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**Knowledge Push Curve (KPC) in retailing: evidence from patented innovations analysis  
affecting retailers' competitiveness**

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**Abstract**

Previous studies have demonstrated the extent to which an analysis of patent growth can be used to study the innovation level of a certain industry, national competitiveness in terms of technological innovation, and the inventive capacity in a specific domain etc. In terms of the retail industry, there is a propensity for patenting and an increasing consumer demand for technological innovation. In fact, integrating innovative technologies, including innovative systems for conducting product searches and comparisons, and for paying, are one of the most efficient ways to create value for businesses. Building on a historical series of patents from 1990 to 2015, this paper explores the trends in the sector, analysing the increasing number of patents. Secondly it develops a predictive curve, a technology-push curve (TPC) for making some predictions about the future directions in the retail industry that might affect retailers' competitiveness and subsequent innovation management strategies.

**Keywords.** Patent analysis; retailing; innovation management; retailer competitiveness; technology-push curve (TPC)

## **1. Introduction**

In recent years, integrating innovative technologies, including innovative systems for product search and comparison, payments, etc., has emerged as one of the most effective ways of engaging potential and existing customers and creating value (Pantano and Priporas 2016; Pantano et al., 2017). These technological innovations involve new shopping experiences and enrich retail services by incorporating convenience, leisure and entertainment into the retail experience (Demirkan and Spohrer, 2014; Poncin and Mimoun 2014; Hristov and Reynolds 2015; Johnson et al., 2015; Pantano and Priporas, 2016). As a result, the available hardware and software-related innovations stimulate the retail industry to search for newer and more efficient applications in order to advance the consumer experience (interaction with retailers), improve retail management (Couteau, 2014; Hagberg et al., 2016; Pantano et al., 2017) and stimulate economic performance (Hristov and Reynolds, 2015). Choosing the technological innovation that best fits a company's strategy is difficult, due to increasingly rapid technological developments, technological complexity, the shorter technology lifecycle (Sternitzke, 2013; Han and Shin, 2014), and the time required (Pantano, 2016). Although consumers experience can be positively affected by means of technological innovation, and through process innovation (Sorescu et al., 2011), or sensory stimuli (D'Ippolito and Timpano, 2016), that not necessarily tap on technological advances, the present manuscript deals exclusively with the technological side of retail innovation. Thus, when we refer to shopping experience, only the technological side of shopping experience is involved.

The literature has indicated that leverage of the innovative forces shaping the retail sector could be fruitful for organisations and managers in their efforts to better plan investments and future strategies (Altuntas et al., 2015). Despite this, only a few preliminary research studies have attempted to examine the effects of innovative forces on the retail industry by providing empirical evidence distinguishing between high innovation and low innovation

sectors (Sorace et al., 2015; Pantano et al., 2017). While these studies have partially provided an understanding of the factors driving consumers' adoption of technological innovation in retail settings and the actual innovation trends and relevant implications, the crucial issues affecting progress in the sector and the future directions still require further investigation. Moreover, the need to constantly track the technological changes so as to maintain business profitability pushes companies to seek and manage a large amount of data regarding the complexity and availability of technological innovations.

Literature indicates that empirical studies in various sectors (i.e. nano-technology, telecommunications, etc.) (Noh et al., 2016; Joung & Kim, 2017) have employed patent analysis to assess the key developments in innovation and technology in the sectors under investigation (Abraham and Moitra 2001; Encaoua et al., 2006; Alfano et al., 2011; Han and Shin, 2014; Nelson et al., 2014; Tsai et al., 2016). Drawing on the current and predicted number of new patents in a given economic sector, managers may better evaluate the technological evolution in the sector. This could potentially help managers and respective organizations to create sustainable competitive advantages by being the first to identify and put in use breakthrough innovations.

Although existing studies focus their analysis on estimating the number of patents and evaluating their applicability and their changes over a particular time period (e.g. Hicks et al., 2001; Cecere et al., 2014), still they do not relate to applications in retailing and, thus, corresponding research in the particular area is scarce.

Taken together and building upon a historical series of European patents submitted from 1990 to 2015 with respect to the retail industry, the aim of this paper is to explore the trends in the sector, analysing the increasing number of patents and attempting to predict the release of new patents in the years to come through the foundation of a technology-push curve in predicting how retailing will be affected. In doing so, we implement a time-series model

drawing on data provided by the European Patent Office. Given that there is a dearth of studies regarding the development of patents to be applied in retail, this study makes some predictions for the future directions in the sector, by developing a predictive model describing the future innovations in retailing.

The current study contributes to the limited body of studies in retailing in the following ways. First, it addresses the gap in the retailing literature by offering empirical findings on key areas for innovation in the sector under research based on patent analysis. Hristov and Reynolds (2015, p.128) point out that innovation literature in retailing is relatively new and fragmented. This is one of the few studies in retailing (Sorace et al., 2015; Pantano et al., 2017) that employs patent analysis. Second, it utilizes bibliometric and patent analytical methods to examine the forces affecting retailing (Daim et al., 2006 and Chang, 2014; Pantano et al., 2017), it advocates that the sector is becoming a steadily innovation-oriented one. From a theoretical viewpoint, the current findings can enable an examination of the evolution of innovation and the distinct technologies that could offer a pattern on how to exploit future opportunities and increase business profits. At a practical level, retailers could use our findings to prioritize investment in technological innovation by identifying some key areas in order to gain a competitive advantage. James et al. (2015) suggest that patent data analysis could lead to helpful discoveries (i.e. trends in innovation, forecasting new technologies).

