: a fixed price could extract more surplus from them, even if it could induce some attendees with low willingness to pay to desert the match.

Kemper and Breuer (2016a) apply their model to Bayern München, i.e. a team that employed a VTP strategy (with two match categories) characterized by a massive underpricing and regular sellouts. In order to evaluate the benefits of the DTP model, they first estimated an optimal fixed price for each match category (i.e. they removed the underpricing issue). Afterwards, they compared potential revenues and attendance with

[91] In figure 2.7 such minimum price is a sort of price floor, that could realistically be zero: since the marginal cost of a ticket sale is zero, the club has an incentive to give it away, hoping that the purchaser will spend some money inside the arena.

the two pricing methods, within each category. They found that revenues would have significantly increased, and attendance would not have been affected. Average prices would have been similar to the optimal fixed one, but they would have obviously fluctuated.

The same authors (Kemper and Breuer, 2016b) analyzed the dynamic pricing scheme adopted by the English team Derby County[92], finding a system that was not consistent with the one developed in the previous paper. In the season under analysis, only one sellout occurred; therefore, price reductions at some moments of the sale period would have been consistent with the model designed by Kemper and Breuer (2016a). However, among the 228 price paths in the sample, not a single price decrease occurred, and most of the price increases took place in the last days before the match[93]. Consequently, the minimum price was the one set at the beginning of the sale period. The authors justified such mechanism with the likely existence of a dynamic price floor that prevented the price to drop. However, the mechanism is perfectly consistent with time discrimination, in that the club tried to extract more surplus from late buyers by charging higher prices[94].

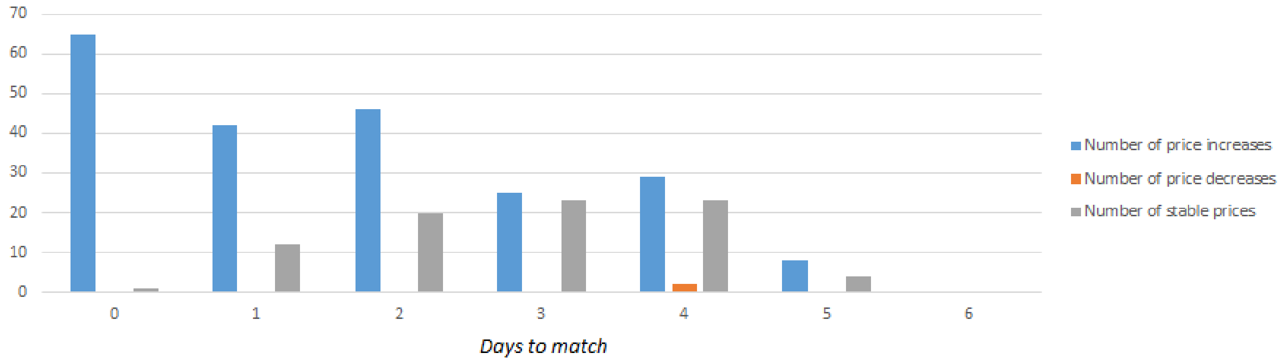
Virtus Entella is the only Italian team that adopted dynamic ticket pricing[95], since 2017. When the team announced the new policy with an official statement, it declared that prices would have been affected by visiting club, league position and sport performance of both teams, rivalry between opponents, probability to see many goals, day of the week, time of the day, weather conditions (in a stadium that is not fully covered) and purchasing date (i.e. all the rest being equal, tickets are cheaper if bought in advance)[96]. Since the sale period usually starts about a week before the match, a VTP strategy would have been able to account for all the variables but the last two, i.e. all the other variables are stable during the selling period.
Prices are updated each day, and the minimum and maximum price that can be charged are communicated at the beginning of the selling period. Moreover, matchday prices cannot be lower than the per-game quota of the season ticket.

Figure 2.8 shows that the DTP strategy adopted by Virtus Entella includes a time discrimination component: in a sample of 66 price paths (366 price points related to the first eleven home matches of the current season), prices decreased in only two occasions, despite an average load factor of only 35%.
In the first half-season of implementation (the last eleven home matches of the past championship), the club claimed that attendance increased by 5%, and revenues by 1%; moreover, 60% of occasional supporters positively evaluated the new method[97].

---

[92] Derby County, which in the last seasons has always participated to the Football League Championship (i.e. the second-tier of English professional football), was the first European football team to implement DTP, in 2012-2013. However, after four seasons, it moved back to a simpler VTP approach. A particular sector of the stadium (the North Stand) was excluded from the DTP system, since it is the one attended by the most loyal fans. Tickets went on sale about four weeks before the match.
[93] Kemper and Breuer (2016b), p.10
[94] Nufer and Fisher (2013) claim that time sensitivity is not a factor in the European football industry (as it happens, for instance, in the airlines one), entailing that a time discrimination strategy should not be much profitable. However, according to Drayer et al (2012), a method that incentivizes early sales would help clubs to better organize the event (e.g. by hiring an optimal number of matchday employees).
[95] Virtus Entella, which participates to the Italian Serie B, implemented a DTP strategy with the assistance of Dynamitick, a start-up firm that designs dynamic pricing models for several industries (entertainment, travel, healthcare, retail).
[96] http://www.entella.it/stagione/news/item/893-tutto-quello-che-c-e-da-sapere-sul-biglietto-a-prezzo-flessibile.html
[97] http://www.calcioefinanza.it/2017/08/21/la-virtus-entella-conferma-biglietto-dinamico-201718/

Figure 2.8: Price movements during the selling periods for Virtus Entella (2017-18, first eleven home matches)



Source: Our elaboration of data retrieved from Virtus Entella's official website

Despite the potential additional revenues that could theoretically be obtained with a DTP strategy, such approach has not spread out in the football industry yet. Given the business-oriented status of modern football, it seems unlikely that managers are not aware of such pricing method. Therefore, it could be that the cost of designing a dynamic ticket pricing scheme (investment in IT tools, cost of outsourcing the service to consultancies) is greater than the potential benefits. The next paragraph discusses some factors that could obstacle the implementation of dynamic pricing in the European football industry.

2.6 Managerial issues concerning variable and dynamic ticket pricing

Although demand-based pricing methods appear to be effective strategies, the literature discusses some delicate issues that could make clubs more cautious in implementing them.

Drayer et al (2012) focus on ancillary revenues. It may be reasonable to assume that concessions prices are not included in the ticket demand function, since consumption inside the stadium is not mandatory and not strictly necessary (given the reduced duration of a football match). However, for some individuals the ticket price may appear in the concessions demand function, having thus an impact on ancillary revenues. In this setting, price increases may depress supplementary revenues, while price reductions could boost them. On the other hand, high ticket prices may serve as a tool to identify those wealthy attendees that could be willing to spend more inside the stadium, while lower ticket prices may attract bargain hunters that do not consume within the arena. Further research and attendees' data collection may clarify which of these effects prevails[98].

Moreover, Leslie (2004) found that the revenue growth due to the implementation of variable ticket pricing is weaker for those events that present a wide menu of prices (i.e. tier pricing): after a price change,

[98] In the Italian football, membership cards ("Tessera del Tifoso") are mandatory for season ticket holders. Ideally, clubs could induce attendees to underwrite them to buy tickets and goods at, say, discounted prices; in such a way, clubs could collect personalized data to investigate customer behavior.

attendees substitute inside the pricelist. Therefore, clubs should be rather cautious, since cross-elasticities between sectors may lead to not straightforward outcomes.

Courty (2015) and Drayer et al (2012) highlight the potential implications of demand-based pricing on the sale of season tickets. Potential reductions corresponding to low-demand matches may lead prices to be lower than the per-game quota of the season ticket, deterring fans to buy the latter. Since season ticket holders are the crucial long-term customer base of a sport club, teams may design policies to incentivize the purchase of a bundle within a variable/dynamic pricing framework. Price floors are the simpler way to deal with such issue: clubs guarantee that matchday prices will never drop below the season ticket per-game quota (as it happens for Virtus Entella). Season tickets refunds represent another solution: at the end of the championship, season ticket holders receive the difference between the per-game quota and the potential matchday lower price. The English football club Arsenal, for instance, applies a similar method. At the beginning of the season, all matches are categorized as A, B or C games: a season ticket holder purchased five A matches, ten B matches and six matches for the current season (2017-18). If Arsenal decided to downgrade (upgrade) the category of a specific match, season ticket holders would receive a refund (be required to pay additional money)[99].

Price floors could be set for other reasons. Since prices may be seen as a signal for the quality of the product, exaggerated underpricing in a VTP framework could harm the value perception of the event (see Drayer et al, 2012). Moreover, in a DTP setting without time discrimination, a price floor discourages supporters to wait for a possible dramatic price drop.

The possible reaction of the fan base is however the more dangerous issue in the implementation of demand-based pricing. A negative reaction could occur for three main reasons: aversion to price variation, persistent upward adjusted prices, rationing effect of such pricing strategies.

When it comes to discussing price variability aversion, both Einav and Orbach (2007) and Courty and Pagliero (2008) report the example of the Coca-Cola vending machine. In 1999, Coca Cola tested a vending machine that adjusted prices with temperature variations, given that hot weather was believed to boost demand. After the negative reaction of the public opinion, Coca cola withdrew the project, even if it was not clear whether the adverse feedback was due to variability aversion per se or to a concern of possible exploitation (i.e. upward adjusted prices).

Einav and Orbach (2007) claim that consumer aversion to price variation is among the main reasons why different movies are uniformly priced in the same cinema. The discussion led them to state that the framing of a variable pricing strategy, after the identification of the causes of such distaste, is crucial in determining the customer reaction.

Courty and Pagliero (2008), for instance, designed a survey (seeking to replicate the Coca-Cola example) that allowed them to find that, tough consumers in the sample were averse to price variation, they were willing to trade it off with rationing; at the same time, however, they were not willing to exchange price

[99] https://www.arsenal.com/membership/2017/18-season-ticket-how-it-is-calculated (last visited on 07/02/2018). After the 2016-17 campaign, Arsenal season ticket holders received a refund because of an additional A match and three B matches less.

variation with lower expected prices. Therefore, in such a framework, a variable pricing strategy should have better been advertised as a rationing solution than a way to reduce expected prices through price drops at off-peak times.

Moreover, in a DTP framework, consumer may be averse to the diverse prices that they pay: customers buy the product on different dates (thus at different prices) but they consume it in the same moment. Therefore, upon consumption they may realize to be paying different prices for basically the same service, with negative consequences on fairness perception. According to Choi and Mattila (2005), providing more information to the customer upon reservation is an effective method to deal with such issue. In particular, consumers should be made aware about which variables are determinant in the price setting, and how they affect it. In this way, customers learn how to bargain-hunt, i.e. they realize that the price paid is also up to them. This is consistent with experimental findings by Haws and Bearden (2006), whose results suggest that fairness perception improves when customer behavior plays a role in the price paid.

A negative reaction is also likely to occur if the adoption of a demand-based pricing strategy entails an upward adjustment. This is particularly true if such methods would be applied by clubs that regularly sellout their capacity. Einav and Orbach (2007) and Wirtz et al (2003) agree on the fact that raised prices following cost increases are perceived as fair, while price increases after a demand strengthening are alleged to be unfair. Price ceilings are a solution to such negative response, that would also give to every income category the opportunity to attend prestigious matches where demand is particularly strong (see Drayer et al, 2012, and Nufer and Fisher, 2013).

Eventually, Wirtz et al (2003) consider the case of capacity-constrained customer oriented firms that use revenue management techniques as a rationing tool. In such cases, customers with the highest willingness to pay are not rationed. However, such consumers may not be the most loyal ones. Such outcome may entail resentment in the loyal part of the fan base that is typical to a sport club (see the Giulianotti's matrix in the previous chapter). The implementation of loyalty programs (such as membership cards) is a good solution to deal with a similar issue; an alternative is the exclusion from demand-based pricing for those sectors that are mostly attended by loyal fans, as it was proposed by Kemper and Breuer (2016a) in their model designed for Bayern München.

2.7 Concluding remarks

Chapter 2 has provided a literature review concerning the pricing strategies that are implemented in ticket-related industries, especially in the football one.

At first, a simple model allowed to identify the ticket price that a football team optimally sets. The possible existence of binding capacity constraints, and the consideration of the club as a multiproduct monopolist are key factors that drive the optimal decision. If the constraint is not binding and the football club chooses the ticket price in order to maximize overall revenues, the elasticity will be lower than unity, i.e. the revenue maximizing level for a mono-product monopolist with zero marginal costs.

Such price level is set in the framework of several price discrimination strategies that aim at extracting more surplus from the attendees, and to reduce the deadweight loss that arises since potential low-willingness to pay consumers would pay a positive price for their attendance, which entails a negligible marginal cost. Tier pricing, bundling and market segmentation represent price discrimination strategies that are regularly implemented by football teams.

Moreover, revenues can be further optimized by adopting demand-based pricing approaches, i.e. variable and dynamic ticket pricing.

Variable ticket pricing arises from the consideration that some match-specific variables change the attractiveness of a game, thus shifting the demand curve and the point elasticity level if a fixed price is set for each event. In such cases, the football team should react by changing the price to restore the elasticity level that is deemed to be optimal. Moreover, a (very) simple modeling of the relationship between other revenues and attendance allows to state that the optimal elasticity level varies with the demand strength.

Dynamic ticket pricing allows firms to adjust price in real time, as a reaction to the shifting demand, the monitoring of ticket inventories, and the implementation of time discrimination. Although the European football industry seems to fit the requirements for a successful implementation of DTP, such strategy is not spread in it yet. The last paragraph of the chapter discusses some possible explanations, especially those related to customer fairness perceptions.

Chapter 3

ESTIMATION OF GAME TICKETS DEMAND IN THE ITALIAN SERIE A

3.1 Introduction

Chapter 2 displayed the qualitative background necessary to run the empirical work of the final chapter, i.e. to verify the consistency with data of the propositions derived from the theoretical model and to estimate the impact of the multi-product monopolist behavior and of the implementation of a variable ticket pricing strategy. The objective of chapter 3 is to deliver instead the quantitative framework that the final chapter will be based on. Therefore, the next paragraphs present the econometric study that aims at estimating a demand function for game tickets in the Italian Serie A. Such estimation work entails the identification and the quantification of the relationship between price and quantity of game tickets sold, the detection of the variables other than price that significantly affect ticket demand, and the estimation of the demand strength for each match (a in the notation of chapter 2).

First, a literature review of attendance studies is shown in order to gather valuable insights for the empirical work (paragraph 3.2). The recurrent issue of such studies is the limited availability of sector-specific price-quantities data. Therefore, different proxies are adopted in order to collapse the price menu in a unique value, thus reducing the accuracy of the studies. Such limitation is among the reasons why many works do not include the price variable in the attendance equation: such studies focus on factors other than price, thus without estimating price elasticities. In any case, the literature is helpful for the identification of the key attendance determinants and their correct modeling; moreover, it allows to recognize the econometric issues involved, in order to effectively deal with them.

Afterwards, the methodology adopted (i.e. regressors chosen, data and type of model) is illustrated (paragraph 3.3). We run three panel models with fixed-effects, in order to control for team-specific unobserved variation, and instrumental variables, to deal with the endogeneity condition of the price variable. Censoring issues are not dealt with, given the rare occurrence of sellouts in the Italian Serie A. The three models differ for the assumed functional form of the price-quantity relationship.

Finally, the empirical results are presented in paragraph 3.4. A diagnostic testing is helpful to run a meaningful inference and to remove a model that, at first sight, yields valuable coefficients. Estimations allow to compute aggregated average price elasticities and to identify some statistically significant determinants of attendance that should be considered by clubs in the context of the choice of the optimal price. Moreover, the database allows to re-estimate the model on a specific subsample, in order to compare the price sensitivity and the effect of the other key factors.

Paragraph 3.5 summarizes the work done, highlights the limitations of the study and concludes.

3.2 Literature review

Stadium attendance has been empirically investigated since the 1970s, with a wide variety of works concerning several sports (especially football and baseball) and countries (particularly Anglo-Saxon ones), and focusing on different issues.

Garcia and Rodriguez (2002), Avgerinou and Giakoumatos (2009) and Buraimo (2008) investigate the determinants of attendance in the Spanish La Liga, Greek first division and English Football League Championship respectively; in particular, the former focuses on matchday tickets sold and estimates the average team-specific price elasticity.

Caruso and Di Domizio (2015) examine the effect of anti-hooliganism policies introduced by the government on the Italian Serie A game tickets demand. Buraimo and Simmons (2008 and 2009) study how uncertainty of outcome affects attendance in the English Premier League and in the Spanish La Liga. Marburger (1997) estimates ticket price elasticity in the American MLB, while Coates and Humphreys (2007) extended the analysis to concessions price elasticities and to the other main American leagues (NBA and NFL).

Despite the differences in the leagues analyzed and in the objectives of the work, such papers allow to gain valuable insights for the modeling of a demand equation for matchday tickets. This paragraph discusses the possible determinants of attendance, and how such factors can be modeled in an econometric work.

3.2.1 Determinants of attendance

Borland and Macdonald (2003), Simmons (2006) and Villar and Guerrero (2009) provide literature reviews that identify the main variables affecting sport events attendance. Such determinants can be grouped in four categories: purely economic variables, factors related to the quality of the contest, elements that describes consumer preferences, and other variables that may entail opportunity costs for the attendee.

Economic variables deemed to affect demand are ticket price, price of other complementary goods (such as concessions), income, market size, availability of substitutes and travel costs.

According to standard consumer theory, ticket price should negatively affect attendance. The empirical literature confirms such theoretical result, since the coefficients of the price variables are almost always negative. However, there are some instances of not significant coefficients (Villar and Guerrero, 2009), suggesting that in some cases attendance could not be much responding to price. Furthermore, as remarked in the previous chapter, the literature provides a wide evidence of inelastic pricing (Feehan, 2006).

The price of other complementary goods could theoretically negatively affect ticket demand, but this is not straightforward: Coates and Humphreys (2007) found that concession prices were not significant in explaining stadium attendance in MLB, NBA and NFL.

When it comes to the role of income, Villar and Guerrero (2009) claim that there is mixed evidence for attendance being an inferior or normal good. Garcia and Rodriguez (2002), found a positive income elasticity in the Spanish La Liga, concluding that attendance is a normal good.

Market size, instead, is deemed to positively affect attendance (see, for instance, Coates and Humphreys, 2007).

Given the strong market power that characterizes sport clubs, competition does not come from other teams but from substitute goods. Watching the same match on television is an immediate substitute for attendance, more than attending other sports' matches or moving to other forms of entertainment. The effect of TV broadcasting on attendance is not straightforward. Coefficients of broadcasting variables are often negative or not significant. Many studies found that television negatively affects attendance for a specific match[100]; however, Borland and Macdonald (2003) claim that broadcasting may entail a positive long-run impact, since it raises interest in a particular sport/league.

Eventually, travel costs are deemed to negatively affect attendance, especially the one related to the supporters of the visiting team[101].

The quality of the contest contributes in capturing the heterogeneity of the different matches. Simmons (2006) underlines that the quality of the contest is *expected*, given the inherent uncertainty of sporting performances. However, several variables can be ex-ante suitable indicators of the attractiveness of the event, such as those related to the sporting quality of the clubs, the historical rivalry among them, seasonal performance, the uncertainty of outcome and the significance of the contest.

Several variables (see next paragraph) may proxy the quality of the opposing teams and are strongly significant in basically all the works reported in the literature reviewed.

Rivalry between the competing teams is not a sporting factor, but it is related to the quality of the event, in that it improves the atmosphere within the stadium. Rivalry may arise because of geographical reasons or it could be merely related to sporting tradition.

[100] Garcia and Rodriguez (2002) found that broadcasting reduces the number of game tickets sold, especially if the match is televised by a public free channel. Buraimo and Simmons (2008) and Buraimo (2008) also reported negative effects. Buraimo and Simmons (2009) found that the negative impact is particularly strong when the match is broadcasted on a free channel on weekdays; broadcasting on pay-tv channels was not significant instead.

[101] see Garcia and Rodriguez (2002), Buraimo and Simmons (2008), Buraimo (2008)

Current sporting performance is a crucial measure of event quality, especially the one related to the home team, while there is mixed evidence on the impact of the performances of the visiting club (Borland and MacDonald, 2003).

The theory of uncertainty of outcome assumes that even contests attract larger crowds. Such theory has been widely discussed for the policy implications that it may entail[102]. Borland and MacDonald (2003), Feehan (2006) and Villar and Guerrero (2009) distinguish three types of outcome uncertainty:

- Match-level uncertainty: evenness of the single match. The evidence concerning the impact of match level outcome uncertainty on attendance is mixed and discussed (Borland and MacDonald, 2003). Caruso and Di Domizio (2015) found that tickets sold are *minimized* when the probability of victory of the home team is 0.53[103], i.e. when the outcome of the match is rather uncertain. The turning point was 0.35 in Buraimo and Simmons (2008)[104] and 0.39 in Buraimo and Simmons (2009)[105]; such results suggest that fans prefer to attend fixtures where the probability of home victory is either very low[106] or very high;
- Intra-season uncertainty: uncertain competitions are such that the tournament winner arises late in the championship, or relegated teams fight until the very last stages. For instance, the German, French and Italian top football leagues have recently been characterized by very low intra-season uncertainty, since Bayern Munich, Paris Saint German and Juventus have secured the title some stages before the end. Borland and MacDonald (2003) claim that the evidence related to seasonal uncertainty of outcome is much stronger than in the match level case; Garcia and Rodriguez (2002) confirmed such claim.
- Inter-season uncertainty: uncertain leagues are characterized by different winners in the subsequent years. The existence of "sporting dynasties" (such as Juventus in the current decade) may decrease the attractiveness of a league (see Borland and MacDonald, 2003, and Villar and Guerrero, 2009).

Three factors affecting consumer preferences are cited in the literature reviewed: habits in attendance, social interactions ("bandwagon effect") and partisanship. According to Borland and MacDonald (2003), fan loyalty leads the customer to be prone to repeat his attendance choice, thus creating a habitual behavior; several studies confirm such result[107].

The so-called "bandwagon effect" theory assumes that the utility of a customer is enhanced by attendance of other fans. Such clue draws upon the insights derived by Becker (1991), according to which the positive effect

[102] If empirical evidence demonstrated that uncertainty of outcome positively affects attendance and TV audience, league regulation should be oriented to the enhancement of competitive balance. Buraimo and Simmons (2009) demonstrated that, though Spanish football attendees did not seem to be interested in uncertainty of outcome, TV spectators preferred even matches; the subsequent simulation of the authors demonstrated that, if outcome uncertainty had been maximized, the lost revenues from the matchday division would have been more than compensated by additional proceeds derived by broadcasting rights.