The remainder of the article is organized as follows. Next, we give a brief overview of the retailing changes that have emerged due to technology progression, and the measures utilised to evaluate levels of technological innovation based on patent analysis. Thereafter, we analyse the historical series of patents in retailing so as to detect the most critical areas and propose a technology-push curve (TPC) for the sector. Finally, we discuss the outcomes and offer suggestions for both academics and practitioners on how these insights could be used to design novel retailing management strategies.

## **2. Innovation protection, patent propensity and motives**

### *2.1 Innovation in retailing*

Several studies have highlighted the emerging demand for innovation in retail settings (Demirkan and Spohrer, 2014; Pantano, 2014; Hristov and Reynolds, 2015) and have focused on consumers' desire to have more pleasant shopping experiences. As a result, consumers expect that technology-based innovations will offer them both utilitarian value (support) and hedonic value (entertainment) during their shopping activities online and offline.

The potential to innovate successfully by engaging consumers is a requirement of continuous technological progression, which offers many and various innovative and interactive systems with different financial costs, risks and benefits (Pantano et al., 2013). For example, topics such as augmented reality, haptic technologies, social networks, mobile technologies and multichannel environments are considered emerging and avant-garde for research in marketing (Kushwaha and Shanka, 2013; Demirkan and Spohrer, 2014; Hagberg et al., 2016; Willems et al., 2016). Moreover, the positive impact of this technology on retailing practices emerges as another important driver of innovation in the particular sector (Hagberg et al., 2016; Inman and Nikolova, 2017; Pantano, 2014; Priporas et al., 2017). However, the heterogeneity of the potential new innovative solutions creates new opportunities and challenges for retailers, who in turn have to identify the most efficient one, so that they can deliver new stimuli and provide innovative sensorial experiences that can communicate and promote products, services, and brands (Renko and Druzijanic, 2014). Therefore, emerging technologies are dramatically changing the marketplace where companies perform. As a consequence, retailers need to develop and manage a particular technological innovation to meet consumers' expectations and organizational goals, which are important for business profitability and marketing strategy success (Grewal et al., 2017; Inman and Nikolova, 2017).

On the one hand, the contemporary viewpoint in retailing centres on creating new, more cost effective, experiences for customers, and on designing direct and highly customized marketing campaigns, while handling more channels synchronously in a consumer-centered view (Cao, 2014; Cao and Li, 2015; Demirkan and Spohrer, 2014; Herhausen et al., 2015; Leeflang et al., 2014). On the other hand, prior literature on technological innovation in retailing settings mainly investigated consumers' willingness to accept these innovations, while the emerging focus has started acknowledging an innovation management approach in the sector (Cao, 2014; Demirkan and Spohrer, 2014; Hristov and Reynolds, 2015; Pantano, 2014; Pantano, 2016; Willems et al., 2016).

## *2.2 Patents and patents growth*

The introduction and gradual diffusion of emerging technologies is mainly based on the successful combination of innovations in different technological areas, e.g. digital technology and cognitive science. This creative process serves as a means of identifying new business opportunities and designing new products that could potentially help organizations create a competitive edge or maintain their competitive advantage (Lee et al., 2011). To achieve this goal, individuals and organisations standardize the outcomes of research and development via corresponding published patents. This may help the protection and beneficial exploitation of intellectual property and any new methods and tools related to technological progress in specific fields of study (Choi and Hwang, 2014; Jun, 2014; Lapple et al., 2015; Lee et al., 2011; Venugopalan and Rai, 2015; Yoon and Park, 2004).

In this vein, a number of academics have acknowledged the value of studying technological innovation and introduction of inventions via patents analysis, and some of them have also articulated the need to examine patent growth using special dedicated measures (Archibugi and Pianta, 1996; Basberg, 1987; Kim et al., 2015). For example, some indices have

been proposed to measure the advancement of technology and the introduction of innovative systems in terms of patent quantity (Daim et al., 2006). This is due to patents' unique trait of effectively reflecting innovation and echoing the evolution of technology at a certain area of interest (be it geographical areas, specific sectors/industries, or countries) (Basberg, 1987). In fact, Park et al. (2005) suggest that patent documentation is a "source of technical and commercial knowledge about technical progress and innovative activity" (p. 473). Specifically, patents inform interested parties about technological foundations, including technical features and market attributes, criteria for claiming originality of the patent, such as technical feasibility and commercial value, as well as details about the inventor (Lee et al., 2011; Park et al., 2005). Issuing a patent is regarded as the most common way of safeguarding organizations' intellectual property (Archibugi and Pianta, 1996), and capturing the proprietary and competitive dimensions of technological evolutions (Archibugi and Pianta, 1996; Basberg, 1987; Jun and Park, 2013; Kim et al., 2015). Since the "locus of innovation" strongly depends on the expected profit emerging by its exploitation (Ogawa, 1998), retailers and manufacturers might differ on how they use patenting as a protection of the intellectual property of their innovation. Although, a retailer might adopt a certain technological innovation (i.e. novel payment system) patented by their technological supplier, and the patents registered by retailers might somehow underestimate the magnitude of technological innovation in the retail industry, the present approach consider all the patented innovation that might affect the industry indecently of the patent owner (can be an individual, technology supplier, retailer, etc.). This might partially explain why there are not current official codes describing the industry.

Actually, patents indicate innovation activity from different outlooks, e.g. technological, and also at a national level. Their analysis may offer various insights that are classified across various technological attributes and grouped according to similar characteristics among different countries (Abraham and Moitra, 2011).



Finally, patents information is a standardized and precise way of communicating state-of-the-art scientific achievements that can be easily accessed through public and commercial databases (Lee et al., 2011; Choi and Hwang, 2014). Accordingly, the technology life cycle curve (TLC) is a theoretical framework that provides insights into the potential success of a technology in terms of potential investment areas, possible future diffusion after large scale commercialization, and the power of a patent itself as a source of reliable and up-to-date managerial intelligence (Daim et al., 2006; Altuntas et al., 2015).

All in all, patent analysis is a management process for monitoring technological advancement in a certain commercial field, because it (i) may indicate managerial indices that integrate technological development with economic growth rates, (ii) it evaluates the relevant technological flows and also their resulting impact on productivity, (iii) it appraises firms' business competitiveness, while encompassing innovative performances within national and international contexts and (iv) it serves as a basis for conducting technology plans that may better determine the investment required to run R&D activities. Consequently, patent analysis establishes a measure of the latest technological changes, while envisaging future trends via sophisticated numerical analysis of the data representing systems and comprising patent documentation (Lee et al., 2011; Choi and Hwang, 2014). This is partly because acquiring patent rights requires a lot of time and financial resources (Lee et al., 2011; Yoon and Park, 2004).

Therefore, many previous studies in different sectors successfully employed a patent analysis. For instance, the agri-food industry adopted this analysis to evaluate farm-level innovation and develop an agricultural innovation index (Lapple et al., 2015), nanomechanics evaluated the innovativeness of the systems used for the mechanical characterization of materials at the micro/ and nanoscale (Alfano et al., 2011), family businesses evaluated the effect of technology push for family firms (Block et al., 2013), as well as information and

communication technologies (Choi et al., 2007), and green energy (Jun, 2014), etc. Both innovation patterns and the effects of innovation differ across various sectors (Park et al., 2005). Moreover, the retail sector does not offer specific measures for monitoring the evolution of innovations, thus retail would also benefit from new analyses that evaluate the innovative forces and technology progress for a better understanding of technological change, with benefits in terms of the development of more successful response strategies.

More specifically, text mining techniques and bibliometric analysis (i.e. the number of patents in a certain period of time) are supporting tools for patent analyses (Lee et al., 2011), in fact these specific kinds of analysis support the outlining of the level of innovation (Ogawa and Kajikawa, 2015). These techniques have been used with different approaches to organize, investigate and evaluate large amounts of historical data, to support the identification of complex patterns and the prediction of future trends (Daim et al., 2006; Han and Shin, 2014). For instance, the most common analyses employed time series regression (Daim et al., 2006; Jun and Park, 2013), (ii) cluster analysis (Jun and Park 2013), and (iii) citation networks (Daim et al., 2006; Jun and Park, 2013; Ogawa and Kajikawa, 2015; Patel and Ward, 2011). Therefore, bibliometrics emerge as a suitable approach for the actual research based on the granted patents.

### *2.3 Patents in retailing*

Since the actual classification systems for patents do not use specific categories of patents for retailing, which might lie at the intersection of different broad domains (i.e. digital communication, computer technologies, etc.), the patent selection based on classifications codes limits the ability to investigate the wealth of innovations that have been introduced on a product or market basis across the traditional patent domains (Venugopalan and Rai, 2015). Researchers tried to overcome this issue by focusing on specific technological innovations that have been applied to a retail setting. In example, Trappey et al., (2011) implemented patent

analysis regarding the growth of patents with respect to radio frequency identification (RFID) applications. There are some rare cases where patent analysis has a sectorial or inter-sectorial interest (Motohashi, 2008). However, researchers did not previously touch on patent analysis with a predictive scope, and some of them call for studies on the future growth of patents within a broader retail agenda (Trappey et al., 2011). The present research employs the approach proposed by Lee and colleagues (2009) to use text mining to transform patent documents into structured data to identify specific keywords.

### **3. Methodology**

Patents have long been considered an avant-garde and valid technical source that reflect current technological advancements and combine inventive knowledge with economic value (Yoon et al., 2013). To study the growth of patents and their penetration in the retail markets a bibliometric analysis approach was followed, analysing historical data and projecting to the future (Daim et al., 2014).

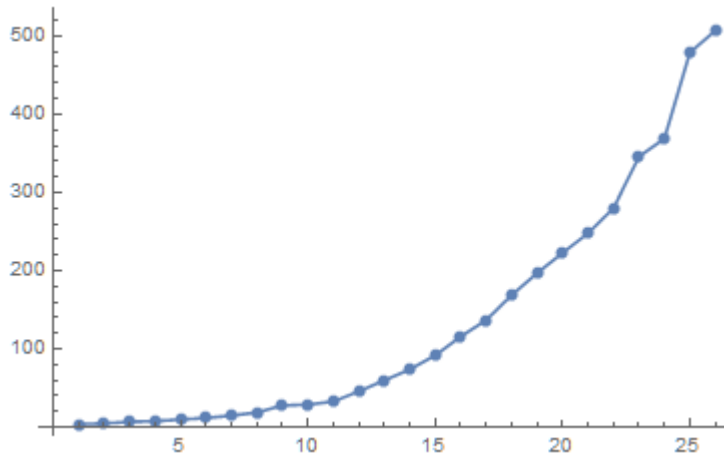
To date, the patents classification system of European Patents Office (which is the same used by other similar offices) does not identify specific categories for retailing. Retailing patents might be found in broad domains such as audio-visual technology, digital communication, computer technology, IT methods for management, and other consumer goods. This classification might limit patent selection based on classification codes which limits the ability of the researcher to select patents related to a specific sector and investigate the inventive activity in such products or market areas (Venugopalan and Rai, 2015). For this reason, we used a text mining approach proposed by Lee and colleagues (2009), suggesting that patent documents are converted into structured data to identify keyword vectors.