[103] Caruso et al (2015), p.135

[104] Buraimo and Simmons (2008), p.153

[105] Buraimo and Simmons (2009), p.333

[106] Buraimo and Simmons (2008) described such phenomenon as a "David vs Goliath effect": the odds are clearly against the home team, but fans do not want to miss the rare case of a victory.

[107] See Avgerinou and Giakoumatos (2009), Coates and Humphreys (2007), Buraimo and Simmons (2008), Buraimo (2008), Buraimo and Simmons (2009).

of social interactions may explain the reason why similar social activities (such as nearby restaurants, plays, concerts) exhibit extremely different demand patterns. The working paper by Kang et al. (2017) builds a theoretical model for the bandwagon effect in the sport industry. They show that social interactions entail the possible existence of an upward part of the demand curve and the possibility of two different equilibria for each price level. However, they admit that the method for empirically testing such model is not straightforward. Supporters partisanship, eventually, entails that fans prefer to attend matches where the home team wins. Such idea can explain the mixed evidence concerning the effect of outcome uncertainty on attendance at the match level: preferences could be such that there is a trade-off between the willing to attend uncertain games and the desire to watch a victory of the favorite team.

Eventually, other variables may impact on the attractiveness of a sport event, by changing the opportunity cost of attendance. Weather and temperature may affect attendance for outdoor sports, such as football. According to Borland and MacDonald (2003) the empirical evidence shows that the effect of weather depends on the geographic area: for instance, it has a significant effect in the United States, but not in the United Kingdom. Garcia and Rodriguez (2002) found that the absence of rain positively affects the number of tickets sold in the Spanish La Liga.

Match scheduling may also be a determinant of attendance: games played on weekends or holidays usually attract larger crowds (Borland and MacDonald, 2003) than those set during the week[108]. On the other hand, Villar and Guerrero (2009) report that the time of the day is not significant.

Eventually, stadium age (as a proxy for the quality of the facility) is another factor that can negatively influence attendance, as reported by Borland and MacDonald (2003). Coates and Humphreys (2007) found mixed evidence of that claim[109].

3.2.2 Econometric modeling

When it comes to the estimation of a tickets demand function, several issues should be considered to design the right econometric model. First, problems that can possibly yield biased estimates must be carefully evaluated and dealt with; second, the right set of attendance determinants needs to be chosen and modeled in the correct way to identify the true relationship with the demand of tickets.

Several econometric issues drive the choice of the type of model able to yield unbiased estimates. If the demand equation is estimated from different clubs' data referred to several time periods, the model should account for the panel dimension of the dataset (Villar and Guerrero, 2009). Alternatively, team specific dummies could be inserted, as in Garcia and Rodriguez (2002), thus simulating the home team fixed effect. Caruso and Di Domizio (2015), run both a random and fixed effect models, and their diagnostic testing called for the inconsistency of the former. Buraimo and Simmons (2008) use a random effect model, assuming that team-specific effects were not correlated with the regressors. Buraimo (2008) and Buraimo and Simmons

[108] The finding is confirmed by Garcia and Rodriguez (2002), Caruso and Di Domizio (2015), Buraimo and Simmons (2008), Buraimo (2008). Buraimo and Simmons (2009) show that such effect is still valid when the weekday match is not televised.

[109] Stadium age resulted to be negatively significant for the NBA, not significant for the MLB and NFL.

(2009) exploit fixed-effect models in order to control for omitted variables that are team-specific and not time-varying.

Another issue derives from the existence of capacity constraints. If the clubs under analysis persistently sell-out their capacity, the demand equation is estimated from attendance data that do not represent the true demand (Borland and MacDonald, 2003)[110]. Models that effectively deal with censored regressions, such as Tobit ones, should be exploited to avoid biased estimates. Buraimo and Simmons (2008) exploit a Tobit model, since 54.7% of the observations in their sample (English Premier League) were constrained[111]. However, if the amount of capacity constrained observations is not remarkable, censoring issues could be ignored[112]. In the empirical work by Coates and Humphreys (2007), the model does not account for the censored dimension of the data; such factor can explain the reason why the coefficient on ticket price is significant for the MLB and the NBA but not for the NFL, were sellouts are business as usual.

Furthermore, the price-quantity relationship entails potential endogeneity problems, that could be dealt with an instrumental variables approach. Coates and Humphreys (2007) suggest that the problem is particularly relevant because of the monopolistic status of the sport club, that implies the unlikeness of the exogeneity of the price variable. Garcia and Rodriguez (2002) estimate a reduced-form equation for price, choosing the position of both teams in the previous season's league, the tier to which they belonged in the previous campaign, and the stadium capacity as instruments. Such instruments represent the information available to the club at the beginning of the season, when the price categories of the matches may be planned.

Eventually, if habit persistence is a determinant of attendance, autocorrelation problems may arise, especially if the lagged dependent variable is excluded from the specification (Borland and MacDonald, 2003). Garcia and Rodriguez (2002) and Caruso and Di Domizio (2015) do not account for autocorrelation issues; however, the dependent variable in their model excludes season tickets, i.e. those bought by the most habit-driven share of the fan base.

The design of the econometric model must start from the dependent variable, which could be represented by either aggregate attendance or disaggregated one (distinction between season and matchday tickets). The choice depends on the research objective of the work, and on data availability. The usual lack of sector and consumer specific data does not allow to run a more specific investigation, for instance into attendance in a specific sector or by a specific customer category (Villar and Guerrero, 2009). In each case, the dependent variable could be modeled in the logarithmic form, in order to directly estimate the price elasticity (see below).

The previous paragraph shows that a wide array of independent variables can be chosen from the possible determinants of attendance. The modeling of the price variable is the main issue in the sport demand literature,

---

[110] Note that in the sport events literature a sellout occurs when at least 95% of capacity is sold (see Buraimo and Simmons, 2008) because some seats are not on sale for security reasons (segregation of home and away fans) and a part of the stadium is left to away fans that often do not fill it.

[111] Buraimo and Simmons (2008), p.148.

[112] Garcia and Rodriguez (2002) did not use a Tobit model since only 3.4% of the observations in their dataset were constrained; they claim that a not-published Tobit model yielded similar estimates. Buraimo (2008) also did not consider censoring issues, since 97% of the observations in the sample were not constrained. The same holds for Buraimo and Simmons (2009), who chose the Spanish La Liga framework instead of the English Premier League with the purpose to overcome censoring problems.

since clubs offer a menu of prices and sector specific data (i.e. inventory and transactions) are not publicly available (see Drayer and Rascher, 2013, and Villar and Guerrero, 2009). Consequently, many studies that are not interested in measuring price elasticities do not include a price proxy in the specification[113]. The literature adopts several solutions to deal with the issue. Specifically, price has been proxied by (Villar and Guerrero, 2009):

- Minimum price in the menu (as in Garcia and Rodriguez, 2002).
- Average price of tickets sold (as in Avgerinou & Giakoumatos, 2009)[114]
- Average price in the menu: such average can be weighted for the number of seats that are sold at each price (as in Marburger, 1997), if such information is available.

Other works exploit alternative/more sophisticated proxies. Caruso and Di Domizio (2015), exploit a Tickets Price Index that is computed after the Football Match Price Index and the Consumer Price Index[115]; however, such price proxy is not team-specific, and it only allows to compute an average league elasticity. The authors were indeed interested in measuring the impact of the anti-hooliganism reform in the Italian Serie A, thus they included the price variable as a control. Marburger (1997) adds the relative price between sectors in order to control for the fact that customers substitute in the price menu after a sector-specific price increase. Buraimo (2008) and Buraimo and Simmons (2009) (whose works were not interested in detecting price elasticities) claim that the team-specific fixed effect captures the result of the ticket pricing strategies implemented by the clubs. When it comes to the functional form, Villar and Guerrero (2009) report that the logarithmic one is usually set, but linear functions are often employed as well. Garcia and Rodriguez (2002) use a cubic logarithmic relationship between price and quantities, in order to compute team-specific elasticities.

Income is modelled with real income per capita in the home club area in Garcia and Rodriguez (2002) and Coates and Humphreys (2007). The former estimates a log relationship between income and tickets, in order to derive club-specific income elasticities.

Market size is reflected by variables concerning the local population. In the case of two teams playing in the same city, Garcia and Rodriguez (2002) allocate the population according to the pattern of season ticket holders, as suggested by Villar and Guerrero (2009).

The availability of substitutes is described by dummy variables representing the TV broadcasting of the match. Garcia and Rodriguez (2002), Buraimo (2008) and Buraimo and Simmons (2009) fine-tune the analysis by distinguishing among the kind of channel (free/pay TV) that televised the match. Moreover, Buraimo (2008) includes dummies that detect the effect of the contemporary broadcasting of European competitions games, since the work focuses on the lower tiers of English football.

[113] Garcia and Rodriguez (2002). The authors also claim that endogeneity issues are another motivation for the exclusion of the price variable in several works.

[114] Feehan (2006) claims that the minimum price and the average price of tickets sold should yield similar estimates, since they are highly correlated.

[115] The authors retrieved such data from the Italian National Institute of Statistics (ISTAT).

Travel costs are captured by the distance between the two cities that host the opposing teams, as in Garcia and Rodriguez (2002) and Buraimo and Simmons (2008); Buraimo (2008) also includes the square of the distance, to reproduce its decreasing effects.

Several variables can be suitable ex-ante indicators of the quality of the event, such as wages, the number of internationals (i.e. player belonging to their national team), the prestige of the opponent, teams' performance.

Players wages are a good proxy for the quality of the teams, given the competitiveness of the sport labor market (see Buraimo, 2008); Caruso and Di Domizio (2015) includes the ratio between the home team payroll and the sum of both teams' ones, in order to capture the relative quality of the home team in comparison with the visiting one. Buraimo and Simmons (2008) and Buraimo (2008) insert the ratio between the teams' payroll[116] and the league average one, to control for the growth of player wages in the period under consideration.

The number of internationals is another good indicator of the quality of the visiting team (see Garcia and Rodriguez, 2002). Dummy variables for historically prestigious teams could also be added: some visiting teams with a historical winning record could generate interest towards the match, setting aside their budget and sporting performance in a specific season. In two works concerning Spanish football (Garcia and Rodriguez, 2002, and Buraimo and Simmons, 2009), dummies for Barcelona or Real Madrid playing away are included and found significant.

Historical rivalry is another factor that affects attendance, which was included as a dummy for derby matches in all the studies reported in the literature reviewed except Caruso and Di Domizio (2015); Garcia and Rodriguez (2002) also consider matches characterized by rivalries that did not derive from geographical reasons.

A wide array of variables can capture the sporting performance of both teams, such as the number of victories, goals scored, league position, points per game or winning percentages. All variables could be referred to the whole ongoing season or to a couple of games preceding the observation, to capture the most recent trend.

Uncertainty of outcome can be modelled with the difference in league positions of the two teams (as in Garcia and Rodriguez, 2002), or with the probability of victory of the home team, computed after the betting odds[117]. Simmons (2006), Buraimo and Simmons (2008) and Villar and Guerrero (2009) claim that betting odds are a good measure of the probability of victory in that bookmakers have an incentive to correctly forecast a match outcome. Moreover, they capture information that are not reflected in league positions[118]. Probabilities of victory are added with a linear and a quadratic term, in order to capture the U-shaped relationship with attendance that allows to analyze the trade-off between preferences for uncertainty and partisanship.

The inclusion of weather and temperature represents an issue when it comes to data collection: information about weather conditions and temperature at the time of the event is quite difficult to gather. Such issue could represent the reason why only Garcia and Rodriguez (2002), among the works analyzed, include

[116] They include two relative wage variables, for both teams.
[117] See Caruso and Di Domizio (2015), Buraimo and Simmons (2008 and 2009).
[118] For instance, a team on a losing streak or with several injured key players could be ranked in the high part of the league table anyway, because of former good results.

weather dummies in the specification. Dummies for the months of the year could explain variability related to weather conditions; however, they also capture the different stages of the championship, thus the effect of weather alone is not clear (Villar and Guerrero, 2009).

Eventually, the effect of match scheduling in the weekend or on a bank holiday is assessed with a dummy variable. Garcia and Rodriguez (2002), Buraimo and Simmons (2008 and 2009) include the interaction of such variable with another dummy representing the broadcasting of the match.

3.3 The model

3.3.1 Variables and sources

The aim of the model is to correctly estimate a demand function that can replicate the theoretical one represented in chapter 2:

$$q_t = a + bp_t$$

Therefore, the number of tickets sold q_t are regressed on a vector of variables and parameters that describe the attractiveness of the event *(a)*[119] and on a price proxy p_t; the parameter *b* will be estimated by the model. Furthermore, the model must allow to compute an elasticity value at the team and match level.

In order to estimate the model, we build a database with information related to all the Italian Serie A matches from the season 2014-15 to the stage 26 of the current championship (2017-18): a total of 1,400 observations. However, due to availability issues of the price proxy (see below), only 749 observations of seventeen teams are effectively used for the estimation[120]. Three models, that identify three different functional forms for the price-quantity relationship, are tested.

In the first two models, the dependent variable, *Tickets/000*, is the amount of matchday tickets sold, in thousands. In the third model we exploit the logarithm of the number of tickets sold, *lTickets*. Data were retrieved from http://www.stadiapostcards.com/, which displays an archive of attendance and season tickets figures of the Italian Serie A, Serie B and Serie C[121].

The explanatory variables are the following:

- *Price/price2/lprice2:* the price proxy variables are represented by the average price of tickets sold, i.e. gate receipts divided by the number of game tickets sold. In the framework of the simulations that will

[119] Control variables and team specific effects are also included in *a* (see below).

[120] The estimation sample includes data related to the following home teams: Atalanta, Bologna, Carpi, Cesena, Empoli, Fiorentina, Genoa, Hellas Verona, Juventus, Milan, Palermo, Parma, Pescara, Roma, Sampdoria, Sassuolo, Torino. The panel dataset is unbalanced because of data availability issues and the fact that some clubs did not participate to the Serie A in each season.

[121] Therefore, we obtained matchday tickets sold by subtracting season tickets from total attendance. However, when the newspapers reported the effective number of season ticket holders that showed-up, we preferred to subtract that value. Such procedure is particularly important for observations related to Juventus as a home team, given the secondary ticketing framework cited in chapter 2.

be performed in chapter 4, the average price of tickets sold is a more suitable proxy than the minimum price of the menu. In fact, some clubs, like Atalanta in the current season, apply variable ticket pricing by keeping the price of the cheapest sector (i.e. the one mostly attended by loyal fans, so-called *"curva"*) fixed. If the minimum price were chosen, some information concerning the variation of the price menu would be lost. Data were retrieved from online national or local newspapers, with a detailed internet search, and converted in 2015 values with the IPCA (Consumer Harmonized Price Index, provided by the Italian National Institute of Statistics, ISTAT). Several football teams communicate to the press the attendance and/or total ticket revenues after every game; most of the teams provides such data with the distinction between matchday and season tickets related figures. However, some of the clubs do not communicate such data[122]. Furthermore, the press does not always communicate such information, especially when it comes to some teams such as Udinese and Crotone. Since we had only a few observations related to some clubs, they were removed from the dataset. Three different functional forms were estimated: Model 1 estimates a linear relationship between tickets and price, while Model 2 estimates a quadratic one, with the squared term only; eventually, Model 3 estimates a log-log relationship, where the quadratic term of the logarithm was included in order to be able to compute a team and match specific elasticity value[123]. We expect a negative and significant sign on each variable; the magnitude of the coefficient is also crucial, in that it will be determinant in computing the elasticity values.

- *ProbW_h and ProbW_h2* (i.e. the squared term) are intended to capture the U-shaped relationship between the probability of a home team victory and the number of tickets sold, reported by several works in the literature. Probabilities were computed after the bookmakers betting odds retrieved from http://www.sportstats.com/ [124]. Probabilities of each match outcome (home victory, draw, away victory) were obtained by dividing 1 for the relative odds. Since the three probabilities sum up to more than 100% (because of the bookmaker's margin), the real probability of a home victory is the ratio of the "gross probability of home victory" over the sum of all the gross probabilities[125]. The sign of the squared term is especially of interest, in that it determines the concavity of the quadratic relationship between the probability of home victory and the amount of tickets sold: a negative sign entails that

[122] For instance, Lazio and Chievo do not communicate any kind of data; Internazionale only provides a total attendance figure; Napoli and, from season 2017-18, Milan, only communicate total attendance and total revenues, without distinguishing between matchday and season tickets. Caruso and Di Domizio (2015) deal with the same issues while collecting game tickets data for the Italian Serie A.
[123] When it comes to Models 2 and 3, a quadratic function with both the level and squared terms did not yield significant coefficient estimates. The possible existence of upwards parts of such function may explain such result. Conversely, if the coefficient of the squared price variable is negative, with the linear one missing, the function is downward sloping in the positive parts of the axis.
[124] Such website publishes the betting odds of almost thirty different bookmakers. Average odds were exploited in this work.
[125] See Buraimo and Simmons (2008) Here is an example of the odds for Roma-Milan, which took place on 25/02/2018:

Home Team	Away Team	Home Victory Odds	Draw Odds	Away Victory odds	Gross probability of a home victory	Gross probability of a draw	Gross probability of an away victory	Sum of gross probabilities	Real probability of a home victory
Roma	Milan	1.9	3.48	4.12	52.6%	28.7%	24.2%	105.5%	49.8%

fans value uncertainty of outcome, while a positive one implies that other effects (i.e. "David vs Goliath" and partisanship) prevail.

- *Derby* is a dummy that equals 1 if the opposing teams belong to the same region. We do not include historical rivalries (such as, for instance, the one between Juventus and Fiorentina), since we could have ended up with arbitrary choices in assigning the dummy value. The sign expected is positive and strongly significant.
- *Wage_a* represents the payroll of the visiting team (million, net of taxes) in 2015 prices, as a proxy for the away club sporting quality. Data were retrieved by the Italian sport newspaper *La Gazzetta dello Sport* (as in Caruso and Di Domizio, 2015), which publishes net of taxes players' salaries at the beginning of each season. Since average salaries did not grow significantly in the period under analysis, we did not model it via the ratio between away payroll and the average league one, as it is done in other works in the literature (see above). We expect such variable to be a positive strong determinant of the quantity of tickets sold[126].
- *Juventus_a, Milan_a and Inter_a* are dummy variables that equal 1 if the away team is either Juventus, Milan or Internazionale, i.e. the three most winning teams in the Italian football history[127]. The two Milanese teams, despite being rather unsuccessful in the last years, maintain their appeal because of the historical record. Such binary variables should positively affect the dependent one.
- *PPG_h* is the points per game that the home team has achieved prior to the match. The role of such variable is to capture the fan enthusiasm generated by the sporting performances of the club. When it comes to the first stage of each championship, the value of *PPG_h* is given by the points per game obtained in the previous season. A positive effect is expected[128].
- *WE_Hol* is a dummy that equals 1 1 if the match is played either on Saturday, Sunday or on a bank holiday. Since weekdays matches usually attract smaller crowds, the sign expected is positive.
- *Winter* is a dummy that equals 1 if the game occurs in November, December, January or February, i.e. the coldest months of the year in Italy. The role of such variable is to capture the attendance discouraging effect of cold weather. It could be argued that such kind of modeling can also capture the possible interest of attendees for the central part of the championship; however, when we included the variable *Stage* in an alternative specification, the coefficient of *Winter* did not change. Since football is an outdoor sport, we expect a negative effect of such determinant on the dependent variable.
- *2014-15, 2015-16, 2016-17* represent seasonal effects, with the current campaign (2017-18) being the reference term. The role of such variables is to control for possible intra-season unobserved variation.

Summary statistics of the variables are displayed in Table 3.1.

[126] *Wage_a* was included in the logarithmic form in Model 3
[127] In the last thirty years, the three clubs have won 83% of the championships.
[128] *PPG_h* was included in the logarithmic form in Model 3

Table 3.1: Descriptive statistics for dependent, explanatory and instrumental variables.

Variable	Mean	Std. Dev.	Min	Max
Tickets/000	7.679	7.471	0.192	62.977
		Explanatory variables		
Price	23.73	14.27	3.608	81.642
ProbW_h	0.447	0.182	0.063	0.904
Derby	0.069	0.254	0	1
Wage_a	21.717	17.557	4.08	81.68
Juventus_a	0.053	0.224	0	1
Milan_a	0.041	0.199	0	1
Inter_a	0.05	0.219	0	1
PPG_h	1.38	0.593	0	3
WE_Hol	0.838	0.368	0	1
Winter	0.449	0.497	0	1
2014-15	0.298	0.457	0	1
2015-16	0.272	0.445	0	1
2016-17	0.274	0.446	0	1
		Instrumental variables		
Cap_av	0.598	0.105	0.33	0.871
Pos_PY_h	7.34	5.347	0	17
Pos_PY_a	7.474	5.527	0	17
B_PY_h	0.15	0.357	0	1
B_PY_a	0.16	0.366	0	1

Source: Elaboration of personal database (see paragraph 3.3).

3.3.2 Econometric model

The choice of the right model for the estimation of the tickets demand draws upon the discussion of the econometric issues presented in the literature review.

Given the longitudinal dimension of the data, we run a panel model with fixed-effects, where the unit of analysis is the home club, and the time dimension is given by the series of home matches that took place. We prefer such type of model to a pooled-effect one since we believe that team-specific effects are not zero. Moreover, time invariant determinants such as market size and income have been excluded from the specification. Since we expect that such factors play an active role in describing the dependent variable (i.e.

they are not a mere unit-specific error component) we preferred a fixed-effect model over a random effect one. Another motivation to prefer fixed-effects over random-effects is that such team-specific error component would likely be correlated with the variables *PPG_h* and *ProbW_h*[129] thus violating the orthogonality condition of the error term.

As reported in the literature review, endogeneity of the price variable may be a serious econometric issue, in that it generates biased and inconsistent estimates. In the model, price is endogenous by construction, in that the average ticket price is computed after the quantity of tickets sold. Therefore, the model is estimated with a two-stage least squares (2SLS) approach: the first stage regresses the price on the other explanatory variables and on a set of instruments; such step allows to predict the variation of the price that is explained by the instruments only. Afterwards, in the second stage the dependent variable (*Tickets/000*) is regressed on the explanatory exogenous variables and on the fitted values of the price one, which by construction are exogenous. Such method allows to obtain consistent estimates of the parameters, provided that the instruments are relevant (i.e. they are significant in explaining the endogenous variable) and valid (i.e. they are not correlated with the error term of the second stage).