Our research started by selecting patents which included the word “retail” either in the title or in the abstract from the European Patent Office (European Patent Office, 2016). This

means that the patents search refers to the patents identifying technological innovation for retail operations and systems rather than new products (which might be patented only concerning the design, while the formula of new products if food/beverage can be protected through trademarks, according to the European rules for patented inventions). Limiting the research to the patents granted between 1990 and 2015, we collected 4,417 patents. Each recorded patent includes a unique number, a title, an abstract, a date of patent requested, a date of patent effective release, and the details of the assignees (patent owners) and the country. However, this chosen set of keywords was not sufficient to filter those patents that fall exactly into the retailing domain; hence, we further manually checked the identified patents and limited the selection to those strictly related to retailing, resulting in a total of 3,513. This process involved reading each patent description/abstract and manually deleting the patent from the database which might include the word “retail” without specifically referring to the sector (i.e. a patent not strictly related to the sector might be one related to innovative packaging for better food preservation, etc.).

The emerging database includes patents of different nature, such as methods for identifying the optimal number of products in the shelves, new augmented reality systems for enhancing the shopping experience, or methods of developing more efficient recommender systems based on consumers’ profiles (including budget, or shopping list, etc.), etc.

Figure 1 reports the trend summarizing the number of patents (y axis) and year considering 1990 as year 0 (x axis).

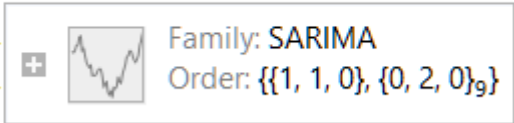


**Figure 1.** Patent growth in retailing 1990- 2015 (in patents per year)

#### **4. Predictive model for patents growth in retailing: Technology-Push Curve (TPC)**

To predict the future patent trends in the retail industry, we made use of a historical time series analysis. This technique is deemed a powerful one for statistical modelling and forecasting (Chao et al., 2007; Wagner et al., 2017). The software Mathematica was employed and the “Time Series Model Fit” algorithm was utilized to render the mathematical model, which would best analyse the historical patents-related data among the available family (group) models ("AR", autoregressive model family; "MA" moving-average model family; "ARMA", autoregressive moving-average model family; "ARIMA", integrated ARMA model family; "SARMA", seasonal ARMA model family; "SARIMA", seasonal ARIMA model family; "ARCH", ARCH model family; "GARCH", GARCH model family). In particular, SARIMA (Seasonal Arima Model) was automatically identified by the software as the most suitable and efficient technique for the particular dataset object of the study (a Seasonal ARIMA model is classified as an  $ARIMA(p,d,q) \times (P,D,Q)$  model, where P=number of Seasonal AutoRegressive (SAR) terms, D=number of seasonal differences, Q=number of Seasonal Moving Average (SMA) terms) (Hillmer and Tiao, 1982; Tseng et al., 2002). The benefit of this model is usage of both non-seasonal and seasonal factors in a multiplicative model.

To predict the trend followed by the number of patents for the next 10 years (from 2016 to 2025) the system of functions (1) was run in Mathematica:

```
In[50]:= tsm = TimeSeriesModelFit[ll]
Out[50]:= TimeSeriesModel [  ]
```

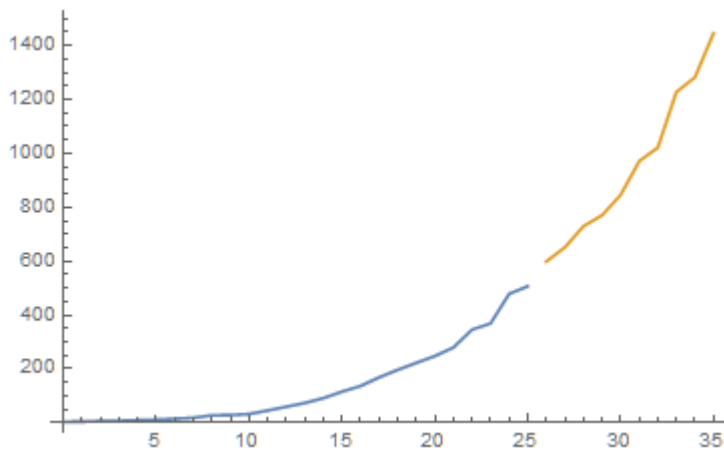
(1)

## 5. Results

Results extracted from *Mathematica* are summarized in Table 1. Starting from the previous trend in retail number of patents, with 1990 as 0 and 2015 as 26 year, we can obtain the graphical trend for the next years, in Figures 2 with a yellow curve.

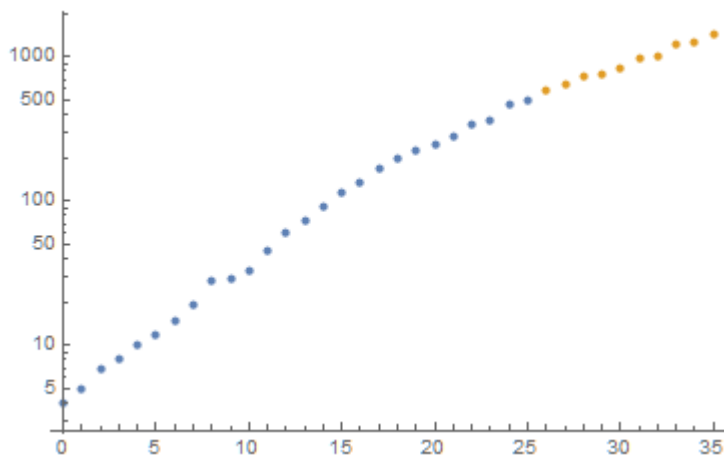
**Table 1.** Predicted number of patents from 2017 to 2025.

Year	Patent number
2017	651
2018	729
2019	770
2020	845
2021	971
2022	1021
2023	1227
2024	1282
2025	1446



**Figure 2.** Actual number of patents growth (in blue) and predicted one (in yellow)

The properties of the model can be found in Appendix A. The trend can be further represented through the logarithmic scale to better describe the data (Figure 3), where the yellow part represents the predicted trend.

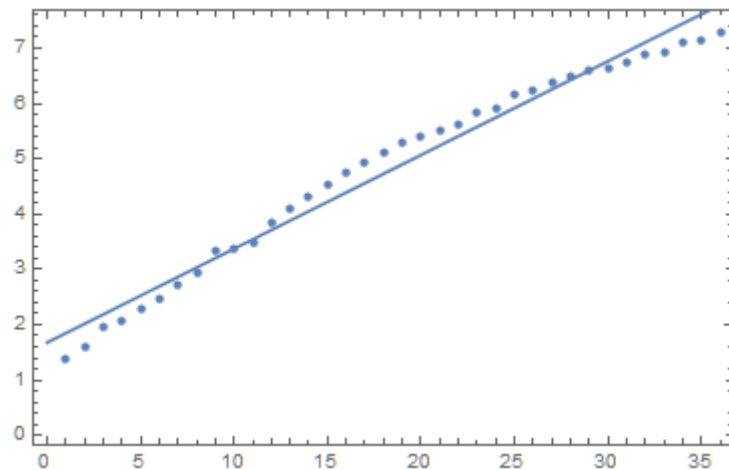


**Figure 3.** Logarithmic scale to represent the actual number of patents growth (in blue) and predicted one (in yellow)

In this case, the exponential increase in the number of patents clearly emerges. To evaluate the increase coefficient we can build the function of linear interpolation among data, by obtaining:

$$\text{Log } n = 1.68 + 0.17 x$$

Where  $n$  is the number of patents,  $x$  the time calculated considering as 1990 as starting point (0). Figure 4 shows the data over the emerging interpolation curve for all the data between 1990 and 2025 (35 years).



**Figure 4.** Interpolation curve.

Therefore,

$$n(x) = 5.37 * e^{0.17 x}$$

This model shows that the annual number of patents classified duplicates every 2 years. Moreover, it is possible to apply our predictive model to the previous set of data to compare the “expected results” with the collected ones to evaluate the quality of the predictive measure (Table 2).

**Table 2.** Application of the predictive model to the previous set of data to compare the predicted number of patents with the collected ones.

Year	Number of patents (effective)	Number of patents (predicted)
1990	4	5
1991	5	6



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1992	7	7
1993	8	8
1994	10	10
1995	12	12
1996	15	14
1997	19	17
1998	28	20
1999	29	24
2000	33	29
2001	46	34
2002	60	41
2003	74	48
2004	92	57
2005	116	68
2006	137	80
2007	169	95
2008	197	113
2009	223	134
2010	248	159
2011	280	188
2012	346	223
2013	369	264
2014	479	313
2015	507	371
<b>2016</b>	<b>598</b>	<b>440</b>
<b>2017</b>	<b>651</b>	<b>521</b>
<b>2018</b>	<b>729</b>	<b>618</b>
<b>2019</b>	<b>770</b>	<b>732</b>
<b>2020</b>	<b>845</b>	<b>867</b>
<b>2021</b>	<b>971</b>	<b>1027</b>

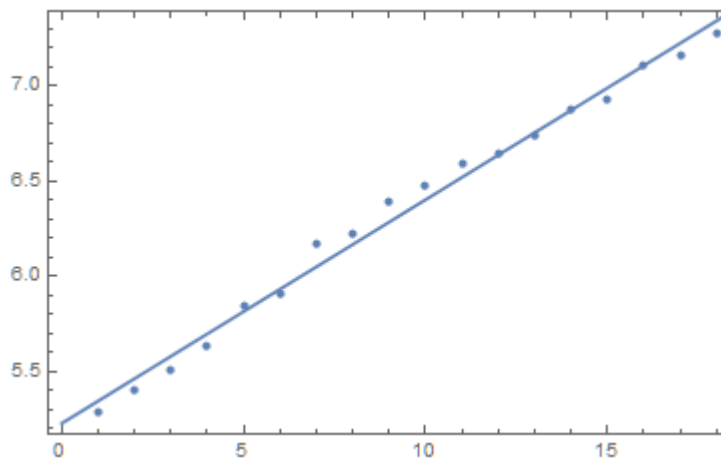
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<b>2022</b>	<b>1021</b>	<b>1217</b>
<b>2023</b>	<b>1227</b>	<b>1442</b>
<b>2024</b>	<b>1282</b>	<b>1709</b>
<b>2025</b>	<b>1446</b>	<b>2024</b>