When it comes to the choice of the instruments, we follow Garcia and Rodriguez (2002). The set of instruments represent the information that is available to the club in order to design the pricing strategies at the beginning of the season, and it is composed by:

- *Cap_av*: the share of capacity that is available after the sale of season tickets. We expect a negative effect of the capacity available on ticket price, for the law of supply and demand. Such variable is deemed to be exogenous in that, in a framework where capacity constraints are not an issue, the amount of tickets sold is not affected;
- *Pos_PY_h:* i.e. the league final position of the home team in the previous season[130]. It represents the fan enthusiasm generated by the results of the previous campaign; while such variable is expected to positively affect the price[131], in that clubs may exploit recent sporting achievements as a justification to increase prices, the enthusiasm of fans during the new season is likely to be progressively generated by new results. If this is the case, the variable should not affect the quantity of tickets sold;
- *Pos_PY_a*: i.e. the league final position of the away team in the previous season[132]. Such variable plays a role in the grouping of matches in price categories, since, as it was shown in the previous chapter, the opponent seems to be a primary source of price variation. Moreover, if fans are interested in the current quality of the opposing teams (proxied by the payroll) and not in the past achievements (with the exception of Juventus, Milan and Internazionale), such variable should not remarkably affect the number of tickets sold;

[129] An ex post estimation of the fixed effect from Model 2 found a correlation of the fixed effect with the cited variables of 0.6 and 0.53 respectively.

[130] Such variable is interacted with a dummy that equals 1 if the home team participated to the Serie A in the previous season, and 0 if it belonged to the Serie B.

[131] The sign is on the contrary expected to be negative, in that the best rank is given by the lowest value (1).

[132] As in the previous case, the variable is interacted with an equivalent dummy one.

- *B_PY_h*: a dummy that equals 1 if the home team participated to the Serie B in the previous season, since in that case *Pos_PY_h* equals 0.
- *B_PY_a*: a dummy that equals 1 if the away team participated to the Serie B in the previous season, since in that case *Pos_PY_a* equals 0.

Eventually, the model does not account for capacity constraints[133]. Estimates should not be affected, in that only 4.6% of the observations in the database are censored.

Therefore, the model is formally described by the following equation:

$$T_{it} = \alpha + u_i + \gamma X'_{it} + \delta V'_t + \beta P_{it} + \varepsilon_{it}$$

where:

- T_{it} represents the quantity of tickets sold by the home team *i* at match *t*;
- α is the constant term;
- u_i is the team-specific effect, that captures time invariant information such as income, market size, availability of substitutes[134], age of the club and of the stadium, consumer preferences, management ability, stadium ownership or stadium sharing with another club;
- X'_{it} is a vector of variables whose value varies with both the home club *i* and the match *t*, i.e. *ProbW_h* and *ProbW_h2, Derby, PPG_h;*
- V'_t is a vector of variables whose value is affected by the match *t* only, i.e. *wage_a, Juventus_a, Milan_a, Inter_a, WE_Hol, Winter, 2014-15, 2015-16, 2016-17*;
- P'_{it} represents the price variable, i.e. *price, price2, or lprice2*;
- ε_{it} describes the error term.

The model is estimated by a first-stage, in which the endogenous variable (*price, price2* or *lprice2*) is explained by the exogenous ones and by the instruments:

$$\widehat{P_{it}} = \hat{\theta} + \widehat{v_i} + \hat{\pi} X'_{it} + \hat{\rho} V'_t + \hat{\sigma} Z'_{it} + \hat{\tau} W'_t$$

where:

- Z'_{it} is the set of instruments whose sources of variation are given by the club and time, i.e. *cap_av, Pos_PY_h, B_PY_h*;
- W'_t is the set of instruments that are time-varying only, i.e. *Pos_PY_a, B_PY_a;*
- $\hat{\theta}$ is the constant term;
- $\widehat{v_i}$ is the unit-specific effect;

[133] The main reason is a "technical" one, in that we were not able to run a Stata command that allows to estimate a panel model with instrumental variables and different censoring values, since each team faces a different capacity constraint.
[134] Note that it is not possible to measure the effect of TV broadcasting, since all Serie A matches are televised by at least one of the two main Pay TVs that operate in Italy (i.e. Sky and Mediaset Premium).

The second stage, instead, regresses the number of tickets sold on the exogenous variables and on the fitted values of the price proxy, estimated in the first stage:

$$\widehat{T_{it}} = \hat{\alpha} + \widehat{u_i} + \hat{\gamma} X'_{it} + \hat{\delta} V'_t + \hat{\beta} \widehat{P_{it}}$$

3.4 Empirical results

3.4.1 Diagnostics

Diagnostic testing is performed before presenting the empirical results. Statistics and p-values of the tests are reported in Table 3.2.

Table 3.2: Diagnostic testing

Issue	MODEL 1 Statistic	MODEL 1 p-value	MODEL 2 Statistic	MODEL 2 p-value	MODEL 3 Statistic	MODEL 3 p-value
Heteroskedasticity	Chi-sq(19) 125.948	0.000***	Chi-sq(19) 110.979	0.000***	Chi-sq(19) 67.122	0.000***
Autocorrelation	z=1.30	0.1935	z=1.13	0.2580	z=0.62	0.5345
Relevance of the instruments	F(5,714) 8.98	0.000***	F(5,714) 8.10	0.000***	F(5,714) 9.84	0.000***
Validity of the instruments	Chi-sq(4) 7.704	0.1031	Chi-sq(4) 8.150	0.086*	Chi-sq(4) 19.96	0.000***
Endogeneity of price/price2/ln(price)2	Chi-sq(1) 6.515	0.0107**	Chi-sq(1) 7.408	0.006***	Chi-sq(1) 4.081	0.043**

Source: Our elaboration of personal database (see paragraph 3.3)

Heteroskedasticity was detected first. If different error terms have different variances, the standard errors estimates are biased. Consequently, inference is not reliable. The Pagan-Hall test of heteroskedasticity for instrumental variables was run for the three models, and the null hypothesis of homoscedastic disturbance was rejected in each case. Therefore, robust standard errors are applied to all models.

Afterwards, autocorrelation issues were investigated, i.e. correlation of different error terms. The Arellano-Bond test for autocorrelation was run, and in each case the null hypothesis (absence of serial correlation) was not rejected. Therefore, we do not deal with autocorrelation, for instance by including the lagged dependent variable in the specification.

In order to obtain consistent estimates of the coefficients in a setting characterized by endogeneity, the appropriateness of the instruments must be checked. A test for the relevance of the instruments was first performed: instruments are jointly significant for each model. Second, a test of overidentifying restrictions was run, in order to assess the validity of the instruments. When it comes to the first two models, the null hypothesis of validity was accepted at the 5% level (though not at the 10% for Model 2). In the third model, instead, we rejected the null hypothesis at the 5% level as well; therefore, while estimates of the first two models could be considered reliable (although with caution), the same cannot be stated in the case of the third one. Consequently, Model 3 results will not be discussed in the next sub-paragraph.

Eventually, the endogeneity of the price variable was checked. In fact, if endogeneity was not an issue, a model without instrumental variables would yield more efficient estimates. While the test for Model 3 is not reliable, since the instruments are not valid, the results related to the first two models allow to ascertain the presence of endogeneity in the price variable, i.e. the motivation for the adoption of an IV approach.

3.4.2 Results

Tables 3.3 (first stage) and 3.4 report the empirical estimates for both models.
A glance at the first stage of the regression supports the claim according to which clubs mostly set ticket prices based on the opponent: coefficients of variables that are somehow related to the visiting team are all significant, while regressors concerning the sporting performance of the home club, the weather and the match scheduling are not so.

When it comes to the second stage, the price proxies' coefficients are significant at about the 1% level in both cases. Such coefficients allow to estimate the average price elasticity at the league level:

MODEL 1: $\varepsilon_1 = \beta_1 * \frac{avg\ price}{avg\ quantity} = -0.349 * \frac{23.73}{7.679} = -1.07$

MODEL 2: $\varepsilon_2 = 2 * \beta_2 * avg\ price * \frac{avg\ price}{avg\ quantity} = 2 * -0.0042 * 23.73 * \frac{23.73}{7.679} = -0.61$

Model 1 is not consistent with other works in the sport events literature, and with the theoretical model of the previous chapter; estimates of the second model are instead comforting. Chapter 4 will display a deeper analysis of the elasticity values, at team and match-specific level

Coefficients of the probability of a home victory are not significant in Model 1; when it comes to the second model, both are significant at the 5% level. Setting aside the estimates for the first model, such results describe an *inversed U*-shaped relationship between the probability of a home victory and attendance. The .

attendance maximizing value is 0.36, weakly suggesting that matchday tickets buyers may value uncertainty of outcome[135].

Table 3.3: First Stage Regression

VARIABLE	MODEL 1		MODEL 2		MODEL 3	
Dependent Var.	*Price*		*Price2*		*Ln(price)2*	
Explanatory Var.	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Cap_av	-31.39	0.000***	-2754.00	0.000***	-7.4311	0.000***
H_prev_pos_A	-0.04	0.624	3.63	0.485	-0.0342	0.220
A_prev_pos_A	-0.23	0.000***	-20.08	0.000***	-0.0633	0.001***
H_prev_B	-1.44	0.338	232.13	0.013**	-0.0817	0.860
A_prev_B	-2.11	0.038**	-160.19	0.049**	-0.4178	0.173
ProbW_h	17.70	0.038**	4758.37	0.000***	-6.1231	0.003***
ProbW_h2	-25.21	0.003***	-5406.54	0.000***	5.2184	0.006***
Derby	4.34	0.000***	267.31	0.001***	1.1791	0.000***
Wage_a/lWage_a	0.24	0.000***	15.32	0.000***	1.3157	0.000***
Juventus_a	3.54	0.013**	316.48	0.004***	1.3488	0.000***
Milan_a	3.85	0.014**	126.88	0.279	1.4334	0.000***
Inter_a	5.26	0.000***	317.31	0.013**	1.5007	0.000***
PPG_h/lPPG_h	0.36	0.472	-4.26	0.911	0.0904	0.691
WE_Hol	-0.56	0.300	-3.90	0.923	-0.2204	0.142
Winter	0.08	0.835	9.29	0.760	0.0585	0.597
2014-15	-1.74	0.014**	-140.53	0.029**	-0.4297	0.018**
2015-16	-0.48	0.488	-37.10	0.540	-0.1607	0.366
2016-17	0.15	0.829	37.30	0.511	-0.0750	0.690
N = 749 Heteroskedasticity-robust standard errors						

Source: Our elaboration of personal database (see paragraph 3.3)

Note: **Significant at the 10% level*

***Significant at the 5% level*

****Significant at the 1% level*

[135] Such value is not consistent with the literature review presented in the previous paragraph; however, note that such studies provide different specifications. For instance, Buraimo and Simmons (2008) studied the effect on *total* attendance, and they did not include the price variable, while Caruso and Domizio (2015) exploited a proxy for price that was not team-specific, thus avoiding endogeneity issues. The coefficients on the same variables for Model 3 are consistent with the latter work, though not reliable as demonstrated in the previous sub-paragraph.

Table 3.4: Estimation of tickets demand: panel fixed-effects model with instrumental variables.

	MODEL 1		MODEL 2		MODEL 3	
Dependent Var.	*Tickets/000*		*Tickets/000*		*Ln(Tickets)*	
Explanatory Var.	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Price	-0.349	0.005***				
Price2			-0.0042	0.005***		
Ln(Price)2					-0.1271	0.008***
ProbW_h	2.972	0.670	17.079	0.047**	-3.7625	0.000***
ProbW_h2	-9.419	0.239	-23.651	0.014**	3.6033	0.000***
Derby	5.572	0.000***	5.200	0.001***	0.5577	0.000***
Wage_a/lWage_a	0.152	0.001***	0.133	0.001***	0.4064	0.000***
Juventus_a	8.164	0.000***	8.285	0.000***	0.7194	0.000***
Milan_a	2.936	0.002***	2.123	0.020**	0.5186	0.000***
Inter_a	6.982	0.000***	6.515	0.000***	0.6427	0.000***
PPG_h/lPPG_h	1.799	0.002***	1.650	0.004***	0.3059	0.000***
WE_Hol	0.695	0.087*	0.873	0.026**	0.1296	0.012**
Winter	-0.931	0.007***	-0.920	0.007***	-0.1233	0.000***
2014-15	-1.452	0.004***	-1.416	0.005***	-0.0549	0.307
2015-16	-0.636	0.228	-0.611	0.245	0.0035	0.947
2016-17	0.114	0.823	0.209	0.687	-0.0292	0.577
N=749 Heteroskedasticity-robust standard errors						

Source: Our elaboration of personal database

*Note: *Significant at the 10% level*

***Significant at the 5% level*

****Significant at the 1% level*

Goodness-of-fit statistics are not reported, as it is common for models estimated by instrumental variables (See Verbeek, 2004).

As it was expected, local rivalries attract larger crowds (more than 5,000 additional tickets on average, in both models). The payroll of the away team is another strong determinant, as the dummy variables representing the most prestigious Italian teams. In fact, if salaries of the away team grow by 1 million, more than 100 additional tickets are sold; moreover, if the away team is either Juventus, Milan or Internazionale, sales grow by 8,000, 2,000 and 6,000 respectively.

The variable representing the current sporting performance of the home team is also significant at the 1% level: every additional point per game increases attendance by about 1,700 matchday spectators.

The coefficient related to *WE_Hol* is significant at the 10% only in Model 1, while it is at the 5% in Model 2 (more than 800 additional matchday attendees when matches are scheduled on weekends or bank holidays). The literature usually finds stronger evidence of a positive effect (especially in comparison with Model 1).
The effect of cold weather, captured by the dummy variable *Winter* is instead strongly significant and as expected: fans are discouraged of attending winter matches (about 900 spectators less for both models).
Among the seasonal effects, which were included to control for unobserved intra-seasons variability, only the one related to the 2014-15 campaign (i.e. the first one of the sample) is significant, at 1% in both models, with an average of more than 1,000 spectators less in comparison with the current 2017-18 season.

3.4.3 Subsample: matches against "David"

Data aggregation is among the main limitations of the econometric exercise performed above. First, the database aggregates data concerning different home teams, thus it estimates average marginal effects across units. It is quite reasonable to expect different marginal effects for different home clubs: for instance, the price sensitivity may be stronger in clubs related to poorer areas of the country; reactions to the sporting performances may be different as well: the enthusiasm of Atalanta's supporters hit the roof when the club achieved two points per game in the 2016-17 season, while the same figure is less than business as usual for Juventus; again, the effect of *Winter* is probably weaker in the warmer areas of the country.

Furthermore, the econometric model aggregates information on another crucial dimension, i.e. the visiting team: coefficients were estimated for the matches that the home team played against top ones (from now on "Goliath") and against less prestigious clubs ("David"). It is quite reasonable to expect different coefficients for some regressors, e.g. a different price sensitivity.
If we consider Juventus, Milan, Inter, Napoli and Roma as top teams, the database can be split into 572 observations related to matches against David, and 177 ones of games against Goliath. While the size of the second sub-sample is too small to perform a structural break test, it is anyway interesting to estimate a model for the first subsample. An econometric regression was thus performed following the pattern of Model 2, as it was the one that yielded more comforting results[136]. Table 3.5 reports the output and a comparison of the coefficients on significant variables. Such estimates are more reliable, since the result of the test for the validity of the instruments is much more reassuring.

The coefficient on the price variable is higher for the sub-sample: casual attendees seem more price sensitive when the opposing team is not a prestigious one. Since games against top teams are only 5 for each season, price is less determinant in the decision to buy a ticket.
The effect of *Derby* is stronger in the subsample. Such result is also reasonable: if Torino and Juventus came from different regions, attendance in the derby where the former plays at home could be high in any case, given the prestige of the visiting team. The marginal effect of an increase in the opponent's payroll is also higher: in the subsample, prestige issues do not arise, thus the payroll is the only indicator of the appeal of the opponent.

[136] The exercise was replicated with Model 1, with similar findings.

The effect of the sporting performance is much weaker instead, though still significant. The interpretation of such result is not straightforward: perhaps, since David is not an unbeatable opponent, the hope for a home possible win compensates for the poor sporting performances.

Table 3.5: Model 2.1 (subsample "vs David"). Comparison with Model 2.

	MODEL 2.1		MODEL 2		
Dependent Var.	*Tickets/000*		*Tickets/000*		
Explanatory Var.	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Δ%**
Price2	-0.0062	0.001***	-0.0042	0.005***	+47%
ProbW_h	9.122	0.332	17.079	0.047**	
ProbW_h2	-10.904	0.307	-23.651	0.014**	
Derby	6.407	0.000***	5.200	0.001***	+23%
Wage_a	0.175	0.000***	0.133	0.001***	+31%
Juventus_a	(excluded)		8.285	0.000***	
Milan_a	(excluded)		2.123	0.020**	
Inter_a	(excluded)		6.515	0.000***	
PPG_h	0.922	0.011**	1.650	0.004***	-44%
WE_Hol	1.376	0.001***	0.873	0.026**	+57%
Winter	-1.263	0.000***	-0.920	0.007***	+37%
2014-15	-0.948	0.062*	-1.416	0.005***	
2015-16	-0.153	0.787	-0.611	0.245	
2016-17	-0.477	0.354	0.209	0.687	
N=572 Heteroskedasticity-robust standard errors					
Relevance of the instruments	F(5,540) 7.00	0.000***			
Validity of the instruments	Chi-sq(4) 4.164	0.384			
Endogeneity of price2	Chi-sq(1) 5.902	0.015**			

Source: Our elaboration of personal database

*Note: *Significant at the 10% level*

***Significant at the 5% level*

****Significant at the 1% level*

Goodness-of-fit statistics are not reported, as it is common for models estimated by instrumental variables (See Verbeek, 2004).

The coefficient on *WE_Hol* is higher and it becomes significant at the 1% level in the subsample. Attendees may not be willing to miss matches against top teams even if scheduled on a weekday. When David is the opponent, the opportunity cost of attendance after a working day is higher. The same reasoning could be applied to explain the stronger effect of *Winter*.

3.5 Limitations and concluding remarks

Chapter 3 provided the quantitative framework necessary to run the empirical study of the last chapter. The literature review about attendance estimation in the sport industry was useful to identify the key determinants and to gather modeling suggestions. Specifically, the literature identifies four types of explanatory variables: economic, those related to the quality of the event, factors seeking to capture consumer preferences, and elements that create an opportunity cost for attendance. Moreover, four kinds of econometric issues have been found in the literature: the panel dimension of the data, the existence of censoring values of the dependent variable due to capacity constraints, the endogeneity of the price variable and the autocorrelation of the error term.

Therefore, the review allowed to choose the type of model and the regressors included in the specification. A panel model with fixed-effects was described, with the adoption of instrumental variables in order to deal with the endogeneity of the price variable. When it comes to the specification, determinants related to the quality of the match and of some kinds of opportunity costs were included, while economic time-invariant variables and factors related to consumer preferences were assumed to be contained within the team-specific fixed effect.

Before discussing the results, a diagnostic testing was performed. A problem of heteroskedasticity was detected, leading us to perform the regression with robust standard regressors, in order to be able to run a meaningful inference. Autocorrelation issues were not detected, while the analysis of the instruments induced us to remove the results of the logarithmic model.

The results implied an aggregated average elasticity level that is in line with the literature and with the theoretical model discussed in the previous chapter, for the quadratic specification. The linear specification is instead not supportive. The variables describing the quality of the event were found to be significant and with the expected sign; however, the relationship between the probability of a home victory and tickets sold is different than in other works: game-tickets buyers seem to value uncertainty of outcome more than partisanship. Concerning the factors that create opportunity costs, cold weather seems to have a negative impact on attendance, while the effect of a match scheduling during non-working days was not found as strong as in other works, specifically with respect to Model 1.

The size of the database allowed to run an additional regression on a subsample comprehending matches against the less prestigious teams. Among the main findings, it seems that attendees are more price-sensitive in those cases, and the opportunity costs play a more important role in determining attendance.

The findings of this work must in any case be interpreted with caution, for two main reasons. First, as it happens for all the empirical works in the sport events literature, a proxy for the price variable is used. In this case we chose the average price of tickets sold since it was the more appropriate approximation in view of the empirical exercise of the next chapter. If sector specific data had been available, a more accurate and deep analysis could have been run, by including the role of second and third-degree price discrimination strategies. Second, the database aggregates data concerning different types of home and away teams; given the divergence between small and top clubs that has been developing in contemporary football, marginal effects of the determinants may be different, as it was shown with the sub-sample regression.

Chapter 4

EMPIRICAL ANALYSIS

4.1 Introduction

The theoretical model presented in Chapter 2 has based some hypothesis about how football clubs set optimal game tickets prices, after the examination of the football industry performed in Chapter 1, and the literature review of the pricing strategies implemented, especially with respect of variable ticket pricing.
The econometric work performed in Chapter 3 allows to verify and discuss the consistency of such hypothesis with real data, in order to obtain stronger insights than those arising from a mere mathematical exercise. Moreover, data analysis may allow to identify other valuable intuitions, which could restart a new theoretical work investigating other related issues.

Chapter 2 has indeed mainly focused on one side of the problem, i.e. the determination of an optimal ticket price, which generates a certain amount of tickets sales and thus ticket revenues. The other side of the issue, i.e. the indirect effect of game ticket prices on other revenues, has been mainly exploited to derive the conclusions concerning the tickets side. The main reason strictly depends on data availability, since other revenues data are not publicly accessible. Moreover, a discussion of the modeling of the relationship between other revenues and attendance would need a whole research work, that would have gone beyond the scope of the present one. Nonetheless, an analysis of the estimates arising from Chapter 3 allows to shed some lights on the other side of the problem and to obtain interesting inputs for an additional research work.

Furthermore, the estimates available allow to run simulations to quantify the impact of two components of the current pricing strategies of football teams: the choice to deviate from the ticket revenues maximizing price (i.e. the one implying unitary elasticity), and the adoption of a variable ticket pricing (VTP) scheme.
Finally, the discussion concerning the implementation of VTP, from which Proposition 5 arose, leads us to propose a further price optimization procedure for the clubs that adopted it by charging different prices for different *match categories*, and to evaluate its possible impact on tickets revenues and attendance.

While the remainder of Paragraph 4.1 illustrates the methodology adopted and comments the seasonal demand elasticity values directly derived from Model 2, Paragraph 4.2 discusses the first four propositions about the setting of the optimal ticket price.

Specifically, Proposition 1 allows to identify the clubs that may be characterized by a stronger effect of a ticket price increase on other revenues; Proposition 2 tests the effect of a higher price sensitivity on the underpricing behavior[137] of the club, and it helps to formulate some hypothesis on the variation of the effect of a ticket price increase on other revenues across different opponents. Proposition 3 detects the variation of the optimal elasticity level across match categories arising from the implementation of VTP. Proposition 4, eventually, focuses on the seasonal elasticity values by trying to motivate the deviations from the theoretical model.

Paragraph 4.3 quantifies the impact of the current strategies. The estimation of the ticket revenues left on the table by deviating from unitary elasticity pricing (i.e. mono-product monopolist outcome) may represent a lower bound of the gains accruing by behaving as a multi-product monopolist. Furthermore, a simulation of a fixed-pricing scenario allows to quantify the impact of the variable pricing strategies currently adopted by the Serie A teams, whether in the form of a match-specific VTP or a category-specific one.

Paragraph 4.4 will then simulate a scenario characterized by a further optimization procedure consistent with Proposition 5, which can thus be assessed.

Lastly, Paragraph 4.5 concludes by summarizing the main results of the empirical work and highlighting the potential inputs for the modeling of other ticket-related revenues.

4.1.1 Methodology

Some general comments concerning the methodology adopted for the empirical work should be underlined, especially when it comes to the econometric model(s) exploited for the estimations, the consistency with the theoretical framework of Chapter 2, and the simulation method exploited.

The econometric work of Chapter 3 endowed us with two different models for the estimation of a demand equation. While Model 1 describes a linear relationship between tickets sold and price, Model 2 assumes a quadratic function instead; the empirical part of the present chapter exploits Model 2, since the quadratic relationship entails a more realistic increasing marginal effect of price on sales.

Moreover, Chapter 3 performed a regression (with Model 2.1) on a sub-sample that excluded matches against top teams (“Goliath”), in order to detect differences in the marginal effects. Despite the more appropriateness of such model for the prediction of quantities sold in less prestigious matches, we prefer to apply Model 2 for all matches to be consistent across the different simulations. Model 2.1 will only be exploited for the discussion of Proposition 2, in that it allowed us to distinguish among matches with a different price sensitivity. Therefore, the implicit assumption underlying each simulation is that only parallel demand shifts occur (i.e. variation in the potential demand, a), as in Rascher et al (2007).

Furthermore, note that the theoretical model discussed in Chapter 2 assumes a linear demand function for game tickets, in order to display a simpler demonstration. Despite such functional form may appear as inconsistent with the quadratic model adopted in Chapter 4, the qualitative conclusions summarized by the propositions are unaffected (see the appendix at the end of the chapter)[138].

[137] i.e. pricing in the inelastic part of the demand curve.

[138] Note here that the main assumptions continue to hold: monopoly status, zero marginal costs and separability of the revenue sources.

Finally, it is worth to express some comments about the simulation method.
First, as it will be remarked in specific points, it should be highlighted that the optimal price determination method used later in the chapter is an application of the approach designed by Rascher et al (2007).
Second, the empirical work is based on two crucial additional assumptions: the current clubs' pricing objectives (represented by the elasticity levels) are optimal and price variation does not enter consumers' utility functions. The former assumption must be set in that we are not endowed with data concerning other ticket related revenues, and a rigorous discussion of the modeling of such other revenues is left to further research that could exploit the present work to gain some insights; the latter assumption is crucial, given that the empirical work will simulate the impact of moving from an optimal fixed price approach to the actual variable one (sub-paragraph 4.3.2) and subsequently to a match-specific VTP for clubs that implement a category-specific VTP. If price variation was included in attendees' utility functions, the estimated impact would be biased.

Besides, note that even in the scenarios where actual prices and quantities are available, each simulation will be performed by excluding the error term, in order to be able to discuss comparable results. In this framework, indeed, the error term may represent a relevant share of the actual quantity of tickets sold, for two reasons in particular: first, instrumental variables models, although yielding consistent coefficient estimates, are not the best tools to be exploited for predictions (see Verbeek, 2004); second, possible unpredictable outliers may have a severe impact on the analysis: while in the case of estimates reported at the sample level (e.g. aggregation of hundreds of observations), outliers' effects might cancel each other out, the influence of an outlier when discussing results for each team-season combination (i.e. 19 observations at most) could be huge and distort the analysis.

For instance, consider the match between Fiorentina and Benevento, which took place on 11/03/2018. Such event, that in a normal case would not have been attractive at all (given the low prestige of the visiting team, by far the last club in the league table), exhibited the highest number of game ticket sales for Fiorentina in the current season. Such exploit is explained but the willing of many Florence citizens to commemorate the tragic passing of Fiorentina's former captain Davide Astori. If the simulation included the error-term, the quantity predicted with an optimal price inferior to the actual one would be much lower than real sales, and the impact of a further optimization procedure on ticket revenues would appear disastrous.

Therefore, in each simulation such that an "actual" scenario is discussed, quantities are in fact the fitted values predicted by a model including the actual price[139]. An alternative method could have been developed by adding the error-term to the quantity predicted with the optimal price, since the error component is assumed to be uncorrelated with the regressors (i.e. if the price variable is changed by the optimization process, the error-term should be unaffected). However, we prefer to simplify the analysis by removing the random component in each scenario.

[139] Buraimo and Simmons (2009) estimate the impact of a competitive balance maximization policy on tickets sales and television audience with a similar approach.

Actual quantities sold are thus employed in the computation of seasonal elasticities (see next-sub-paragraph) and category-specific elasticities (see the discussion of Proposition 3) only.

4.1.2 Team-specific seasonal elasticities

The estimates of Chapter 3 allow to derive and analyze the team specific elasticity values. Table 4.1 displays data concerning demand elasticity at the team/season level of detail, computed after the coefficient of the price variable estimated with Model 2[140].

A first glance permits to notice that 5 teams applied elastic pricing in the period under analysis:

- Juventus: across all seasons;
- Parma: in the only championship to which it participated;
- Roma: in all seasons except the current one, characterized by a price reduction and a growth of sales;
- Sampdoria: from season 2015-16 onwards; in 2014-15, prices where on average lower;
- Genoa: in the last two seasons (2016-17, 2017-18), where prices increased.

The 95% confidence interval[141] of the seasonal elasticities of the above teams comprehends inelastic values as well. On the other hand, a relatively small part of the interval is consistent with elastic pricing for Cesena, Empoli and Torino. Inelastic pricing is instead a robust finding for nine clubs in the sample: Atalanta, Bologna, Carpi, Fiorentina[142], Hellas Verona, Milan, Palermo, Pescara, Sassuolo.

Furthermore, Table 4.1 reports statistics related to the *match-level* point elasticity values. A quick observation allows to notice that the team-specific average of such values is different from the related seasonal elasticity. The latter is instead computed after average prices and quantities, while the former is the average of values generated by match-specific figures. The standard deviation of the match-level elasticity values is in many instances a remarkable share of the average, suggesting a wide variation within the team-season cluster. Minimum and maximum values strengthen such hint: apart from a few instances, every team highly deviated from the average level in at least one match, reaching extreme point elasticity values in some cases. The inefficient grouping of heterogeneous matches in the same price category, as it was suspected in Chapter 2 (see Table 2.2), may entail game-specific elasticities that are far from the average value, which may represent the objective of the club's pricing strategy. The simulation performed in paragraph 4.4 will try to estimate the impact of a price optimization procedure within the price category.

[140] Note that we are assuming that such coefficient is the same across teams and seasons.
[141] The interval is derived by applying the boundary values of the 95% confidence interval of the *price2* coefficient to the elasticity formula (see paragraph 3.4.2).
[142] When it comes to the 2015-16 season, unit elasticity is at the very low end of the confidence interval.

Table 4.1: Analysis of elasticity estimates, by club and season

Club	Season	N	Avg Price	Avg Quantity (000)	Seasonal Elasticity	95% Conf. Interval		Avg match-specific elasticity	Std. Dev.	Min	Max	Load Factor	STH/Att*
Atalanta	2014-15	15	12.57	5.275	-0.25	-0.43	-0.08	-0.27	0.17	-0.56	-0.10	66%	68%
	2015-16	19	12.40	5.399	-0.24	-0.41	-0.07	-0.28	0.18	-0.62	-0.02	66%	67%
	2016-17	19	15.92	6.123	-0.35	-0.60	-0.11	-0.38	0.23	-0.82	-0.12	70%	65%
	2017-18	13	17.46	5.531	-0.46	-0.79	-0.14	-0.79	0.32	-1.29	-0.27	72%	81%
Bologna	2015-16	18	19.27	6.341	-0.49	-0.84	-0.15	-0.55	0.30	-1.28	-0.10	52%	69%
	2016-17	19	16.52	7.741	-0.30	-0.51	-0.09	-0.35	0.27	-0.86	-0.04	58%	65%
	2017-18	14	18.85	7.310	-0.41	-0.70	-0.13	-0.45	0.32	-1.03	-0.08	57%	67%
Carpi	2015-16	17	14.76	4.951	-0.37	-0.63	-0.11	-0.48	0.39	-1.13	-0.05	41%	46%
Cesena	2014-15	16	17.45	3.935	-0.65	-1.11	-0.20	-0.73	0.30	-1.41	-0.30	68%	77%
Empoli	2014-15	16	13.70	2.653	-0.59	-1.02	-0.18	-0.68	0.31	-1.37	-0.26	54%	73%
	2015-16	16	14.86	3.011	-0.62	-1.06	-0.19	-0.72	0.37	-1.30	-0.09	60%	72%
	2016-17	17	15.02	2.676	-0.71	-1.21	-0.22	-0.99	0.61	-2.17	-0.03	57%	75%
Fiorentina	2014-15	17	20.06	6.568	-0.51	-0.88	-0.16	-0.63	0.56	-2.49	-0.13	64%	79%
	2015-16	19	23.27	7.735	-0.59	-1.01	-0.18	-0.71	0.41	-1.48	-0.14	61%	74%
	2016-17	18	20.47	6.265	-0.56	-0.96	-0.17	-0.74	0.56	-2.36	-0.09	57%	77%
	2017-18	13	20.76	7.747	-0.47	-0.80	-0.14	-0.51	0.32	-0.93	-0.10	54%	70%
Genoa	2014-15	13	22.37	4.327	-0.97	-1.67	-0.30	-1.59	0.81	-2.82	-0.20	56%	81%
	2015-16	6	19.51	4.513	-0.71	-1.21	-0.22	-1.15	0.41	-1.46	-0.37	60%	82%
	2016-17	17	24.06	3.322	-1.46	-2.51	-0.45	-2.94	1.67	-5.73	-0.06	58%	86%
	2017-18	12	25.91	4.236	-1.33	-2.28	-0.41	-2.81	1.94	-6.71	-0.43	59%	83%
Hellas	2014-15	14	15.77	4.720	-0.44	-0.76	-0.14	-0.56	0.40	-1.37	-0.07	61%	76%
	2015-16	10	14.14	4.643	-0.36	-0.62	-0.11	-0.43	0.20	-0.71	-0.18	57%	75%
	2017-18	12	14.94	6.590	-0.28	-0.49	-0.09	-0.34	0.13	-0.53	-0.10	58%	67%
Juventus	2014-15	19	48.64	12.399	-1.60	-2.75	-0.50	-1.67	0.75	-3.02	-0.83	94%	68%
	2015-16	10	51.12	14.214	-1.54	-2.65	-0.48	-1.70	1.06	-3.61	-0.67	95%	64%
	2016-17	13	51.21	15.155	-1.45	-2.49	-0.45	-1.63	1.11	-3.61	-0.56	96%	62%
	2017-18	6	56.32	15.731	-1.69	-2.90	-0.52	-1.93	1.28	-3.96	-0.73	97%	61%
Milan	2014-15	16	29.29	18.000	-0.40	-0.69	-0.12	-0.51	0.18	-0.88	-0.27	47%	58%
	2015-16	17	29.68	19.464	-0.38	-0.65	-0.12	-0.46	0.18	-0.88	-0.13	48%	55%
	2016-17	19	29.23	25.355	-0.28	-0.49	-0.09	-0.30	0.08	-0.47	-0.20	50%	40%
Palermo	2014-15	19	15.17	7.756	-0.25	-0.43	-0.08	-0.42	0.56	-1.65	-0.01	48%	59%
	2015-16	9	14.73	8.662	-0.21	-0.36	-0.07	-0.26	0.27	-0.78	-0.07	51%	56%
Parma	2014-15	19	21.56	2.517	-1.55	-2.66	-0.48	-3.59	5.45	-24.25	-0.27	54%	80%
Pescara	2016-17	14	11.34	4.244	-0.25	-0.44	-0.08	-0.26	0.13	-0.54	-0.10	62%	69%
Roma	2014-15	17	50.11	13.072	-1.61	-2.77	-0.50	-1.94	0.94	-4.38	-0.92	57%	69%
	2015-16	17	51.30	12.348	-1.79	-3.07	-0.55	-2.43	1.28	-5.57	-0.50	51%	69%
	2016-17	19	45.82	13.830	-1.28	-2.19	-0.39	-1.91	1.16	-3.92	-0.36	46%	62%
	2017-18	14	39.97	15.580	-0.86	-1.48	-0.27	-0.98	0.44	-2.04	-0.48	52%	60%
Sampdoria	2014-15	18	19.35	3.870	-0.81	-1.39	-0.25	-1.01	0.42	-1.95	-0.34	60%	83%
	2015-16	19	23.38	3.116	-1.47	-2.53	-0.46	-2.08	0.83	-3.74	-0.46	60%	87%
	2016-17	17	21.76	2.613	-1.52	-2.61	-0.47	-1.90	0.96	-3.85	-0.36	53%	87%
	2017-18	12	23.18	3.228	-1.40	-2.40	-0.43	-1.94	1.05	-4.10	-0.88	54%	85%
Sassuolo	2014-15	10	14.25	4.820	-0.35	-0.61	-0.11	-0.49	0.78	-2.65	-0.09	58%	63%
	2015-16	8	11.40	4.754	-0.23	-0.39	-0.07	-0.23	0.10	-0.43	-0.09	51%	58%
	2016-17	15	13.34	6.253	-0.24	-0.41	-0.07	-0.25	0.22	-0.64	-0.04	59%	55%
	2017-18	9	18.96	5.834	-0.52	-0.89	-0.16	-0.67	0.77	-2.57	-0.09	51%	51%
Torino	2014-15	15	21.28	6.363	-0.60	-1.02	-0.19	-0.77	0.44	-1.74	-0.20	59%	64%
	2015-16	19	21.32	7.401	-0.52	-0.88	-0.16	-0.69	0.47	-1.81	-0.10	69%	64%
	2016-17	19	23.95	7.876	-0.61	-1.05	-0.19	-0.72	0.31	-1.31	-0.14	69%	61%
	2017-18	10	22.74	6.195	-0.70	-1.20	-0.22	-0.79	0.39	-1.65	-0.31	65%	67%

*Source: Our elaboration. *Ratio of season ticket holders and average attendance.*

4.2 Propositions discussion (1-4)

The quantitative framework derived by the econometric estimation of Chapter 3 allows to discuss the propositions resulted from the theoretical model of Chapter 2. The discussion arises from an analysis and elaboration of the estimates, with the purpose of verifying, when possible, the consistency of the propositions with data. Note, however, that further empirical research, with more appropriate data (especially those related to other revenue sources) and that controls for all the possible factors, should empirically test such conclusions. Nonetheless, the estimates available allows to identify some patterns that could represent inputs for other works. The remainder of the paragraph discusses the first four propositions. While Proposition 5 will be discussed with the simulation of paragraph 4.4, Proposition 6, which is a corollary of Proposition 3 in a category-specific VTP setting, cannot be tested with the data available (see the concluding remarks of the chapter).

4.2.1 Proposition 1

Proposition 1: the higher the price reduction/quantity increase (from the mono-product optimal level) and the distance of the optimal elasticity from unity, the stronger the effect of a ticket price increase on other revenues;

According to proposition 1, assuming a fixed price sensitivity (parameter *b*), the clubs that apply greater discounts from the mono-product price level (and, consequently, a lower elasticity in absolute value) should represent the teams characterized by a stronger effect of a ticket price increase on other revenues.
Since the output of Model 2 implicitly assumes that price sensitivity (i.e. the coefficient of the price variable) is the same for each club and for each match (i.e. only parallel demand shifts occur), an estimation of the mono-product optimal price allows to identify the clubs that may exhibit the strongest relationship between the tickets market and other revenue sources[143].

We thus estimate an average mono-product optimal price (at the seasonal level) with the following procedure, derived from Rascher et al (2007)[144].
We start from the average elasticity equation:

$$\bar{\varepsilon} = 2\,\widehat{\beta_2}\,\bar{p}_{i,t} \cdot \frac{\bar{p}_{i,t}}{\bar{q}_{i,t}}$$

[143] Note that a glance at Table 4.1 would allow to identify the same clubs; however, it is of interest here to estimate the size of ticket underpricing by means of the procedure below.
[144] Rascher et al (2007) re-optimized prices at the match level to estimate the impact of a variable ticket pricing strategy in the MLB. Such method will be further exploited later in the chapter.

where $\bar{p}_{i,t}$ is the average ticket price for club *i* in season *t*, $\bar{q}_{i,t}$ the average tickets sold and $\widehat{\beta_2} = -0.0042$ (from Model 2).

We plug the demand equation $\hat{q} = \bar{a}_{i,t} + \widehat{\beta_2}\,\bar{p}_{i,t}^2$ and we impose $\bar{\varepsilon} = -1$ (i.e. the mono-product optimal level)[145]. Re-arranging, we obtain a formula for the ticket revenues maximizing price:

$$\bar{p}_{i,t}^{MP} = \sqrt{-\frac{\bar{a}_{i,t}}{3\widehat{\beta_2}}}$$

where *MP* stands for "mono-product". We thus plug $\bar{p}_{i,t}^{MP}$ in the demand equation to estimate $\bar{q}_{i,t}^{MP}$. Table 4.2 displays the output[146].

Palermo, Sassuolo and Atalanta appear to be the clubs that most underpriced tickets, in specific seasons. Although further research should investigate the causation channels that link attendance to other revenues, a discussion of the latter two cases may shed some light on the interpretation of Proposition 1.

Sassuolo is the historical club of a small town, which achieved the first qualification to the Serie A in 2013, thanks to the crucial investments on the players' market made by its owner. After the successful fight to avoid relegation in the first Serie A appearance, results on the pitch improved progressively until the achievement of an amazing qualification to the Europe League in 2015-16.

A rather wealthy ascending team with good results on the pitch only missed a sizeable fan base. Such claim should explain the generous underpricing from the tickets revenue maximizing level, in the first seasons. In the current campaign, however, the management appears to be applying a different strategy, since underpricing is less relevant. Nonetheless, sales remained at the same level of the past seasons: Sassuolo could have built its status of an established Serie A team, with sales of around 5,000 tickets on average[147], and the spillovers of potential additional attendees may not be as valuable as before.

Formally, the consolidation of Sassuolo in the Serie A may have modified the other revenues function $R_O(q_t)$. Consequently, the same q_t may have yielded a lower amount of other revenues, thus decreasing the incentive to underprice tickets:

$$R_{O1}(q_t) > R_{O2}(q_t)$$

where $R_{O1}(q_t)$ is the other revenues function of the past years, and $R_{O2}(q_t)$ the current one.

[145] For each observation, $\bar{a}_{i,t}$ is given by the sum of all the regressors (constant term and unit-specific fixed effect included), multiplied by the relative coefficient, i.e.: $\widehat{a_{it}} = \hat{\alpha}_2 + \widehat{u_{2i}} + \hat{\gamma}_2 X'_{it} + \hat{\delta}_2 V'_t$ (see Chapter 3 for notation).
$\bar{a}_{i,t}$ is the average of such fitted values.

[146] Note that, despite Parma average elasticity displayed in Table 4.1 was higher than 1, Table 4.2 reports a price discount. While the seasonal elasticity is computed after actual prices and quantities (with the application of an estimated price-sensitivity coefficient), the mono-product optimal price is estimated only. Since Parma went bankrupt in 2014-15, the model probably fails in reliably estimating a mono-product optimal price, given that such season can be considered as a series of outliers.

[147] The theory of habits in attendance, touched upon in Chapter 2, also contributes to explain Sassuolo's behavior.