Comparing the results, this model underestimates the values between 2005 and 2015, as well as the predictions starting in 2016. It seems that the number of patents increases differently between 2005 and 2015, thus another curve would better synthesize this increase. Software Mathematica was employed once more with the “Time Series Model Fit” algorithm to render the mathematical model. Results propose a new curve to better describes the trend between 2005 and 2015 is:

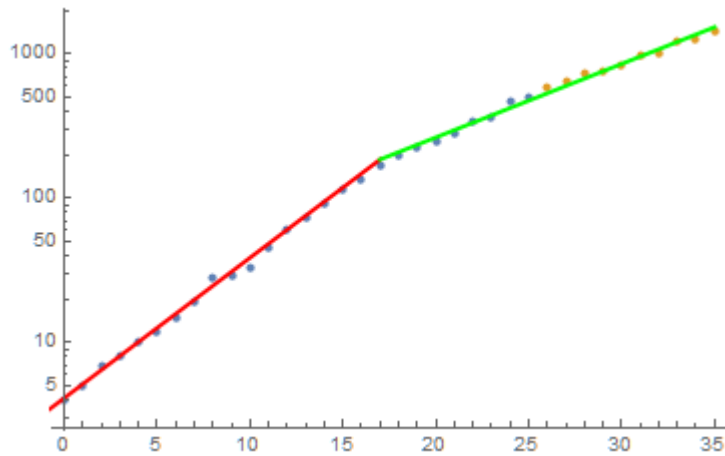
$$\text{Log } n = 5.23 + 0.12 x$$

Figure 5 graphically shows the new predictive model:



**Figure 5.** Predictive curve considering patented innovations between 2005 and 2015.

Therefore, the final model is based from a combination of the two formulas to describe the trends in patents number (Figure 6), formerly our technology push curve (TPC) for retailing, while the results are summarized in Table 3:



**Figure 6.** Final technology-push curve (TPC) combining the two formulas.

**Table 3.** Comparison between the effective number of patents with the predicted ones

Year	Patents number (effective)	Patents number (predicted)
<b>1990</b>	<b>4</b>	<b>4</b>
<b>1991</b>	<b>5</b>	<b>5</b>
1992	7	6
1993	8	7
1994	10	9
<b>1995</b>	<b>12</b>	<b>12</b>
<b>1996</b>	<b>15</b>	<b>15</b>
<b>1997</b>	<b>19</b>	<b>19</b>
1998	28	24
<b>1999</b>	<b>29</b>	<b>29</b>
2000	33	37

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2001	46	46
2002	60	57
2003	74	72
2004	92	89
2005	116	112
2006	137	139
2007	169	174
2008	197	209
2009	223	235
2010	248	265
2011	280	298
2012	346	335
2013	369	377
2014	479	424
2015	507	477
2016	598	536
2017		603
2018		678
2019		763
2020		858
2021		965
2022		1085
2023		1221
2024		1373
2025		1544

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As emerged from this model, in four years (in 1990, 1995, 2000, and 2005, exactly every 5 years) the effective number of patents and the predicted one are similar in numbers (4, 12, 33, 116 respectively).

## **5. Discussion**

Numerous technological advances have been introduced in retailing over the last few years that have rapidly changed the shopping experience as we know it (Blázquez, 2014; Piotrowicz and Cuthbertson, 2014; Priporas et al., 2017). Patents' growth is an important indicator of new technologies penetration in any given economic sector (Acs et al., 2009; Dubarić et al., 2011; Lee et al., 2016). The literature relates to the modelling of new patent introduction in various sectors (e.g. manufacturing, medicine) (Acs et al., 2002; Alfano et al., 2011; Horbach, 2008; Cheng et al., 2016; Ma and Porter, 2015; Piergiovanni and Santarelli, 2001), including the application of specific technologies in purchasing (e.g. RFID) and transactions from individuals (Tsai et al., 2010; Vlachos, 2014). Yet, the study of patents' future growth in retailing at a macroscopic level has been largely neglected, although patent statistics are considered a key source of information about the level of innovation in any industry (Fabry et al., 2006; Pantano et al., 2017). Thus, to identify a future trend in terms of the release of patents in retailing that would allow us to evaluate the implementation of new technologies in this particular sector, a predictive algorithm was adopted in the current study. In specific, the implementation of a historical time series analysis provided a model that fitted the dataset satisfactorily and also offered projections of what one should expect in terms of new patents to be registered in the future.

As shown above, the absolute numbers and growth of patents release in the retail sector were very low until the mid-1990s. This is in line with the findings of Hristov and Reynolds (2015), who point out the “lower levels of R&D intensity and numbers of patent registrations”

(p. 127) in retailing compared to other sectors of the economy. Furthermore, findings show that from 2000 to 2005 the increase in patent growth was more rapid than in subsequent years; thus, the number of patents tripled every 5 years till 2005, while it doubled every 2 years in the years after 2005, clearly demonstrating a slower patent growth rate during the last decade. Finally, the application of a historical data time series algorithm revealed a similar pattern for the years to come, although growth seems to have a smaller slope, meaning that after year 2018 the number of patents submitted annually will slightly decline. This possibly indicates the start of a new – less aggressive – patent growth cycle, which is usually accompanied by the wide implementation of a number of patents submitted during the last 10 years. Consequently, it is possible that retailers will adopt and introduce a great number of new technologies basically originating from the influx of patents registered in the last patents cycle.