Table 4.2: Average ticket underpricing effect by club and season

Club	Season	N	Avg Price (Actual)	Avg Price (MP)	%Change	Avg Qnt (Act, 000)	Avg Qnt (MP, 000)	%Change
Atalanta	2014-2015	15	12.57	24.88	-49%	7.134	5.198	37%
	2015-2016	19	12.41	23.54	-47%	6.333	4.653	36%
	2016-2017	19	15.92	23.09	-31%	5.650	4.477	26%
	2017-2018	13	17.46	19.61	-11%	3.565	3.231	10%
Bologna	2015-2016	18	19.27	26.28	-27%	7.139	5.799	23%
	2016-2017	19	16.53	26.86	-38%	7.942	6.059	31%
	2017-2018	15	18.85	27.50	-31%	8.033	6.350	26%
Carpi	2015-2016	17	14.76	23.19	-36%	5.863	4.519	30%
Cesena	2014-2015	16	17.45	23.24	-25%	5.527	4.537	22%
Empoli	2014-2015	16	13.71	17.52	-22%	3.081	2.580	19%
	2015-2016	16	14.87	20.62	-28%	4.431	3.573	24%
	2016-2017	17	15.02	18.59	-19%	3.407	2.903	17%
Fiorentina	2014-2015	17	20.07	26.26	-24%	6.995	5.791	21%
	2015-2016	19	23.28	29.09	-20%	8.389	7.110	18%
	2016-2017	18	20.47	27.70	-26%	7.907	6.444	23%
	2017-2018	14	20.76	28.26	-27%	8.254	6.710	23%
Genoa	2014-2015	13	22.37	24.70	-9%	5.585	5.125	9%
	2015-2016	6	19.52	19.46	0%	3.170	3.180	0%
	2016-2017	17	24.06	23.61	2%	4.595	4.684	-2%
	2017-2018	12	25.92	23.02	13%	3.857	4.452	-13%
Hellas	2014-2015	14	15.78	25.43	-38%	7.104	5.433	31%
	2015-2016	10	14.14	21.14	-33%	4.791	3.754	28%
	2017-2018	13	14.94	23.87	-37%	6.242	4.787	30%
Juventus	2014-2015	19	48.64	46.10	6%	16.841	17.853	-6%
	2015-2016	10	51.13	44.93	14%	14.459	16.959	-15%
	2016-2017	13	51.21	45.59	12%	15.168	17.456	-13%
	2017-2018	6	56.32	47.14	19%	14.675	18.666	-21%
Milan	2014-2015	16	29.29	45.51	-36%	22.492	17.397	29%
	2015-2016	17	29.68	45.01	-34%	21.823	17.016	28%
	2016-2017	19	29.23	45.19	-35%	22.146	17.157	29%
Palermo	2014-2015	19	15.17	28.58	-47%	9.327	6.863	36%
	2015-2016	9	14.74	30.29	-51%	10.648	7.707	38%
Parma	2014-2015	19	21.56	22.39	-4%	4.365	4.212	4%
Pescara	2016-2017	14	11.35	19.33	-41%	4.169	3.140	33%
Roma	2014-2015	17	50.12	43.87	14%	13.701	16.167	-15%
	2015-2016	17	51.31	44.15	16%	13.502	16.372	-18%
	2016-2017	19	45.82	43.18	6%	14.679	15.665	-6%
	2017-2018	15	39.97	42.90	-7%	16.479	15.460	7%
Sampdoria	2014-2015	18	19.35	22.20	-13%	4.639	4.141	12%
	2015-2016	19	23.38	21.22	10%	3.378	3.783	-11%
	2016-2017	17	21.77	21.63	1%	3.905	3.930	-1%
	2017-2018	12	23.18	21.61	7%	3.624	3.921	-8%
Sassuolo	2014-2015	10	14.26	23.24	-39%	5.952	4.537	31%
	2015-2016	8	11.40	23.34	-51%	6.318	4.576	38%
	2016-2017	15	13.35	23.79	-44%	6.383	4.754	34%
	2017-2018	9	18.97	25.10	-24%	6.430	5.294	21%
Torino	2014-2015	15	21.28	27.46	-22%	7.599	6.334	20%
	2015-2016	19	21.33	28.40	-25%	8.252	6.775	22%
	2016-2017	19	23.96	27.94	-14%	7.424	6.556	13%
	2017-2018	10	22.75	27.91	-18%	7.639	6.541	17%

Source: Our elaboration

When it comes to Atalanta, the change in the club's status in the past two years can explain the alteration of the underpricing behavior. Atalanta had been an established Serie A team, that usually fought to avoid relegation, from basically the beginning of the current century onwards. In the past year, however, it achieved an historical fourth place in the final league table, qualifying for the Europe League. The investments of the past summer and the current results, though not as amazing as the past season's ones, are confirming that Atalanta has become a club that can permanently lie among the top 10 Italian teams.

Consequently, the increased media interest implies that other revenues are less related to attendance, as in the case of Sassuolo. An alternative and/or complementary explanation arises from the observation of the season tickets market: Atalanta's season ticket holders increased by 40% in the current season; therefore, assuming a decreasing effect of attendance (i.e. season ticket holders *and* game ticket purchasers) on other revenues, Atalanta has now less incentives to attract additional fans, since the marginal spectator generates a lower amount of proceeds. Formally:

$$R_O'(att_1) > R_O'(att_2) \text{ with } att_2 = s_{t2} + q_{t2} > att_1 \text{ and } R_O''(att_i) < 0.$$

where att_i is the sum of season ticket holders and game tickets buyer in period *i*, and the second derivative of other revenues with respect to attendance is negative.

4.2.2 Proposition 2

Proposition 2: the higher the ticket price sensitivity, the lower the optimal price reduction from the mono-product level.

According to Proposition 2, if the negative effect of a ticket price increase on other revenues is fixed, matches characterized by a higher price sensitivity should entail a lower reduction from the optimal mono-product outcome.

Therefore, assuming that the effect of a ticket price increase on other revenues is home-team-specific but constant across the types of opponent, Proposition 2 may not be verified because of three possible reasons:

- Clubs are not optimizing;
- Other factors are not captured by the theoretical model;
- The effect of a ticket price increase on other revenues is not fixed across the type of opponent, i.e. the above assumption does not hold.

In order to discuss Proposition 2, for each team-season combination we repeat the procedure of sub-paragraph 4.2.1 on two different groups of matches: those against "Goliath" (i.e. Juventus, Inter, Milan, Napoli, Roma) and those against "David" (all the others). In the former case, we estimate the ticket revenues maximizing price by exploiting Model 2, as in the previous sub-paragraph[148]; in the latter case, the mono-product optimal price is estimated after Model 2.1:

$$\bar{p}^{MP}_{i,t,G} = \sqrt{-\frac{\bar{a}_{i,t,G}}{3\widehat{\beta_2}}}\ ;\ \bar{p}^{MP}_{i,t,D} = \sqrt{-\frac{\bar{a}_{i,t,D}}{3\widehat{\beta_{2.1}}}}$$

where the subscripts *G* and *D* stands for "Goliath" and "David", and $\widehat{\beta_{2.1}} = -0.0062$ (see Model 2.1).

Sold-out events were excluded, given that proposition 2 is an outcome of the unconstrained solution of the maximization problem[149]. Since the estimation on the subsample of matches against David suggested that price sensitivity is higher in such events, we expect discounts to be higher in matches against Goliath. Table 4.3 reports the price discounts for each team-season-type of opponent combination.

Mixed evidence arises from the analysis. The model seems to correctly describe the behavior of five clubs (Atalanta, Empoli, Hellas Verona, Milan and Torino) that regularly applied higher discounts for matches against Goliath; since the mono-product optimal price for matches against Goliath is underestimated, such outcome is rather robust. On the other hand, seven clubs (Bologna, Carpi, Cesena, Fiorentina, Palermo, Pescara, Sassuolo) recurrently applied more sizeable discounts on matches against David.

As supposed above, the model suggests that either the clubs are not behaving optimally, or the negative effect of a ticket price increase on other revenues is stronger for matches against David. However, the underestimation of the price sensitivity for matches against Goliath may distort such conclusion; in fact, if the true coefficient decreases, the optimal mono-product price raises, thus widening the gap with the actual price and enlarging the discount applied.

Finally, clubs applying elastic pricing (Genoa, Parma, Roma and Sampdoria) overpriced matches against David more; however, since elastic pricing without binding constraints is not consistent with the model (see sub-paragraph 4.2.4), such result does not support Proposition 2.

[148] Note that, since Model 2 was estimated after *all* matches, we are underestimating the mono-product optimal price for Goliath group. An econometric regression was run on such sub-sample, yielding a non-significant price coefficient. However, such outcome may be due to the reduced size of the sub-sample (177 observations). The empirical evidence of Chapter 3 suggests in any case that price sensitivity is lower for such kind of matches.

[149] Consequently, Juventus data are not analyzed.

Table 4.3: Ticket underpricing by club and opponent type (2014-15 to 2017-18, up to stage 28).

Club	Opponent	N	Potential Demand (a,000)	Avg Price (actual)	Avg Price (MP)	%Change
Atalanta	Goliath	18	14.193	21.93	33.55	-35%
	David	48	5.196	11.89	16.70	-29%
Bologna	Goliath	13	14.766	33.76	34.21	-1%
	David	38	6.406	13.05	18.55	-30%
Carpi	Goliath	4	10.902	26.46	29.41	-10%
	David	13	4.825	11.17	16.11	-31%
Cesena	Goliath	2	7.519	25.32	24.43	4%
	David	12	4.072	14.33	14.80	-3%
Empoli	Goliath	12	10.538	26.60	28.92	-8%
	David	37	2.208	10.60	10.80	-2%
Fiorentina	Goliath	17	16.789	34.26	36.48	-6%
	David	50	7.360	16.56	19.88	-17%
Genoa	Goliath	12	13.284	29.03	32.45	-11%
	David	36	6.105	21.47	18.11	19%
Hellas	Goliath	9	12.614	23.48	31.62	-26%
	David	27	5.000	12.63	16.39	-23%
Milan	Goliath	8	31.020	39.39	49.58	-21%
	David	40	18.216	25.25	31.29	-19%
Palermo	Goliath	8	17.423	30.18	37.16	-19%
	David	20	8.036	8.63	20.79	-58%
Parma	Goliath	5	11.374	31.93	30.04	6%
	David	14	3.893	17.86	14.47	23%
Pescara	Goliath	1	6.186	22.07	22.16	0%
	David	12	2.963	9.21	12.62	-27%
Roma	Goliath	14	32.646	56.87	50.90	12%
	David	53	24.095	44.16	35.99	23%
Sampdoria	Goliath	17	13.007	30.75	32.03	-4%
	David	49	4.757	19.09	15.99	19%
Sassuolo	Goliath	5	12.528	29.55	31.48	-6%
	David	35	5.125	11.56	16.55	-30%
Torino	Goliath	15	18.291	29.44	38.08	-23%
	David	48	7.993	20.30	20.72	-2%

Source: Our elaboration. "Goliath" refers to Juventus, Milan, Internazionale, Roma and Napoli; "David" to all the other Serie A participants.

4.2.3 Proposition 3

Proposition 3: the bigger the potential demand, the lower the elasticity reduction (from unity level) needed to attract the optimal number of attendees.

According to proposition 3, matches such that the price charged implies an elasticity nearer to 1 should be characterized by a larger potential demand (i.e. a). However, according to the theoretical model of Chapter 2, such proposition holds if the effect of a ticket price increase on other revenues is fixed; therefore, a positive *within-club* relationship between potential demand and elasticity (in absolute value) should exist, but *between-clubs* comparisons are meaningless.

In order to assess such claim, we exploit data referred to clubs that implemented variable ticket pricing by dividing the league matches in price categories: Proposition 3 is tested by focusing on the elasticity level *per price category*, thus performing a team-specific *intra-season* evaluation.
As reported in Chapter 2, several football clubs apply variable ticket pricing by dividing matches in categories. Therefore, Proposition 3 entails that categories with a higher potential demand a, should be priced such that the elasticity is higher (assuming a fixed effect of a ticket price increase on other revenues). As in the previous sub-paragraph, assuming the clubs' optimal profit maximizing behavior, if data were inconsistent with Proposition 3 they would either represent supportive evidence to claim that the effect of a ticket price increase on low-demand matches is stronger or suggest that the model is not capturing other factors[150].
Pricelists were retrieved through a detailed internet search on clubs' official websites and online newspapers[151]. The average potential demand a was estimated with Model 2, while elasticities were computed from category-specific actual average prices, quantities and the coefficient of the price variable:

$$\bar{\varepsilon}_{ict} = 2\,\widehat{\beta_2}\,\bar{p}_{ict} \cdot \frac{\bar{p}_{ict}}{\bar{q}_{ict}}$$

where the subscripts *i, c and t* indicates the home team, the price category and the season respectively.

Table 4.4 reports the results, where price categories were labeled with capital letters by the author. In this case, data gives support to Proposition 3, in that the model explains the behavior of Atalanta, Bologna, Fiorentina,

[150] On the other hand, consistent data would not imply that the effect of a ticket price increase on other revenues is fixed: the effect of potential demand may simply be stronger.
[151] The problem in retrieving past pricelists is given by the fact that some clubs update the same webpage when they publish the price menu of a new match. All matches of the 2014-15 season were excluded for that reason, as those of Carpi. In other cases, instead, pricelists are published as "news" that could be retrieved in the website archive, or in old pages that still appear as an output of search engines. However, not all the pricelists of other home clubs were retrieved, therefore the sample restricted further. Furthermore, some clubs (such as Juventus and Torino) does not seem to divide matches in strict price categories, but they modify single prices of the menu instead, with an approach that is more similar to a true variable pricing one. The two clubs are excluded for this reason. In other cases, such as Fiorentina in the past seasons, the pricelists applied were too many to identify a clear match categorization approach. Eventually, matches with special pricelists (e.g. resulted from special offers) were excluded as well.

Hellas Verona, Palermo, Pescara, Sassuolo. On the other hand, Genoa, Sampdoria and Roma did not behave consistently with Proposition 3; however, since such clubs applied elastic pricing, they may follow different logics in setting the optimal price (see next sub-paragraph). The behavior of Milan is instead irregular.

4.2.4 Proposition 4

Proposition 4: If the capacity constraint does not bind, elastic pricing is not consistent with revenue maximization.

As it was mentioned in paragraph 4.1, the estimated elasticities suggest that five teams applied elastic pricing in specific seasons. According to Proposition 4, such decision is consistent with revenue maximization only if the capacity constraint binds.

The elastic pricing strategy implemented by Juventus is consistent with the model presented in Chapter 2: the average load-factor reported in Table 4.1 demonstrates that the Italian champions regularly sold-out their capacity during the whole period, and that the stadium is probably undersized. However, Parma, Roma, Genoa and Sampdoria never sold-out their capacity in the past three seasons and a half: therefore, since the model fails to explain their pricing strategy, either some assumptions were violated, or the management did not behave optimally, or the model is not considering other issues.

Table 4.4: Category-specific elasticity, by club and season.

Club	Season	Price Category	N	Average *a* (000)	Average Elasticity
Atalanta	2015-16	A	5	13.541	-0.47
		B	3	5.160	-0.40
		C	10	4.459	-0.14
	2016-17	A	3	13.148	-0.62
		B	7	4.660	-0.30
		C	7	2.619	-0.18
	2017-18	A	3	13.459	-1.03
		B	10	2.263	-0.66
Bologna	2016-17	A	5	14.147	-0.67
		B	6	7.811	-0.36
		C	7	6.011	-0.08
	2017-18	A	2	13.070	-0.90
		B	7	8.878	-0.35
		C	4	5.584	-0.16
Fiorentina	2017-18	A	2	16.674	-0.81
		B	4	8.431	-0.71
		C	5	6.865	-0.19
Genoa	2016-17	A	9	7.544	-1.51
		B	6	6.231	-2.58
	2017-18	B	6	6.020	-2.58
		C	3	2.761	-2.61
Hellas	2015-16	A	1	11.410	-0.67
		B	9	4.988	-0.33
	2017-18	A	3	14.790	-0.35
		B	9	4.643	-0.29
Milan	2015-16	A	2	39.641	-0.37
		B	13	24.179	-0.47
		C	2	20.145	-0.16
	2016-17	A	3	36.723	-0.38
		B	1	29.664	-0.31
		C	13	23.262	-0.28
Palermo	2015-16	A	2	20.871	-0.68
		B	1	14.370	-0.38
		C	6	7.988	-0.08
	2016-17	A	2	12.187	-0.52
		B	1	4.145	-0.37
		C	10	3.416	-0.21
Roma	2015-16	A	5	31.030	-1.66
		B	9	21.000	-1.74
	2016-17	A	5	30.781	-1.35
		B	12	20.144	-1.44
	2017-18	A	3	31.948	-0.90
		B	7	21.897	-0.95
		C	3	19.017	-0.91
Sampdoria	2015-16	A	6	11.198	-1.40
		B	13	3.125	-1.81
	2016-17	A	4	13.030	-1.76
		B	12	3.865	-1.64
	2017-18	A	2	16.738	-1.19
		B	8	3.979	-1.93
Sassuolo	2017-18	A	3	12.688	-1.04
		B	5	4.622	-0.25

Source: Our elaboration

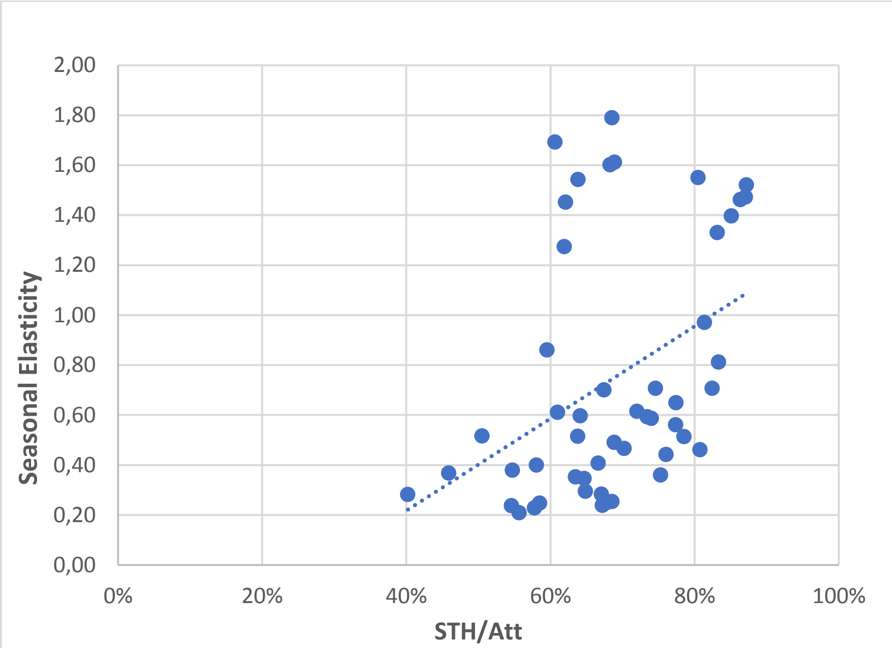
Monopoly status of the football club, marginal costs of tickets equal to zero, and the profit maximization objective are the main assumptions on which the model is based.
Since Genoa and Sampdoria belong to the same city (Genoa), as well as Roma and Lazio (of which we do not have data), it could be reasonable to claim that the market power of such clubs is weaker than in other cases, especially when it comes to the game tickets market, which is less affected by loyalty issues. Average prices are indeed similar for the two Genoese clubs. On the other hand, however, a possible duopoly does not explain such outcome either: since the two clubs would compete on prices, a Bertrand market structure would entail equilibrium prices closer to the marginal cost (i.e. zero). The average prices of the two clubs (€20-25), which is higher than several other teams' fares, do not support such hypothesis.

While the assumption of minimal marginal ticket costs seems reasonable[152], the possibility of a non-optimal behavior sheds light on the elasticity level of Parma. Since data related to that club refer to the season in which it went bankrupt (at about the half of the campaign), inefficient behavior can be assumed. However, such explanation is not suitable for the other three teams[153]. The objective function of a sport team (attendance maximization vs profit maximization) has been discussed in the literature as an explanation for inelastic pricing, thus other behavioral goals do not seem to explain the result.

Therefore, the model is probably missing something. A possible justification may concern the existence of a season tickets market alongside the game tickets one. The last column of Table 4.1 displays the incidence of season ticket holders on the total number of attendees; Genoa and Sampdoria are the two teams that exhibit the higher ratios. Further research should theoretically and empirically investigate such claim, but the strategy of the Genoese clubs may be such that game ticket prices are kept high to induce customers to buy season tickets[154]. Figure 4.1 (weakly) supports that claim: the scatterplot (in which each point represents average values per team and season) shows a positive relation between the season tickets/attendance ratio and the seasonal elasticity[155]. Still, such idea does not explain the pricing strategy of Roma.

[152] Moreover, the marginal ticket cost should be very similar across clubs.
[153] Considering that the leading shareholder of Roma co-owns an NBA team as well, it is not reasonable to assume that Roma is not behaving optimally. Nevertheless, Table 4.1 shows that Roma progressively decreased average ticket prices in the last two seasons, reaching the inelastic part of the demand curve. If such inelastic approach was confirmed in the future, the hypothesis of a past inefficient strategy would strengthen.
[154] Such hypothesis could be valid in a duopoly framework, in which the two clubs cooperate by fixing similar game ticket prices, in order to induce fans to purchase the season ticket.
[155] Consider that, in the last two seasons, Juventus capped the quantity of season tickets on sale; otherwise, the incidence of season ticket holders could have been much higher.

Figure 4.1: Relationship between STH/Attendance and the season-specific elasticity, by club and season (2014-15 to 2017-18, up to stage 26).



Source: Our elaboration

4.3 Simulations

4.3.1 Impact of deviating from unitary elasticity

According to the theoretical model of Chapter 2, profit maximizing clubs should deviate from the unit elasticity level in setting the optimal price. Such deviation occurs for several reasons:

- Maximization of overall profits instead of tickets ones;
- Binding capacity constraint, i.e. the unitary elasticity quantity cannot be sold;
- Inefficient behavior, or other reasons that may not be captured by the model.

In any case, the club is not maximizing tickets-related profits. Therefore, it is interesting to estimate the foregone tickets revenues[156], which may proxy, respectively:

- The lower bound of the "other revenues" that are generated by inelastic pricing: if the club's behavior is optimal, inelastic pricing is applied because other profits generated by additional attendees *at least* compensate for the foregone tickets proceeds[157];

[156] i.e. the difference between actual tickets revenues and the hypothetical maximized ones.
[157] Note that foregone tickets revenues are actually foregone *profits*, given that they would have arisen without additional costs.

- The foregone revenues due to the stadium under-sizing: such estimation would allow a club to evaluate the additional revenues that could accrue with a capacity enlargement;
- The foregone game-tickets-related revenues arisen from the application of elastic pricing, whatever its motivation (inefficient behavior or other reasons not captured by the model).

Such estimate should arise from a comparison of actual proceeds with a simulation of revenues that may have accrued with a mono-product behavior. However, since the evaluation should control for the implementation of variable ticket pricing, we should restore a situation such that fixed-pricing is applied in both scenarios.
In other words, in the actual scenario we predict the quantity of tickets sold when the price charged is the actual average seasonal price, accounting for capacity constraints[158]:

$$\hat{q}_{act,i,m,t} = \hat{a}_{it} + \widehat{\beta_2}\bar{p}_{act,i,t}$$

where $\hat{q}_{act,i,m,t}$ represents the fitted values for match *m*, when the home team *i* charges the average price of season *t*, i.e. $\bar{p}_{act,i,t}$.
In the mono-product scenario, we predict the tickets sold when the fixed price charged is the one such that seasonal elasticity is equal to -1 (see sub-paragraph 4.2.1), accounting for capacity constraints[159]:

$$\hat{q}_{MP,i,m,t} = \hat{a}_{it} + \widehat{\beta_2}\bar{p}_{MP,i,t}$$

where *MP* stands for the mono-product scenario. Table 4.5 displays the results, for each team.
Clubs that applied inelastic pricing in the period under analysis left ticket revenues on the table in order to attract more attendees; if the clubs behaved optimally in a profit maximization framework, such revenues would at least be compensated by other attendance-correlated sources. For instance, Atalanta renounced an average of €21,260 per match of ticket revenues (i.e. €403,942 per-season, without considering the games of other competitions) to attract 1,104 additional fans; consequently, such attendees may have indirectly generated at least €21,260 of other revenues per game, i.e. a raw estimate of €19.25 per person each match.

Juventus, instead, implemented elastic pricing because of the binding capacity constraint. Had Juventus been able to optimize the stadium capacity, it could have generated €119,068 additional *ticket revenues* per-match (i.e. €2,262,283 per-season) by an average €5 price reduction and an attendance increase of 4,032 fans. Considering that the additional 4,032 spectators could have generated other attendance-correlated revenues, the foregone amount is probably even larger[160].

---

[158] i.e. we imposed that: $\hat{q}_{s,i,m,t} \leq c\_av_{i,t}$, where *s* is the scenario, and $c\_av_{i,t}$ is the capacity available after the sale of season tickets for the home team *i* in season *t*.
[159] When it comes to observations of Juventus playing at home, we did not account for capacity constraints, since the objective is to estimate the foregone revenues arising from the undersize of its stadium. The optimal price for Juventus is thus the one that solves the unconstrained profit maximization problem.
[160] Suppose, for instance, that each of the additional attendees had bought a drink for €3: revenues would have increased by €12,000 more per-match, i.e. €228,000 per season.

On the other hand, teams that implemented elastic pricing despite a non-binding constraint, for inefficiency or other reasons not captured by the model, left both additional attendees and ticket revenues on the table. However, foregone revenues for each of those teams are quite negligible.

4.3.2 Impact of variable ticket pricing

The simulation implemented in the previous sub-paragraph allows to evaluate the impact of the adoption of a variable ticket pricing strategy by the Serie A clubs on attendance and ticket revenues. Specifically, the "actual" scenario of sub-paragraph 4.3.2 (i.e. revenues and attendance generated by charging the average seasonal price for each match) can be compared with the one such that the real prices are charged for each game[161].

In other words, in the fixed pricing scenario we predict the quantity of tickets sold when the price charged is the actual average seasonal price, accounting for capacity constraints, as in the previous sub-paragraph:

$$\hat{q}_{fix,i,m,t} = \hat{a}_{it} + \widehat{\beta_2}\bar{p}_{fix,i,t}$$

Where *fix* stands for "fixed-pricing scenario".

In the actual variable pricing scenario, we estimate the fitted values of tickets sold with the actual variable prices, accounting for capacity constraints:

$$\hat{q}_{VP,i,m,t} = \hat{a}_{it} + \widehat{\beta_2}p_{VP,i,t}$$

Where *VP* stands for "variable pricing scenario".

On average, we expect an increase of revenues from the implementation of VTP, with a rather stable attendance. However, impacts may be different for different kinds of matches, depending on the type of opponent, since clubs mainly set prices on the basis of the visiting team.

Table 4.6.1 displays the results, for each club, aggregating the three seasons and a half under analysis. Ticket revenues increase for almost each club, with rather stable attendance figures (-/+ 5%). Revenues only decreased for Parma and Juventus. While the former did not probably apply VTP in an optimal way, given the bankruptcy that occurred, the latter result may entail that Juventus did not optimally use price as a rationing variable, i.e. price increases did not prevent excess demand in prestigious matches, and price decreases may have been too generous in less attractive ones.

[161] Such simulation is the opposite of the one run by Rascher et al (2007) with respect to the MLB, though with the same purpose; the authors started from an actual fixed price and chose an optimal variable price; in this simulation, we start from an actual variable price and we estimate an optimal fixed price.

Table 4.5: Simulation of the impact of deviation from unitary elasticity, by club (2014-15 to 2017-18, up to stage 26).

Club	N	Actual Price (Fixed, Period Avg)	MP Price (Fixed, Period Avg)	Actual Avg Qnt	MP Avg Qnt	Actual Avg Revenues	MP Avg Revenues	Δ Qnt	Foregone Revenues	Seasonal Foregone Revenues	Foregone Revenues per additional attendee
Atalanta	66	14.45	22.94	5.033	3.929	70,318	91,578	1.104	- 21,260	- 403,942.90	19.25
Bologna	51	18.13	26.83	7.683	6.047	139,032	162,342	1.636	- 23,310	- 442,896.01	14.25
Carpi	17	14.76	23.19	5.863	4.519	86,565	104,816	1.344	- 18,251	- 346,769.95	13.58
Cesena	16	17.45	23.24	5.205	4.339	90,829	100,841	0.866	- 10,012	- 190,219.39	11.56
Empoli	49	14.54	18.91	3.187	2.645	46,465	50,409	0.542	- 3,945	- 74,953.02	7.27
Fiorentina	67	21.22	27.84	7.880	6.519	167,736	181,992	1.361	- 14,256	- 270,861.32	10.48
Genoa	48	23.50	23.24	4.500	4.558	105,724	106,821	-0.057	- 1,098	- 20,854.23	19.22
Hellas	36	15.05	23.72	6.139	4.751	92,953	113,864	1.388	- 20,911	- 397,317.95	15.06
Juventus	48	50.82	45.85	13.629	17.661	690,976	810,044	-4.032	- 119,068	- 2,262,283.35	29.53
Milan	52	29.40	45.23	22.147	17.185	651,067	777,301	4.962	- 126,234	- 2,398,442.71	25.44
Palermo	28	15.03	29.13	9.752	7.134	146,474	208,142	2.618	- 61,668	- 1,171,687.99	23.56
Parma	19	21.56	22.39	4.262	4.117	91,898	92,184	0.145	- 286	- 5,431.03	1.97
Pescara	14	11.35	19.33	3.765	2.810	42,728	54,325	0.956	- 11,597	- 220,340.01	12.13
Roma	67	47.08	43.54	14.508	15.929	678,375	693,771	-1.420	- 15,396	- 292,526.47	10.84
Sampdoria	66	21.83	21.66	3.902	3.944	84,392	85,486	-0.041	- 1,093	- 20,770.85	26.44
Sassuolo	42	14.40	23.85	6.128	4.703	88,156	112,348	1.425	- 24,192	- 459,655.42	16.98
Torino	63	22.34	27.96	7.098	6.020	158,194	168,376	1.078	- 10,182	- 193,449.23	9.44

Source: Our elaboration

Table 4.6.1: Simulation of the impact of VTP over Fixed pricing, by club (2014-15 to 2017-18, up to stage 26).

Club	N	Fixed Price	Variable price (Avg)	Avg Qnt Fixed Price (000)	Avg Qnt Variable Price (000)	Qnt %Change	Avg Revenues (Fixed Price)	Avg Revenues (Variable Price)	Revenues %Change
Atalanta	66	14.45	14.45	5.033	5.118	2%	70,318	87,353	24%
Bologna	51	18.13	18.13	7.683	7.283	-5%	139,032	148,304	7%
Carpi	17	14.76	14.76	5.863	5.568	-5%	86,565	94,000	9%
Cesena	16	17.45	17.45	5.205	5.303	2%	90,829	101,534	12%
Empoli	49	14.54	14.54	3.187	3.244	2%	46,465	67,275	45%
Fiorentina	67	21.22	21.22	7.880	7.549	-4%	167,736	181,013	8%
Genoa	48	23.50	23.50	4.500	4.389	-2%	105,724	114,184	8%
Hellas	36	15.05	15.05	6.139	6.045	-2%	92,953	105,563	14%
Juventus	48	50.82	50.82	13.629	14.014	3%	690,976	678,532	-2%
Milan	52	29.40	29.40	22.147	21.790	-2%	651,067	663,737	2%
Palermo	28	15.03	15.03	9.752	9.216	-5%	146,474	162,550	11%
Parma	19	21.56	21.56	4.262	3.857	-9%	91,898	78,202	-15%
Pescara	14	11.35	11.35	3.765	3.796	1%	42,728	54,066	27%
Roma	67	47.08	47.08	14.508	14.270	-2%	678,375	675,450	0%
Sampdoria	66	21.83	21.83	3.902	3.745	-4%	84,392	97,555	16%
Sassuolo	42	14.40	14.40	6.128	5.922	-3%	88,156	99,278	13%
Torino	63	22.34	22.34	7.098	7.260	2%	158,194	175,918	11%

Source: Our elaboration

Table 4.6.2 disaggregates the results by type of opponent[162].

Focusing on matches against David, VTP entails two-digits price reductions, in percentage terms, and an increase of attendance for all teams[163]. Ticket revenues, instead, decreases for all the teams that applied inelastic pricing. The reason is that a fixed price would have led the elasticity level to approach -1 in low demand matches, thus increasing revenues; the price reduction thus restored an equilibrium that is sub-optimal from the ticket revenues point of view. Juventus also experienced a revenues reduction, despite starting from an elastic equilibrium, probably because the binding constraint did not allow to expand attendance enough to obtain the related benefits in term of ticket revenues. On the other hand, VTP allowed Sampdoria, Genoa and Empoli to increase both attendance and ticket revenues; when it comes to the two Genoese teams, a price reduction entailed an equilibrium nearer to the unitary elasticity one. The same holds for Empoli, since a fixed-price would have implied elastic pricing in matches against David.

When it comes to games against Goliath, VTP entails a massive prices growth, a three-digits one in some cases; the consequence is a conspicuous attendance reduction for basically each team but Atalanta and Torino. The impact on ticket revenues is positive for every club but Roma and Parma. With respect to clubs

[162] For an easier understanding of the below discussion, recall paragraph 2.4 and figure 2.6, about the motivation for variable ticket pricing. The appendix of the present chapter repeats the same exercise in the case of a quadratic function.

[163] Note that fixed-prices are different in the subsamples; data are indeed aggregated for the whole period under analysis, and the fixed price displayed is the average of the seasonal fixed prices; since the number of matches against David/Goliath in our database is different across seasons, the sub-sample restrictions implies different aggregated values, given that the weight of each season in the average differs.

applying inelastic pricing, the fixed-price would have entailed a further right-departure from the unitary elasticity level, thus VTP entails an equilibrium nearer to the ticket revenues maximizing one; the same explanation holds for Sampdoria and Genoa: a fixed-pricing approach would have implied inelastic pricing in matches against Goliath; Juventus, instead, probably increased revenues by more effectively exploiting the rationing function of pricing.

The separated analysis of data related to the different kind of opponents allows to draw an important conclusion: since several clubs that applied inelastic pricing were willing to exchange ticket revenues for attendance in matches against David, while they did the opposite in games against Goliath, it may be that the effect of a ticket price increase on other revenues is different across matches (across types of opponents in this case). Since matches against Goliath usually exhibit higher attendance, the implication of such analysis is that, when a certain attendance level is reached, the positive effect of tickets sales on other revenue sources is no longer strong enough to incentivize tickets underpricing. In other words, the positive effect of the marginal attendee is probably decreasing. Such conclusion supports the hypothesis proposed in sub-paragraph 4.3.1.

Table 4.6.2: Fixed vs Variable pricing results, by club and opponent type (2014-15 to 2017-18, up to stage 26).

		Vs David									Vs Goliath									
Club	**N**	**Fixed Price**	**Variable price (avg)**	**Price %Change**	**Avg Qnt Fixed Price (000)**	**Avg Qnt Variable Price (000)**	**Qnt %Change**	**Avg Revenues (Fixed Price)**	**Avg Revenues (Variable Price)**	**Revenues %Change**	**N**	**Fixed Price**	**Variable price (avg)**	**Price %Change**	**Avg Qnt Fixed Price (000)**	**Avg Qnt Variable Price (000)**	**Qnt %Change**	**Avg Revenues (Fixed Price)**	**Avg Revenues (Variable Price)**	**Revenues %Change**
Atalanta	48	14.52	11.80	-19%	2.913	3.173	9%	39,963	35,966	-10%	18	14.27	21.53	51%	10.688	10.304	-4%	151,264	224,384	48%
Bologna	38	18.14	12.96	-29%	5.815	6.426	11%	105,109	84,542	-20%	13	18.12	33.25	84%	13.146	9.788	-26%	238,191	334,687	41%
Carpi	13	14.76	11.17	-24%	4.594	4.835	5%	67,833	56,994	-16%	4	14.76	26.46	79%	9.986	7.950	-20%	147,443	214,270	45%
Cesena	12	17.45	14.33	-18%	3.974	4.342	9%	69,357	60,711	-12%	4	17.45	26.83	54%	8.896	8.187	-8%	155,246	224,004	44%
Empoli	37	14.51	10.63	-27%	1.681	2.026	21%	24,399	25,626	5%	12	14.63	26.60	82%	7.832	7.000	-11%	114,502	195,693	71%
Fiorentina	50	21.21	16.76	-21%	5.481	6.101	11%	116,547	104,722	-10%	17	21.27	34.36	62%	14.934	11.809	-21%	318,293	405,397	27%
Genoa	36	23.29	21.66	-7%	2.390	2.638	10%	54,408	59,044	9%	12	24.12	29.03	20%	10.832	9.640	-11%	259,669	279,603	8%
Hellas	27	14.99	12.68	-15%	4.219	4.454	6%	63,480	57,969	-9%	9	15.23	22.13	45%	11.901	10.818	-9%	181,372	248,346	37%
Juventus	40	50.87	46.54	-9%	13.444	14.648	9%	682,177	660,985	-3%	8	50.56	72.22	43%	14.552	10.842	-25%	734,972	766,268	4%
Milan	40	29.40	25.22	-14%	19.578	20.478	5%	575,503	516,853	-10%	12	29.40	43.34	47%	30.709	26.161	-15%	902,948	1,153,349	28%
Palermo	20	15.04	8.68	-42%	7.190	7.802	9%	108,167	67,695	-37%	8	15.01	30.92	106%	16.157	12.749	-21%	242,243	399,686	65%
Parma	14	21.56	17.86	-17%	2.560	3.058	19%	55,203	46,727	-15%	5	21.56	31.93	48%	9.026	6.097	-32%	194,645	166,334	-15%
Pescara	12	11.35	9.21	-19%	2.923	3.084	6%	33,170	29,155	-12%	2	11.35	24.20	113%	8.819	8.066	-9%	100,075	203,530	103%
Roma	53	47.09	44.46	-6%	12.192	13.047	7%	569,580	571,991	0%	4	47.06	56.98	21%	23.278	18.902	-19%	1,090,241	1,067,117	-2%
Sampdoria	49	21.88	19.02	-13%	1.662	2.106	27%	35,656	40,414	13%	17	21.70	29.94	38%	10.359	8.470	-18%	224,867	262,255	17%
Sassuolo	35	14.26	11.18	-22%	4.867	5.038	4%	67,973	54,320	-20%	7	15.08	30.48	102%	12.434	10.344	-17%	189,069	324,066	71%
Torino	48	22.32	20.41	-9%	5.237	5.527	6%	116,526	112,118	-4%	5	22.38	28.51	27%	13.055	12.806	-2%	291,535	380,078	30%

Source: Our elaboration

4.4 Further optimization: match-specific VTP vs category-specific VTP

As reported in Chapter 2, several Serie A teams implement variable ticket pricing by dividing matches in two-three price categories. However, such grouping does not always appear efficient, since within-category demand fluctuations of about 25-30% of the group mean occurred (see Table 2.2). Such deviations may have arisen for two main reasons: grouping was performed by ignoring factors other than the visiting team affecting demand, or heterogeneous clubs (e.g. in terms of attractiveness) were included in the same category. The econometric model of Chapter 3 strengthens such suspect: the first stage of the econometric regression showed that only opponent-related variables were significant in explaining price variation; conversely, the second stage regression demonstrated that matches played in winter or on a working day exhibit lower attendance on average, and that the current sporting performance of the home team is positively significant. Moreover, dummies for Juventus, Milan and Inter playing away indicated that the attractiveness of the three most prestigious Italian teams is significant but different across them[164].

In such framework, Proposition 5 suggests that a possible further optimization procedure may be implemented. Demand shifts, indeed, imply within-category variation of the point elasticity value. If the category-specific price elasticity represents the pricing objectives of the home team, prices should be re-optimized when demand varies, in order to restore the initial elasticity value.

Such further optimization procedure crucially depends on the assumption of optimal behavior of clubs. In the absence of other revenues' data, and without a thorough modeling of the other revenues function, we can only hope that the current variable ticket pricing strategy is (sub)optimal, i.e. the category elasticity chosen represents the profit maximizing level, if kept constant across within-category matches, whichever the motivation that led clubs to set such value. Consequently, we assume here that the elastic pricing strategy implemented by Roma, Sampdoria and Genoa is optimal, although we do not know the reason. If that was not true, the further optimization procedure would probably worsen things, by restoring an inefficient value.

Moreover, recall, from Chapter 2, that the outcome of Proposition 5 is profit-maximizing if the optimal elasticity level does not change with the potential demand a, and if the effect of a ticket price increase on other revenues is fixed within the price category. Such simulation is therefore run by assuming that the category elasticity level chosen by the club is optimal, that it does not vary among matches and that consequently it should be restored after a demand shift. Proposition 6 argues that a new further optimization procedure should identify a match-specific optimal elasticity value and set the ticket prices accordingly (see the concluding remarks of this chapter).

The strength of such further optimization procedure lies in the way price is determined: the optimal price depends on the predicted potential demand a, which is estimated by Model 2. Model 2 regressors are attendance factors whose value is known by the football club when pricelists are usually posted (i.e. 1-2 weeks

[164] Recall the Hellas Verona price categories presented in the Introduction of the thesis: Milan and Juventus were grouped in the same category. Model 2 suggests that, all the else being equal, demand is much stronger for Juventus, thus the grouping was not efficient.

before the match, for most clubs). Therefore, the price that keeps the chosen group elasticity constant can be derived before each match.
In order to test the outcome of Proposition 5, we run a simulation by once again exploiting the method implemented by Rascher et al (2007).

First, we predict the fitted values of tickets sold with the actual prices (Model 2):

$$\hat{q}_{act,c,i,m,t} = \hat{a}_{i,m,t} + \widehat{\beta_2} p_{act,c,i,m,t}$$

where $\hat{q}_{act,c,i,m,t}$ represents the predicted number of tickets sold in the *actual* scenario (i.e. actual prices are charged), for a match *m* included in category *c*, played by home team *i*, in season *t*[165].
Afterwards, we compute the category-specific price elasticity, after the price coefficient of Model 2, the average price charged and the average sales within category:

$$\bar{\varepsilon}_{act,c,i,t} = 2 * \widehat{\beta_2} * \bar{p}_{act,c,i,t} * \frac{\bar{p}_{act,c,i,t}}{\bar{q}_{act,c,i,t}}$$

where $\bar{q}_{act,c,i,t}$ is the average of $\hat{q}_{act,c,i,m,t}$.
Such step allows to observe the elasticity predictions. Table 4.7 displays elasticity descriptive statistics, concerning the season 2016-17. First, notice that the category specific elasticity (i.e. computed after average prices and sales) is different than the average of match-specific elasticities, as in Table 4.1. Second, the standard deviation represents a remarkable share of the average in several occurrences. Minimum and maximum elasticity values explain such variation: for instance, data of Category C for Atalanta show that despite a group elasticity value of -0.41 only, a specific match (Atalanta-Crotone) exhibited an elasticity value of -6.18; On the other hand, Atalanta-Genoa, which belonged to the same price category, exhibited an elasticity value of -0.15. The predicted potential demand *a* for the two matches was indeed 5,886 and 677 spectators respectively. Eventually, note that it was not possible to compute elasticity statistics for two categories related to the Genoese teams. In some occurrences, indeed, prices were so high that the predicted quantity was zero[166], entailing an infinite elasticity value.

[165] Note that the price charged is both category and match specific. The price proxy we used is indeed the average price of tickets sold; though the price menu is category specific, the collapsed average price paid depends on how many tickets are sold in each sector; consequently, average prices are match-specific, though rather similar.
[166] It was actually a negative figure, adjusted to zero.

Table 4.7: Predicted Category-specific elasticities, by club (2016-17).

Club	Category	N	Category specific elasticity	Avg match-specific elasticity	Match-specific elasticity (std. dev.)	Std. Dev./Avg (match-specific elasticity)	Min	Max
Atalanta	A	3	-0.48	-0.53	0.17	33%	-0.69	-0.35
	B	7	-0.51	-0.67	0.50	75%	-1.76	-0.32
	C	7	-0.41	-1.30	2.17	166%	-6.18	-0.15
Bologna	A	5	-0.77	-0.86	0.26	30%	-1.13	-0.52
	B	6	-0.29	-0.30	0.12	39%	-0.42	-0.17
	C	7	-0.10	-0.11	0.08	71%	-0.27	-0.06
Genoa	A	9	-1.35	-	-	-	-∞	-0.63
	B	6	-0.92	-1.62	1.04	64%	-3.32	-0.36
Milan	A	3	-0.78	-0.78	0.24	31%	-0.93	-0.51
	C	13	-0.27	-0.27	0.04	15%	-0.32	-0.19
Pescara	A	2	-0.61	-0.74	0.36	48%	-0.99	-0.49
	C	10	-0.23	-0.24	0.10	43%	-0.39	-0.10
Roma	A	5	-1.39	-1.59	0.68	43%	-2.64	-0.89
	B	12	-1.29	-1.39	0.45	32%	-2.03	-0.76
Sampdoria	A	4	-0.98	-1.06	0.19	18%	-1.22	-0.79
	B	12	-1.38	-	-	-	-∞	-0.46

Source: Our elaboration

We then derive the optimal match-specific price, i.e. the price that keeps the category-specific price elasticity fixed.

Starting from the price elasticity formula:

$$\varepsilon_{m,i,t} = 2 * \widehat{\beta_2} * p_{opt,m,i,t} * \frac{p_{opt,m,i,t}}{\hat{q}_{opt,m,i,t}}$$

where $\varepsilon_{m,i,t}$ is the match-specific elasticity, $p_{opt,m,i,t}$ is the optimal price set for match m in season t by the home team i, and $\hat{q}_{opt,m,i,t} = \hat{a}_{m,i,t} + \widehat{\beta_2} * p^2_{opt,m,i,t}$ is the predicted value of tickets sold when $p_{opt,m,i,t}$ is charged. Note that the price is no longer category-specific.