In general terms, this growth pattern corroborates findings provided by Pantano et al. (2017) diachronically showing an increasing number of technologies that are able to support retail management, in terms of product offer and display, customized recommendations, monetary transactions, etc., by allowing the definition of a new model to the literature in retailing: the technology-push curve (TPC) in retailing predicting the continuous growth of technology push in the sector, by stating that the: *number of patents tripled every 5 years till 2005, while it doubled every 2 years in the years after 2005.*

In particular, this model provides a measurement of technological innovation push in retail industry, while indicating the future developments. It extends the past studies on innovation and technology management for retailing, by identifying (predicting) the future patterns. Moreover, it reinforces the idea that retailing is a sector strongly affected by innovation and knowledge push.

Finally, the extant literature on patent analysis exploited the patents classified according to the specific classification codes assigned by European or American patent offices, thus

referring only to such sectors. These analyses limited the focus to some sectors that are not representative of all the possible business sectors. Our paper extends the analysis to the investigation of another sector that even without a specific classification codes, is largely impacted by technological innovation patented under other classification categories. Thus, it shows how additional patents analysis for other sectors are necessary to have a more comprehensive overview of the business sectors orientation towards technological advancements and invention efforts.

### *5.2. Managerial Implications*

This study highlights the usefulness of employing patent analysis in business management, and particularly in retailing, to support strategic planning and competitive analysis in the retail sector (Fleisher and Bensoussan, 2003; Lee et al., 2009). Our findings provide important practical insights to retail managers regarding the value of monitoring evolutions in innovative technologies via patent analysis. This is of paramount importance, because the retail industry is facing continual changes as a result of introducing new technologies to manage operations and improve the customers' final shopping experience (Sorace et al., 2015; Willems et al., 2016; Venkatesh et al., 2017). Patents provide detailed information on newly developed technologies and, thus, forecasting the number and types of technologies is important for establishing future management strategies successfully (Kim and Bae, 2017). Managers, by forecasting innovation trends, may make more sound decisions on technological innovation investments in retailing and create significant competitive advantages for their firms' own benefit (Kumar et al., 2017). Moreover, it should be underlined that retailers with limited innovation management capabilities would need to improve them through proper investment in knowhow and relevant equipment (e.g. sophisticated digital apparatus and software) in order to become more competitive.

Finally, this research provides managers with an overview of the number of possible inventions that might be transferred into effective innovative technological applications for retailing. On the one hand, our findings show the number of available inventions, representing potential opportunities. On the other one, it provides also the number of inventions that are protected, representing potential threats. This would push retailers to consider innovation management strategies of competitors and their position towards the exploitation of those opportunities/threats as integrative part of new retail strategies.

## **6. Conclusion**

A variety of methods and techniques have been used in the past to assess diffusion of new technologies and innovation in retailing via the patent portfolio approach (Kim et al., 2015). Also, patent citation analysis has been previously conducted to evaluate organisational capabilities and technological positioning (Chang, 2012). The current study demonstrates a similar general pattern with regards to technology applications in retail, though with some differences to results reported by other researchers. For example, in Daim and Suntharasaj (2009), a bibliometric analysis of RFID in retail applications showed that the increase in patents between 2005 and 2017 would slow down, whereas the growth rate would rise in the period 2018-2029. The same researchers show that the increase in number of RFID-related patents would decline after 2030.

Nevertheless, although there is a clear trend in patents registration growth in the retail sector over the last 5 years (Pantano et al., 2017), the number of patents claimed in this particular field of business is low compared to others, showing a clear under-representation of the retail industry in terms of patents (Sundström and Reynolds, 2014). This fact could be explained by the types of technological innovation introduced in retailing. As Hristov and Reynolds (2015) clarify, most technological innovations implemented in retail operations are



incremental and, thus would not be represented by new patents granted, as in the case of introducing radical innovations or new inventions (Rotolo et al., 2015). On the other hand, the adoption of technological innovations mainly based on software engineering applications (e.g. smart retailing and augmented reality) has recently boosted the number of patents granted and also supports relevant projections for the future (Hristov and Reynolds, 2015; Pantano, 2016; Priporas et al., 2017).

The findings of this study provide insights for the retailing literature, as this is one of the very few studies analyzing technological innovation through patent analysis in the retail sector. Retail strategists, administrators of leading offline retailers and e-tailers may take into account the projections regarding patents growth trend, and accordingly plan their future investments in order to stay ahead of the competition.

### *6.1. Limitations and Future Research*

As with any study, this one has also some limitations that could potentially become the starting points for future research. First, a time series regression model was implemented to render projections of patent registrations in retailing. Future studies may apply different techniques to compare the current results and extract useful conclusions about the future trends in retailing-related patents. Second, in this study patent analysis was conducted as a way to evaluate technological innovation in retailing. However, this is clearly not the only methodology to do so, and therefore future studies may implement different methodologies to assess future growth trends. The outcomes of this study could be further validated using various techniques (e.g. patent indicator analysis, F-term analysis) used in other areas of science (Abbas et al., 2014; Kim and Base, 2017; Song et al., 2017). Third, since incremental innovation is a big part of overall innovation in retailing and patents are mainly related to radical innovation, future research may consider incremental innovation using a different criterion.

Although many patents are registered in the both European Patent Office and US specific one, the present study only considers the patents registered in Europe. Future research studies might also consider the patents registered in both Europe and US and the ones only registered in US to provide a more comprehensive overview of the patented technological innovations for retail industry worldwide.

Finally, the patent analysis approach described in the empirical section lies on the fact that the available data do not take into account the adoption rate of the innovation by retailers. Since a patent does not imply that the patented innovation has already been used or exploited by a retailer, future studies might compare and contrast the rate of patents and effective integrated technological innovation, in order to deepen our understanding of how the patented innovations might become successfully adopted innovations in the retail industry.