We thus replace $\varepsilon_{m,i,t}$ with $\bar{\varepsilon}_{act,c,i,t}$ and $\hat{q}_{opt,m,i,t}$ with $\hat{a}_{m,i,t} + \widehat{\beta_2} * p^2_{opt,m,i,t}$. Re-arranging, we obtain:

$$p_{opt,m,i,t} = \sqrt{\frac{\hat{a}_{m,i,t} * \bar{\varepsilon}_{act,c,i,t}}{\widehat{\beta_2} * (2 - \bar{\varepsilon}_{act,c,i,t})}}$$

However, note that such price is optimal when the capacity constraint is not-binding; therefore, we add a further condition: if $\hat{q}_{opt,m,i,t}$ is larger than the capacity available after the sale of season tickets, the price charged becomes the highest that is compatible with a sold-out stadium:

$$p_{opt,m,i,t} = \sqrt{\frac{c\_av_{i,t} - \hat{a}_{m,i,t}}{\widehat{\beta_2}}}$$

Summarizing:

$$p_{opt,m,i,t} = \begin{cases} \sqrt{\dfrac{\hat{a}_{m,i,t} * \bar{\varepsilon}_{act,c,i,t}}{\widehat{\beta_2} * (2 - \bar{\varepsilon}_{act,c,i,t})}} \; if \; \hat{q}_{opt,m,i,t} \leq c\_av_{i,t} \\ \sqrt{\dfrac{c\_av_{i,t} - \hat{a}_{m,i,t}}{\widehat{\beta_2}}} \; if \; \hat{q}_{opt,m,i,t} > c\_av_{i,t} \end{cases}$$

We thus predict the fitted values and compare prices, attendance and revenues[167]. Note that the impact should be assessed by considering that clubs are interested in ticket revenues *and* attendance. Therefore, the impact of the optimization procedure is positive if both attendance and ticket revenues increase, while it is negative if both decrease. If a growth of the former and a reduction of the latter (or vice-versa) occurs, the impact is uncertain, given that the data available do not allow to quantify the effects of attendance on other revenues.

Moreover, since several clubs implemented an inelastic pricing strategy, we do not expect demand to be much responsive to price changes: the lower the point elasticity in absolute value, the lower the demand variation after a price adjustment. Conversely, we expect larger effects for the clubs that applied elastic pricing. Finally, the reduced number of pricelists that was retrieved and exploited for such simulation entails that results should be evaluated with caution; nonetheless, such simulation designs a method whose results could be strengthened by adding pricelists in the next future.

Table 4.8.1 displays the aggregated results for the whole period under analysis. Average prices are rather stable: for most teams they are slightly decreasing, while a more remarkable increase occurs for Atalanta, Empoli and Pescara (see below). The effect on attendance is positive for all clubs but Genoa, though not much strong. When it comes to average ticket revenues, the impact is positive for all teams except for Empoli, though the growth is not remarkable. The impact is huge on Atalanta and Pescara, with two-digits growth. The main reason is that five sell-outs were predicted for the former and one for the latter: the further optimization procedure allowed to capitalize on the sell-outs by selling the same number of tickets at a much higher price (+68% for Atalanta, +45% for Pescara), suggesting that the actual strategy implies tickets underpricing even when capacity constraints bind. If sell-outs are not considered, the further optimization procedure *reduces* average prices for both clubs, with a little further improvement on sales; when it comes to revenues, Atalanta still exhibits a +4%, while tickets proceeds slightly decrease for Pescara. The general results suggest that the effect of the further optimization process is positive, though not impressive, for all clubs apart from Empoli, for whom the impact is uncertain: if the 100 additional attendees allowed the club to increase other revenues by at least €1,500 per-match, the impact would be positive overall.

[167] As explained in footnote 151, the database was massively reduced for pricelists collection related issues. Moreover, we removed observations that represented the only match in the category; eventually, observations such that the predicted *a* was negative were excluded as well. A negative *a* occurred because the econometric model represents fixed-effects as deviations from the mean; therefore, for several teams they are negative. Consequently, when the attractiveness of the match is low, the resulted *a* is still negative. Such issue concerned some matches where the visiting teams exhibited very low payroll values (e.g. Crotone, Benevento). The dataset exploited for such simulation is composed by 299 observations.

Table 4.8.1: Simulation of a further optimization procedure, by club (2015-16 to 2017-18, up to stage 28).

Club	N	Actual Price	Optimal Price	%Change	Qnt (Act., 000)	Qnt (Opt., 000)	%Change	Revenues (Act.)	Revenues (Opt.)	%Change
Atalanta	47	14.61	15.63	6.99%	4.525	4.560	0.77%	77,009	100,626	31%
Bologna	32	16.62	16.55	-0.44%	7.172	7.211	0.53%	132,814	135,326	2%
Empoli	6	12.97	12.60	-2.87%	3.041	3.176	4.46%	50,897	49,365	-3%
Fiorentina	12	19.09	19.00	-0.47%	7.052	7.076	0.35%	151,444	152,534	1%
Genoa	29	23.41	22.20	-5.16%	3.544	3.532	-0.34%	91,871	97,601	6%
Hellas	22	13.97	13.80	-1.23%	5.515	5.529	0.25%	88,885	91,237	3%
Milan	33	29.81	29.80	-0.05%	21.530	21.574	0.20%	666,938	669,566	0%
Palermo	8	14.55	14.52	-0.21%	9.854	9.858	0.04%	183,711	183,722	0%
Pescara	12	11.58	12.27	5.99%	3.886	3.952	1.70%	57,587	69,340	20%
Roma	45	45.96	45.91	-0.12%	14.591	14.620	0.20%	674,666	685,126	2%
Sampdoria	44	23.43	23.15	-1.19%	3.713	3.728	0.41%	103,465	107,749	4%
Sassuolo	8	19.27	18.92	-1.79%	5.535	5.565	0.53%	132,092	136,389	3%

Source: Our Elaboration

Such results appear to give a weak support for Proposition 5. However, even if data allowing to study the relationship between attendance and other revenues are not available, a more detailed analysis that distinguishes between the cases of price increases and those of price reductions should be run, in order to better investigate the issue.

Table 4.8.2 reports the same indicators of the previous one by distinguishing between matches where a price increase occurs[168] (left part), and those characterized by a price reduction (right part).

The left part of the table shows a clear pattern: the impact is negative for elastic pricing teams, i.e. Roma and Sampdoria (and probably Genoa[169]), uncertain for the others. In the actual scenario, the resulting equilibrium is nearer to unitary elasticity: a price increase restores the inefficient elastic equilibrium, by decreasing both sales and revenues. When it comes to the other clubs, further optimization reduces attendance and increases revenues. In the actual scenario, the resulting equilibrium lies in a "more inelastic" part of the demand curve; the price optimization procedure allows it to move closer to unitary elasticity, thus increasing revenues. Note that, since the actual equilibrium was in the inelastic part, the increase of revenues is stronger than the decrease of attendance[170], given that in such part of the demand curve sales are not much responding to price.

[168] Sell-outs are not considered.
[169] The further price optimization reduces attendance by 1,100 fans, who could probably have compensated for the €4,000 tickets revenues gain.
[170] The only exception is given by Sassuolo, which implements an elastic pricing strategy in the A category, and inelastic in the other one.

Table 4.8.2: Simulation of a further optimization procedure, by club and price variation (2015-16 to 2017-18 up to stage 28).

	Price Increases										Price Reductions									
Club	N	Actual Price	Optimal Price	%Change	Qnt (Act., 000)	Qnt (Opt., 000)	%Change	Revenues (Act.)	Revenues (Opt.)	%Change	N	Actual Price	Optimal Price	%Change	Qnt (Act., 000)	Qnt (Opt., 000)	%Change	Revenues (Act.)	Revenues (Opt.)	%Change
Atalanta	19	12.22	14.91	21.98%	4.489	4.185	-6.79%	58,242	66,057	13%	23	14.62	10.97	-24.94%	2.720	3.043	11.87%	43,715	41,130	-6%
Bologna	18	14.19	16.22	14.34%	7.834	7.560	-3.50%	134,451	147,046	9%	14	19.75	16.97	-14.09%	6.322	6.762	6.95%	130,710	120,257	-8%
Empoli	3	8.76	10.75	22.73%	2.316	2.171	-6.26%	22,578	25,133	11%	3	17.18	14.45	-15.92%	3.765	4.181	11.05%	79,217	73,597	-7%
Fiorentina	6	18.38	20.04	9.05%	7.911	7.649	-3.30%	166,999	174,044	4%	6	19.81	17.97	-9.31%	6.193	6.503	5.01%	135,889	131,024	-4%
Genoa	11	24.40	28.69	17.54%	6.561	5.463	-16.74%	177,224	181,083	2%	18	22.81	18.24	-20.01%	1.700	2.351	38.34%	39,711	46,584	17%
Hellas	10	12.77	14.94	17.07%	6.828	6.561	-3.91%	104,305	116,046	11%	12	14.98	12.85	-14.22%	4.421	4.668	5.60%	76,035	70,563	-7%
Milan	19	26.98	28.60	6.02%	21.505	21.097	-1.90%	592,685	615,162	4%	14	33.66	31.42	-6.65%	21.564	22.223	3.05%	767,709	743,400	-3%
Palermo	3	15.75	16.61	5.47%	10.986	10.883	-0.94%	212,977	219,419	3%	5	13.83	13.27	-4.09%	9.174	9.243	0.75%	166,151	162,304	-2%
Pescara	5	7.40	8.87	19.93%	3.055	2.960	-3.10%	23,392	26,835	15%	6	12.61	10.76	-14.71%	3.228	3.439	6.53%	43,068	39,548	-8%
Roma	20	43.71	48.04	9.92%	17.816	16.128	-9.47%	801,691	796,806	-1%	25	47.77	44.20	-7.47%	12.012	13.413	11.66%	573,045	595,782	4%
Sampdoria	19	22.12	25.62	15.83%	5.188	4.448	-14.26%	141,091	141,750	0%	25	24.42	21.27	-12.90%	2.592	3.181	22.72%	74,870	81,909	9%
Sassuolo	4	21.28	24.30	14.19%	7.863	7.276	-7.47%	214,611	219,905	2%	4	17.26	13.54	-21.51%	3.207	3.854	20.16%	49,573	52,872	7%

Source: Our elaboration

The results of the right part of Table 4.8.2 display a reversed pattern instead: the further optimization process implies a growth of both sales and revenues for Genoa, Roma and Sampdoria[171]. On the other hand, inelastic pricing teams exhibit an increase in attendance and a decrease of revenues, for the same reasons discussed above: the actual scenario allowed the equilibrium to move closer to the unit elasticity one, while the further optimization process implies a departure towards the inelastic part, thus increasing attendance (though it is not much responding to price) but negatively affecting tickets revenues.

Although Table 4.8.2 shows that the impact of the further optimization procedure is uncertain for inelastic pricing clubs, the assumption of the decreasing positive effect of attendance on other revenues supports the claim of an overall positive effect. In other words, since a price increase should occur when demand is stronger, the resulting attendance reduction is less critical than the sales growth occurring after a price reduction, i.e. when demand is weak.

However, further research on the relationship between attendance and other revenues in a sport club should empirically assess such claim.

4.5 Concluding remarks

Chapter 4 has concluded the entire work by discussing the theoretical insights in light of the quantitative framework that has been built with the econometric regression. The purpose of the chapter was threefold. First, to elaborate the estimates in order to verify the consistency of the first four propositions articulated in Chapter 2, and at the same time to base some hypothesis on the relationship between attendance and other related revenues. Second, to estimate a lower bound of the impact of deviating from unitary elasticity pricing and of implementing variable ticket pricing in the current form, which is match-specific for some teams and category-specific for others. Third, an additional simulation tested Proposition 5 by estimating the impact of a further optimization procedure for clubs that implement variable ticket pricing by dividing matches in categories.

The discussion of Proposition 1 allowed to identify the clubs that, according to the theoretical model, may exhibit a closer relationship between attendance and other revenues. A mix of economic and football knowledge led us to observe that the other revenues function may change with the "status" of the club (newly-promoted club, established Serie A club, European competitions participant…). The media interest, which is growing with a club's status, may imply a lower impact of attendance on other revenues. Moreover, the analysis suggested that the effect of attendance on other revenues may be decreasing.

The mixed-evidence arisen from the discussion of Proposition 2 does not exclude that the effect of a ticket price increase on other revenues may be different across the type of opponent (top or small clubs).

Estimates are instead consistent with Proposition 3, in that, for those clubs that adopted category-specific VTP, matches with a higher potential demand are uniformly priced at a higher elasticity level. At the same time,

[171] Both indicators improve for Sassuolo as well; the improvement is mainly due to a price reduction for the match against Lazio (category A, characterized by elastic pricing), which was inefficiently priced in the same way of the ones against Juventus and Milan.

such result does not reject the hypothesis according to which the effect of a ticket price increase on other revenues may be stronger in the case of less attractive events.

The examination of Proposition 4 led us to discuss the elastic pricing (that, according to the theoretical model, is inconsistent with profit maximization) applied by some clubs. The incidence of season ticket holders on total attendance and/or the possible lower market power in the case of similar clubs belonging to the same geographical area represent possible causation channels that deserve to be examined more deeply.

The first simulation aimed at estimating the foregone revenues by deviating from unitary elastic pricing. If profit maximizing behavior is assumed, such revenues represent a lower bound of the additional other profits due to inelastic pricing that may accrue to the football team. Estimates quantify a lower bound of some hundreds of thousands of euros for several clubs. Moreover, the simulation suggests that Juventus, which appears to apply elastic pricing because of a binding capacity constraint, is leaving more than a hundred thousand of euros of ticket revenues per match on the table. Finally, even if the other teams applied elastic pricing because of an inefficient behavior, the foregone revenues do not appear to be remarkable.

The second simulation allowed to evaluate the impact of the current VTP strategies implemented by the selected Serie A clubs. Variable ticket pricing does not seem to have affected attendance relevantly, but the impact on revenues is of a two-digits growth in several cases. A more detailed analysis induced us to observe that the role of VTP may have been to increase attendance in matches against small clubs (at the expense of a ticket revenues reduction) and to raise revenues in games against top ones, despite a decrease of attendance. Such analysis strengthened the hypothesis of a different role of attendance in generating revenues across type of opponents.

Finally, the last part of the chapter performed an additional simulation concerning the clubs that implemented a category-specific VTP strategy in the last seasons. Assuming an optimal grouping of matches, and the category-specific elasticity value as representing the objective of the pricing strategy, the procedure further optimizes prices in line with the club's policy. An important aspect of the proposal is that prices are further optimized on the basis of information that is available to clubs when pricelists are usually published. The estimated impact is positive for several teams, though not remarkable. A deeper observation of price movements confirms that the procedure would be in line with the current behavior of clubs, since it would increase attendance when demand is weak and boost ticket revenues when demand is strong.

Proposition 6 is the only one that has not been discussed. According to such statement, the optimal elasticity level is match-specific, depending on the potential demand and on the effect of a ticket price increase on other revenues. The proposition should be discussed after a proper examination and modeling of other ticket related revenues, which goes beyond the scope of this work. Note, however, that if Proposition 6 were true, the strategy implemented with the further optimization procedure would entail a sub-optimal outcome.

It is finally worth to recall the assumptions upon which the empirical study is based, and the limitations in terms of method and data available.

Most of the discussion and the simulations originated by the assumption of a current optimal clubs' behavior, in terms of season and category-specific elasticity. If the supposition was wrong, most of the work would be less meaningful. The results of the further optimization procedure could especially *worsen* the outcome of the current strategy. Still, a football club could examine the whole work to gain pricing insights and exploit the method employed to adjust its pricing strategy, if deemed to be sub-optimal.

Furthermore, the absence of price variation in consumers' utility functions is the second crucial assumption. The discussion of paragraph 2.6 suggests that such assumption may not hold. Consequently, if supporters were averse to price variation, the impact of the current VTP strategies and of the further optimization procedure would be overestimated. Further research should evaluate such point, ideally, by integrating the current work with information concerning the season tickets market, in that price variation aversion may induce fans to buy season tickets.

Lastly, some limitations of the empirical work, arising from technical reasons and lack of more appropriate data, suggest evaluating the estimates with caution.

First, estimates originated from an econometric model that aggregates several clubs; while the outcome of Model 2.1 demonstrated that marginal effects are different when the visiting team is not a top-club, it is reasonable to believe such effects to be varying across home clubs as well. Moreover, the instrumental variables approach, implemented because of the endogeneity of the price variable, is not the most appropriate in terms of predictive power.

Therefore, further research should re-implement the method proposed with the present work by exploiting more sophisticated predictive tools and a greater amount of data, possibly team specific and accounting for the second and third-degree price discrimination strategies that all clubs are implementing.

4.6 Appendix: optimal price level with a quadratic demand function[172]

4.6.1 Mono-product case

Suppose that a football club is a monopolist that faces a quadratic demand curve for tickets:

$$q_t = a + bp_t^2$$

Where $b < 0$, $a > 0$; q_t and p_t represent the quantity of tickets sold and the relative price respectively.

Assuming variable costs equal to zero, the profit function for tickets will be:

$$\pi_t = q_t \cdot p_t - F$$

Where F represents the fixed costs.

[172] See Chapter 2 for notation.

The football club will choose the ticket price in order to maximize profits, subject to the capacity constraint, *C*.

$$\max_{p_t} q_t \cdot p_t - F$$
$$s.t. q_t \leq C$$

Taking the Lagrangian function, plugging the demand curve and deriving the first order conditions:

$$L = q_t \cdot p_t - F + \lambda \cdot (C - q_t) = ap_t + bp_t{}^3 - F + \lambda \cdot (C - a - bp_t^2)$$

$$\frac{\partial L}{\partial p_t} = 0 \rightarrow \; a + 3bp_t^2 - 2\lambda bp_t = 0 \qquad (1.1)$$

$$\frac{\partial L}{\partial \lambda} = 0 \rightarrow \; C - a - bp_t^2 = 0 \qquad (1.2)$$

Adding the condition allowing for the possibility of a non-binding capacity constraint and the sign of the multiplier:

$$\lambda(C - a - bp_t^2) = 0 \qquad (1.3)$$

$$\lambda \geq 0 \qquad (1.4)$$

Consider the case where λ=0.
The optimal price can be derived from (1.1):

$$p_t^{MP} = \sqrt{-\frac{a}{3b}}$$

Plugging such price in the demand curve, it follows that $q_t^{MP} = \frac{2a}{3}$.
At this point, it is possible to derive the elasticity of demand corresponding to such price-quantity combination:

$$\varepsilon_t^{MP} = \frac{\partial q_t}{\partial p_t} \cdot \frac{p_t^{MP}}{q_t^{MP}} = 2bp_t^{MP} \cdot \frac{p_t^{MP}}{q_t^{MP}} = -1$$

Now move to the case where $\lambda \neq 0$. In such occasion, the capacity constraint is binding, which imply that the tickets sold equal capacity:

$$q_t^{MP} = C$$

The optimal price can thus be derived by (1.2):

$$p_t^{MP} = \sqrt{\frac{C-a}{b}}$$

Note that the numerator is negative: since a represents the demand when the price is zero, it will be surely higher than the capacity, given the binding constraint.
The related elasticity of demand will thus equal:

$$\varepsilon_t = b \cdot \frac{\frac{C-a}{b}}{C} = \frac{2(C-a)}{C}$$

4.6.2 Multi-product case and mono/multi product comparison

Consider the profit function of a multi-product football club, and the related maximization problem

$$\pi = (q_t \cdot p_t - F) + R_C(q_t) + R_{SM}(q_t) + R_B - E$$

$$\max_{p_t} (q_t \cdot p_t - F) + R_O(q_t) + R_B - E$$
$$s.t. q_t \leq C$$

As before, we build the Lagrangian function, plug the demand curve and derive the first-order conditions:

$$L = q_t \cdot p_t - F + R_O(q_t) + R_B - E + \lambda \cdot (C - q_t) = a \cdot p_t + b{p_t}^3 - F + R_O(q_t) + R_B - E + \lambda \cdot (C - a - bp_t^2)$$

$$\frac{\partial L}{\partial p_t} = 0 \rightarrow a + 3bp_t^2 + R_O{}' - 2\lambda b p_t = 0 \qquad (2.1)$$

$$\frac{\partial L}{\partial \lambda} = 0 \rightarrow C - a - bp_t^2 = 0 \qquad (2.2)$$

The other conditions related to the constraint and the Lagrangian multiplier are unchanged:

$$\lambda(C - a - bp_t^2) = 0 \qquad (2.3)$$

$$\lambda \geq 0 \qquad (2.4)$$

The constrained optimization problem presents, again, two sets of solutions, depending on the multiplier lambda.

If $\lambda = 0$, we can derive the optimal price from (2.1):

$$p_t{}^* = \sqrt{-\frac{a + R_O{}'}{3b}}$$

Since $R_O{}'$ is negative, the price set by a multiproduct club with no binding constraint is lower than in the mono-product case:

$$p_t^{MP} - p_t{}^* = \sqrt{-\frac{a}{3b}} - \sqrt{-\frac{a + R_O{}'}{3b}}$$

The price reduction that a multiproduct monopolist applies depends:

- Positively on the effect of a ticket price increase on other revenues, in absolute value: if $R_O{}'$ increases in absolute value, the subtrahend decreases;
- Negatively on the marginal effect of ticket price on ticket demand (b): the higher the ticket price sensitivity, in absolute value, the lower the price reduction necessary to attract more attendees[173];

Consequently, we expect that tickets sold will be higher, and elasticity lower than in the previous case.

Plugging the price in the demand curve:

$$q_t{}^* = \frac{2a - R_O{}'}{3}$$

$$q_t{}^* - q_t^{MP} = -\frac{R_O{}'}{3}$$

The higher $R_O{}'$, the higher the increase of the amount of tickets sold.

The elasticity of demand will thus be:

$$\varepsilon_t^* = \frac{\partial q_t}{\partial p_t} \cdot \frac{p_t^*}{q_t^*} = 2bp_t^* \cdot \frac{p_t^*}{q_t^*} = -\frac{2a + 2R_O{}'}{2a - R_O{}'}$$

Which, in absolute value, will be lower than one.

[173] The derivative of $p_t^{MP} - p_t{}^*$ with respect to b is positive; therefore, if b decreases (i.e., increases in absolute value), the price variation decreases as well.