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## Appendix A. List of commands in Mathematica.

- The following model properties can be obtained using `model["property"]`:

"BestFit"	the fitted model
"BestFitParameters"	coefficient estimates
"ErrorVariance"	model error variance
"FitResiduals"	residuals for the fitted model
"StandardizedResiduals"	standardized model residuals
"TemporalData"	input data as <code>TemporalData</code>

- Properties pertaining to model selection include:

"CandidateModels"	a set of candidate models sorted by selection criterion
"CandidateModelSelectionValues"	selection criterion values for each candidate model
"CandidateSelectionTable"	a table containing models and selection criterion values
"CandidateSelectionTableEntries"	entries from the candidate selection table
"ModelFamily"	the selected model family
"SelectionCriterion"	criterion used for selecting the best model

- Properties that measure goodness of fit include:

"AIC"	Akaike information criterion
"AICC"	finite sample corrected AIC
"BIC"	Bayesian information criterion
"SBC"	Schwartz–Bayes information criterion

- The following properties can be used to assess the whiteness of the model residuals:

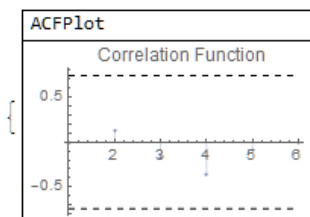
"ACFPlot"	plot of residual autocorrelations
"ACFValues"	values from the "ACFPlot"
"PACFPlot"	plot of residual partial autocorrelations
"PACFValues"	values from the "PACFPlot"
"LjungBoxPlot"	plot of Ljung–Box residual autocorrelation test $p$ -values
"LjungBoxValues"	values from the "LjungBoxPlot"

- The maximum number of lags to include for a residual whiteness property "`wprop`" can be controlled by giving `model["wprop", "LagMax" -> max]`, where `max` is a positive integer.

- Properties and diagnostics for coefficient estimates include:

"CovarianceMatrix"	covariance estimate for model coefficients
"InformationMatrix"	information matrix for model coefficients
"ParameterConfidenceIntervals"	confidence intervals about the coefficient estimates
"ParameterStandardErrors"	standard errors of model coefficients
"ParameterTable"	table of fitted coefficient information
"ParameterTableEntries"	entries in the parameter table

## Appendix B. Computational Process



ACFValues  
`{0.00125314, 0.126271, -0.174572, -0.363569, -0.0920406, 0.00265734}, {-0.740797, 0.740797}`

AIC	AICc	BIC	BestFit
152.182	156.087	168.735	SARIMAProcess[28.4679, {-0.828213}, 1, {}, {9, {}, 2, {}}, 276.55]

BestFitParameters	CandidateModels
<code>{-0.828213}</code>	<code>{SARIMAProcess[28.4679, {-0.828213}, 1, {}, {9, {}, 2, {}}, 276.55],</code> <code>SARIMAProcess[23.3201, {-0.497622}, 1, {-0.90184}, {9, {}, 2, {}}, 261.872],</code> <code>SARIMAProcess[27.4804, {-0.806558, 0.0417606}, 1, {}, {9, {}, 2, {}}, 276.415],</code> <code>SARIMAProcess[4.76089, {-0.0837808, 0.778036}, 1, {-0.97037}, {9, {}, 2, {}}, 263.187],</code> <code>SARIMAProcess[15.5714, {}, 1, {-0.634442}, {9, {}, 2, {}}, 347.588],</code> <code>SARIMAProcess[15.5714, {}, 1, {}, {9, {}, 2, {}}, 676.531]}</code>

CandidateModelSelectionValues  
`{152.182, 152.764, 154.169, 154.895, 158.126, 173.441}`

CandidateSelectionTable		
	Candidate	AIC
1	<b>SARIMAProcess[{1, 1, 0}, {0, 2, 0}]<sub>9</sub></b>	<b>152.182</b>
2	SARIMAProcess[{1, 1, 1}, {0, 2, 0}] <sub>9</sub>	152.764
3	SARIMAProcess[{2, 1, 0}, {0, 2, 0}] <sub>9</sub>	154.169
4	SARIMAProcess[{2, 1, 1}, {0, 2, 0}] <sub>9</sub>	154.895
5	SARIMAProcess[{0, 1, 1}, {0, 2, 0}] <sub>9</sub>	158.126
6	SARIMAProcess[{0, 1, 0}, {0, 2, 0}] <sub>9</sub>	173.441

CandidateSelectionTableEntries  
`{SARIMAProcess[28.4679, {-0.828213}, 1, {}, {9, {}, 2, {}}, 276.55], 152.182},`  
`{SARIMAProcess[23.3201, {-0.497622}, 1, {-0.90184}, {9, {}, 2, {}}, 261.872], 152.764},`  
`{SARIMAProcess[27.4804, {-0.806558, 0.0417606}, 1, {}, {9, {}, 2, {}}, 276.415], 154.169},`  
`{SARIMAProcess[4.76089, {-0.0837808, 0.778036}, 1, {-0.97037}, {9, {}, 2, {}}, 263.187], 154.895},`  
`{SARIMAProcess[15.5714, {}, 1, {-0.634442}, {9, {}, 2, {}}, 347.588], 158.126},`  
`{SARIMAProcess[15.5714, {}, 1, {}, {9, {}, 2, {}}, 676.531], 173.441}`