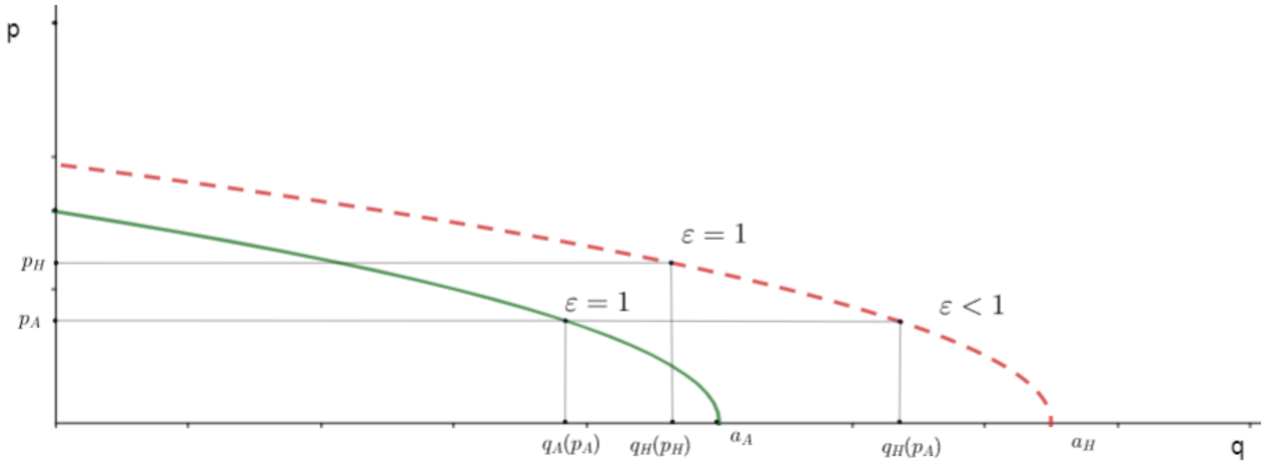
$$|\varepsilon_t^{MP}| - |\varepsilon_t{}^*| = \frac{-3R_O{}'}{2a - R_O{}'} > 0$$

The reduction of the point elasticity will depend:

- Positively on the absolute value of $R_O{}'$: the stronger the effect of a ticket price increase on other revenues, the higher the elasticity reduction;
- Negatively on a: the bigger the potential market, the lower the elasticity reduction needed to attract the optimal number of attendees; consequently, the model suggests that clubs/matches with a bigger potential market should exhibit an elasticity level that is nearer to unity.

4.6.3 Motivation for variable ticket pricing

Figure 4.2: Motivation for Variable Ticket Pricing, quadratic demand function



Source: Author's representation, following the same approach of Rascher et al (2007)

If the monopolist sets a fixed price for all matches, it will do so on the basis of an average demand curve, which represents the average tickets sold at every price point. The mono-product monopolist maximizes ticket revenues if it sets a price such that the elasticity of demand equals one in absolute value:

$$p_A^{MP} = \sqrt{-\frac{a_A}{3b}}$$

$$q_A^{MP}(p_A^{MP}) = \frac{2a_A}{3}$$

$$\varepsilon_A(p_A^{MP}) = -1$$

Where *A* stands for "average demand".

Let us consider a parallel outwards shift of the demand function, which describes a demand increase for a specific match (dotted curve in Figure 4.2): the new intercept with the horizontal axes is $a_H > a_A$, where *H* stands for "high-demand". If the monopolist sets the fixed price p_A, $q_H^{MP}(p_A^{MP}) = a_H - \frac{a_A}{3}$ tickets will be sold. Hence, the elasticity of demand will be lower than one:

$$\varepsilon_H(p_A^{MP}) = -\frac{2a_A}{3a_H - a_A}$$

Therefore, a club that sets a fixed price does not maximize ticket revenues in high demand matches: the optimal price would be the one that restores the elasticity at unity level:

$$p_H^{MP} = \sqrt{-\frac{a_H}{3b}} > p_A^{MP};$$

$$q_H^{MP}(p_H^{MP}) = \frac{2a_H}{3};$$

$$\varepsilon_H(p_H^{MP}) = -1$$

4.6.4 Motivation for proposition 6

Proposition 5 is verified if the demand parallel shift does not affect the optimal elasticity level.

In other words, if:

$$\frac{\partial|\varepsilon^*|}{\partial a} = 0$$

Such condition does not hold, since, assuming that $\frac{\partial R_O'}{\partial a} = 0$ (i.e. the potential demand does not impact on the negative effect of a ticket price increase on other revenues):

$$\frac{\partial|\varepsilon^*|}{\partial a} = \frac{-6R_O'}{(2a - R_O')^2} > 0$$

Therefore, adjusting prices in order to keep a constant elasticity level is sub-optimal: if the potential demand *(a)* increases, prices should be raised further to increase the elasticity level.

Furthermore, let us verify the assumption that $\frac{\partial R'_O}{\partial a} = 0$, by trying to model the other ticket related revenues, with a simple but meaningful function that is increasing in the quantity of tickets sold at a decreasing rate, i.e. the squared-root of the quantity of tickets sold:

$$R_O = \sqrt{q_t}$$

The effect of a ticket price increase on the other revenues will be:

$$R'_O = \frac{\partial R_O}{\partial q_t} \cdot \frac{\partial q_t}{\partial p_t} = \frac{1}{2\sqrt{q_t}} \cdot 2bp_t = \frac{1}{\sqrt{a + bp_t^2}} \cdot bp_t$$

The effect of a ticket price increase on other revenues is negative (since b < 0). We now compute the effect of a parallel shift of the demand curve on R'_O:

$\frac{\partial R'_O}{\partial a} = -\frac{bp_t}{2} \cdot (a + bp_t^2)^{-\frac{3}{2}} > 0.$

Which is different from zero.

CONCLUSION

The purpose of this Economics Master thesis was to understand how a football club should optimally set game tickets prices and to verify if and how a more flexible and demand-driven pricing method could improve the economic results of such teams.

An examination of the European football industry and of the sport demand literature, performed in Chapter 1, has allowed us to understand that, despite gate receipts represent the income stream with the lowest weight in the revenue-mix, tickets sales represent a possible driver of other proceeds, especially commercial ones (sponsors and merchandizing).

Such clue led us to derive a constrained maximization problem in which football clubs choose the ticket price in order to maximize overall profits (Chapter 2).

The theoretical results suggest that a profit maximizing football club with attendance-related revenue sources should sets the tickets price in the inelastic part of the demand curve if the stadium capacity constraint is not binding, thus underpricing tickets in comparison with the case of a mono-product team (i.e. without other income streams). The underpricing behavior should be higher the stronger the effect of a ticket price increase on other attendance related revenues. On the other hand, if the capacity constraint is binding, tickets elastic pricing is consistent with profit maximization.

Moreover, Chapter 2 has discussed the pricing strategies that the sport industry has borrowed from other businesses sharing similar issues; in particular, the work has focused on variable ticket pricing (VTP), which deals with demand fluctuations by optimizing prices accordingly. However, an observation of the price menus of selected Serie A teams hinted that some clubs implement VTP by means of a match categorization that considers the opponent as the main, if not the only, demand driver. Furthermore, actual tickets sales figures showed a certain within-category sales variation, entailing that the opponent-based match grouping may not have been effective and/or that other variables affecting demand might have not been considered in the grouping process.

The econometric estimation of a tickets demand function, performed in Chapter 3, confirms such suspects. The Instrumental Variables procedure has permitted us to observe that, while prices variation is explained by opponent-related variables only (first stage), other factors, such as sporting performance of the home team, match scheduling and weather conditions, affect tickets demand. Therefore, a further price optimization procedure was designed to allow those clubs to more effectively deal with demand fluctuations.

The empirical results have showed that the theoretical price determination model explains the seasonal elasticities of thirteen out of seventeen Serie A clubs analyzed; twelve of them applied inelastic pricing, while Juventus charged prices in the elastic part of the demand curve due to the binding capacity constraint.

The first empirical simulation has estimated a lower bound of the other profits that the twelve inelastic pricing clubs may have generated by underpricing tickets: the deviation from the optimal mono-product elasticity level (i.e. -1) generated foregone tickets revenues[174], which should have been recovered from other income streams if clubs behaved optimally. Such lower bound of other attendance-related profits generated spans from about €70,000 for Empoli to more than €2 million for Milan. On the other hand, the result of the same simulation can be differently interpreted for Juventus: had the Italian champions been able to optimize the stadium capacity, they could have increased tickets revenues by more than €2 million per season, without considering other competitions' games (such as the Champions League ones, where demand is probably much stronger) and positive spillovers on other revenue sources.

The second simulation has estimated the impact of the variable pricing strategies currently adopted by the selected teams. Results show that the VTP strategies implied a two-digits tickets revenues growth for several clubs, without relevantly harming attendance. A detailed analysis of the results suggests that prices were used as a tool to increase attendance in low-demand games (despite reducing tickets revenues) and to boost gate receipts in high-demand cases (despite reducing tickets sales).

The third and last simulation has evaluated the impact of a further pricing optimization strategy that restores the category-specific elasticity value, assumed as the optimal level set by the football club. The quantitative framework derived from Chapter 3 allowed to adjust prices according to the predicted demand[175], consistently with the assumed pricing objective of the football club. The results show that the impact of such a strategy would have been positive, though weak, for most of the clubs: attendance would have been basically unaffected, while tickets proceeds would have grown by some percentage points for basically all clubs. A more detailed analysis confirms that such further optimization procedure would be consistent with teams' behavior, in that it would have increased attendance (by means of price reductions) in low-demand games and raised gate receipts in high demand ones (by means of price increases).

While the results of this thesis may be of interest, especially from the qualitative point of view, further research could develop the work done by including issues that has been ignored for simplicity reasons and data availability problems, by exploiting more sophisticated modeling and predictive tools, and by discussing the assumptions on which most of the empirical part is based.

The theoretical model and the empirical work have excluded the role of season tickets, and ignored tier-pricing and market segmentation strategies. If sector-specific attendance figures were publicly available for both game and season tickets, an integrated analysis may yield much more valuable insights.

Furthermore, the positive effect of attendance on other revenues has been assumed on the basis on the literature reviewed, and not properly modeled: further research should explore such other side of the problem, by considering that this thesis suggests that the effect of attendance on other revenues may be positive but decreasing, in that clubs appear to prefer gate receipts over attendance when demand is strong; moreover, the

[174] It is worth noting that such foregone tickets revenues would have directly increased the clubs bottom line, given that they would have accrued without remarkable cost increases. Therefore, we could refer to them as foregone profits.

[175] Recalling the example presented in the Introduction of this thesis, the potential (i.e. when the price is zero) predicted demand for Hellas-Genoa was about 3,700 tickets, since it took place on a working day in December. On the other hand, the potential predicted demand for Hellas-Chievo was about 10,000 tickets, given that the match was a derby, scheduled in the weekend in March. The optimal pricing procedure slightly reduced the average ticket price in the former case and increased it in the latter.

analysis of tickets underpricing hints that such effect may be decreasing with the media interest towards the club.

Besides, the quality of the results can be improved by increasing the predictive power of the econometric model, given that instrumental variables are not the most appropriate forecasting tool. On the other hand, a more sophisticated econometric model should be club-specific, in that the marginal effects of the explanatory variables on tickets sales are probably different among home teams and along the opponent dimension, as demonstrated by the regression performed on the sub-sample that excluded top visiting clubs. Additionally, in the era of big-data, more explanatory variables may be included to develop the predictive power of the model.

Lastly, a discussion of the assumption set in this work can allow to gain valuable insights for its development. The inconsistency of the elasticity values of the two Genoese clubs might be explained by dropping the monopoly assumption for teams belonging to the same city and investigating possible competitive patterns. Moreover, the interpretation of the results may dramatically change if the profit maximizing behavior of clubs was questioned: for instance, the first simulation would suggest that clubs would be leaving profits on the table by applying inelastic pricing. Additionally, the empirical work assumed that price variation is not included in supporters' utility function. If that did not hold, results could be biased, in that negative reactions to price variations may dramatically affect attendance and gate receipts estimations.

Therefore, while the thesis has shed some lights on the issues investigated, it has raised other questions as well, and possible answers may represent an element that accompanies the development of the growing football industry.

BIBLIOGRAPHY

Adams, W. J., & Yellen, J. L. (1976). Commodity bundling and the burden of monopoly. *The quarterly journal of economics*, 475-498.

AREL, FIGC, Pwc. (2017). *Report Calcio Duemiladiciassette (English Version).* Rome: FIGC.

Avgerinou, V., & Giakoumatos, S. (2009). Price, income & unemployment effects on Greek professional football. *IASE/NAASE Working Paper Series*.

Becker, G. S. (1991). A note on restaurant pricing and other examples of social influences on price. *Journal of political economy, 99*(5), 1109-1116.

Borland, J., & MacDonald, R. (2003). Demand for Sport. *Oxford Review of Economic Policy, 19*(4), 478-502.

Budzinski, O., & Satzer, J. (2011). Sports business and multisided markets: towards a new analytical framework? *Sport, Business and Management: An International Journal*, 124-137.

Buraimo, B. (2008). Stadium Attendance and Television Audience Demand in English League Football. *Managerial and Decision Economics, 29*(6), 513-523.

Buraimo, B., & Simmons, R. (2008). Do sports fans really value uncertainty of outcome? Evidence from the English Premier League. *International Journal of Sport Finance, 29*(6), 146-155.

Buraimo, B., & Simmons, R. (2009). A tale of two audiences: Spectators, television viewers and outcome uncertainty in Spanish football. *Journal of Economics and Business, 61*(4), 326-338.

Caruso, R., & Domizio, D. D. (2015). Hooliganism and demand for football in italy: Attendance and counterviolence policy evaluation. *German Economic Review, 16*(2), 123-137.

Caruso, R., Addesa, F., & Di Domizio, M. (2017). The Determinants of the TV Demand for Soccer: Empirical Evidence on Italian Serie A for the period 2008-2015. *Journal of Sports Economics*, 1-25.

Choi, S., & Mattila, A. S. (2005). Impact of information on customer fairness perceptions of hotel revenue management. *Cornell Hotel and Restaurant Administration Quarterly, 46*(4), 444-451.

Chu, C. S., Leslie, P., & Sorensen, A. (2011). Bundle-size pricing as an approximation to mixed bundling. *American Economic Review, 101*(1), 263-303.

Church, J., & Ware, R. (2000). *Industrial organization: a strategic approach.* Boston: Irwin McGraw Hill.

Coates, D., & Humphreys, B. R. (2007). Ticket prices, concessions and attendance at professional sporting events. *International Journal of Sport Finance, 2*(3).

Courty, P. (2000). An economic guide to ticket pricing in the entertainment industry. *Louvain Economic Review, 66*(2), 167-192.

Courty, P. (2015). Pricing Challenges in the Live Events industry: A Tale of Two Industries. *IMC Roosevelt University*.

Courty, P., & Pagliero, M. (2008). Do consumers care about how prices are set? *International Journal of the Economics of Business, 15*(1), 27-43.

Cross, R. G., Higbie, J. A., & Cross, Z. N. (2011). Milestones in the application of analytical pricing and revenue management. *Journal of Revenue and Pricing Management, 10*(1), 8-18.

De Roos, N., & McKenzie, J. (2014). Cheap Tuesdays and the demand for cinema. *International Journal of Industrial Organization, 33*, 93-109.

Deloitte UK. (2017). *Football Money League.* London: Deloitte UK.

Drayer, J., & Rascher, D. A. (2013). Sport pricing research: Past, present, and future. *Sport Marketing Quaterly, 22*(3), 123-128.

Drayer, J., Shapiro, S., & Lee, S. (2012). Dynamic Ticket Pricing in Sport: An Agenda for Research and Practice. *Sport Marketing Quaterly, 21*, 184-194.

Eichhorn, C., & Sahm, M. (2010). Why were FIFA World Cup tickets so cheap? Monopoly pricing, demand quality and two-sided markets. *Journal of Economic Psychology, 31*(2), 212-217.

Einav, L., & Orbach, B. Y. (2007). Uniform prices for differentiated goods: The case of the movie-theater industry. *International Review of Law and Economics, 27*(2), 129-153.

Feehan, P. (2006). Attendance at sports events. In W. Andreff, & S. Szymanski, *Handbook on the economics of sport* (p. 90-99). Edward Edgar Publishing.

Filistrucchi, L., Geradin, D., & Van Damme, E. (2013). Identifying two-sided markets. *World Competition*.

Fort, R. (2006). Inelastic sports pricing at the gate? A survey. In W. Andreff, & S. Szymanski, *Handbook on the Economics of Sport* (p. 700-708). Celtenham, UK: Edward Elgar.

García, J., & Rodríguez, P. (2002). The determinants of football match attendance revisited: Empirical evidence from the Spanish football league. *Journal of Sports Economics, 3*(1), 18-38.

Giulianotti, R. (2002). Supporters, followers, fans, and flaneurs: A taxonomy of spectator identities in football. *Journal of sport and social issues, 26*(1), 25-46.

Haws, K. L., & Bearden, W. O. (2006). Dynamic pricing and consumer fairness perceptions. *Journal of Consumer Research, 33*(3), 304-311.

Howard, D. R., & Crompton, J. L. (2004). Tactics used by sports organizations in the United States to increase ticket sales. *Managing Leisure, 9*(2), 87-95.

Kang, J. M., Ryu, Y. J., & Liu, P. (2017). Bandwagon Effects and Local Monopoly Pricing In Professional Team Sports Market. *CAES Working Paper Series*.

Kemper, C., & Breuer, C. (2016a). How efficient is dynamic pricing for sport events? Designing a dynamic pricing model for Bayern Munich. *International Journal of Sport Finance, 11*(1), 4-25.

Kemper, C., & Breuer, C. (2016b). Dynamic ticket pricing and the impact of time–an analysis of price paths of the English soccer club Derby County. *European Sport Management Quarterly, 16*(2), 233-253.

Kesenne, S. (2006). The Objective Function of a Team. In W. Andreff, & S. Szymanski (Eds.), *Handbook on the Economics of Sport* (pp. 601-609). Celtenham, UK: Edward Elgar.

Kimes, S. E. (1989). Yield management: a tool for capacity-constrained service firms. *Journal of operations management, 8*(4), 348-363.

Kimes, S. E., Chase, R. B., Choi, S. L., & Ngonzi, E. N. (1998). Restaurant Revenue Management: Applying Yield Management to the Restaurant Industry. *Cornell Hotel and Restaurant Administration Quarterly, 39*(3), 32-39.

KPMG. (2017). *The European Elite 2017.* KPMG Advisory Ldt.

Krautmann, A. C., & Berri, D. J. (2007). Can we find it at the concessions? Understanding price elasticity in professional sports. *Journal of Sports Economics, 8*(2), 183-191.

Leslie, P. (2004). Price discrimination in Broadway theater. *RAND Journal of Economics*, 520-541.

Malasavska, I., & Haugom, E. (2018). Optimal prices for alpine ski passes. *Tourism Management, 64*, 291-302.

Marburger, D. R. (1997). Optimal ticket pricing for performance goods. *Managerial and Decision Economics*, 375-381.

McAfee, R. P., & Te Velde, V. (2006). Dynamic pricing in the airline industry. In T. Hendershott, *Handbook on Economics and Information Systems.* Elsevier.

Nufer, G., & and Fischer, J. (2013). Ticket pricing in European football. Analysis and implications. *International Journal of Human Movement and Sports Sciences, 1*(2), 49-60.

Rascher, D. A., McEvoy, C., Nagel, M., & Brown, M. (2007). Variable Ticket Pricing in Major League Baseball. *Journal of Sport Management, 21*(3), 407-437.

Rochet, J.-C., & Tirole, J. (2006). Two-sided markets: a progress report. *The RAND journal of economics, 37*(3), 645-667.

Sartori, A. (2017, June 20). Sky Football Benchmark - Stadia development. Retrieved from https://www.youtube.com/watch?v=GwbLsv2C-w4&t=4s

Sartori, A. (2017, March 3). Sky Football Benchmark - Stadia Landscape. Retrieved from https://www.youtube.com/watch?v=KvL4A-UdNAU

Simmons, R. (2006). The demand for spectator sports. In W. Andreff, & S. Szymanski, *Handbook on the economics of sport* (p. 77-89). Edward Edgar Publishing.

Smart Pricer. (2017). *3 proven ways sports clubs can improve ticket sales*. Tratto da Smart Pricer Official Website: http://smart-pricer.com/httpsmart-pricer-comblog-3-proven-ways-sports-clubs-can-improve-ticket-sales-e/

UEFA. (2017). *The European Club Footballing Landscape.* Nyon: UEFA.

Verbeek, M. (2004). *A Guide to Modern Econometrics.* John Wiley & Sons.

Villar, J. G., & Guerrero, P. R. (2009). Sports Attendance: a Survey of the Literature 1973-2007. *Rivista di Diritto e di Economia dello Sport, V*(2), 112-151.

ACKNOWLEDGEMENTS

By means of this thesis I conclude with mixed feelings an important cycle of my life, full of satisfactions, experiences and achievements. I take now some lines to express my gratitude for the people that have helped me to arrive here.

I first thank Professor Angelo Zago, who supervised the work and pushed me further than I would have without his suggestions. Almost one year ago I wished to apply what I had learnt to my greatest passion, football, and his help has been crucial to accomplish such desire. The advice of Professor Alessandro Bucciol has also been extremely helpful for the econometric part.

Thanks to my course mates with which I spent the first year, and especially to Elisabetta, who kept me updated while I was abroad and that has been really supportive in the last months.

I am also grateful to Professor Maria Vittoria Levati, who gave me the opportunity to teach the tutorial classes of the undergraduate Microeconomics module. It was an extremely pleasing experience, which also led me to strengthen my microeconomic foundations by revising the course material.

Thanks to Professor Claudio Zoli, the coordinator of the Master's Degree, who has always been available for any kind of suggestion during the past two years and a half, and who proposed to me to spend my second year at the Toulouse School of Economics.

The period that I spent in Toulouse was tremendously enriching from the academic point of view. However, the initial impact with a different academic framework was rather hard. I must thus thank Simon Fuchs, a Macroeconomics teaching assistant, who helped me at coping with the challenging "mathematical wizardries" that I had to deal with.

Still, such experience would not have been so wonderful if I had not spent those months with my traveling companions. I am extremely grateful to Rello, Evelin, Francesco, Paolo, Antonio, Alberto, Isabella, Lorenzo, Diego, Andrea, Felix, Sara, Alexandrina and many others who made me feel at home since the first days.

Thanks to my best friends with which I have grown up and that are still close after so many years: Valentina, Giulio, Niccolò, Luca, Federico, Alessandro, Massimiliano, Riccardo, Lisa, Jacopo, Carlotta, Mariana, Elisa.

Lastly, I must thank the people who have always supported me and born my bad moods when troubles occurred. Thanks to my elder siblings, Roberta and Andrea, their partners, Daniele and Irene, and my nieces Rebecca and Chiara. And an enormous thanks to my parents, Carlo and Francesca, who in the last two years have been closer than ever.