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# Brand Alliances: a Network Perspective with application to the fashion industry

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*"The future belongs to those who believe in the beauty of their dreams"*

— Eleanor Roosevelt

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*To my family...*

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# Glossary

**Betweenness Centrality** is a measure of the extent to which a node lies on the shortest paths between the other vertices.

**Binary Pearson Correlation Coefficient** The Binary Pearson Correlation Coefficient estimates the linear correlation between two binary variables.

**Bipartite Network** is a network containing two sets of nodes. In this kind of network, no connection is allowed between nodes from the same set, that is, only connections between nodes from different sets can be set.

**Brand** is a symbol, name, or any other element that identifies a specific product or seller and distinguish that product or seller from all others in the market.

**Brand Association** in consumer memory, it indicates the association of a brand with a particular attribute, concept, etc.

**Brand Concept Map** is a map showing the network of salient brand associations that underly consumers' perception of brands.

**Brand Dilution Effect** is one of the risks to implement a branding strategy and it may occurs if, after the implementation of the brand strategy the brand lose its value or damage its image in consumers' minds.

**Brand Extension** is a brand strategy that uses an established brand to introduce a product in a new category (category extension) or in its own category (line extension), by leveraging the pre-existing brand name.

**Brand-to-Brand Recall Map** represents the recall process in consumers' minds due to the association between brands. How consumers associate brands.

**Campaign** (within the scope of the thesis) identifies the specific launch and activation of a co-branding alliance. Specifically, the organized course of actions implemented by two companies to achieve the goal they have fixed.

**Category Extension** occurs when a company introduces a new product in a different product category.

**Co-Branding** occurs when two brands jointly appear on the logo and/or package of a new product–two different brands that come from two different companies, which work together to launch a product.

**Community** is a cluster of highly connected nodes.

**Company** identifies a commercial business, which can hold and manage different brands.

**Degree** is the number of connections each node forms with the others.

**Diameter** is the length of the longest geodesic path between any pair of vertices in the network for which a path actually exists.

**Exponential Distribution** is a continuous distribution typically describing the inter-time between events in a Poisson process.

**Graph Genus** is the minimum number of handles needed to embed a graph on a surface.

**Holistic** characterised by the belief that the parts of something are intimately interconnected and explicable only by reference to the whole.

**Hypergeometric Distribution** is a discrete probability distribution that describes the probability of successes of random draws from an urn without replacement.

**K-Shell** (or K-core, of a network) is the largest subnetwork in which each node forms at least K connections with the others.

**Line Extension** occurs when a company introduces a new product in its own category, but with a higher (upscale extension) or lower (downscale extension) positioning in the market.

**Link** (or edge) is the connection between two elements in a network. In the present study a link is established between two brands if the two brands have established a co-branding alliance at some point in time.

**Log-Normal Distribution** is a distribution of a continuous variable $X$ such that $log(X)$ follows a normal distribution.

**Mediator** is a variable that lies between input and output. It addresses how or why an effect occurs and allows specifying indirect effects of the input on the output.

**Moderator** is a factor that changes a given interaction in intensity and direction.

**Modularity** is a standardized measure of strength of the decomposition of a network in a (specific) set of communities (that is, clusters, or modules). A high modularity indicates an apparent structure of the network in communities.

**Network** is a representation of connections (edges or links) among a set of elements (nodes or vertices). In the present study, the elements of the network are brands.

**Node** (or Vertex) is one of the elements of a network. The nodes may represent objects, people, words, etc. In the present study, the nodes are brands.

**P-Value** is the probability to obtain an outcome equally or more extreme than the observed one.

**Planar Graph** is a network which can be embedded in a sphere without edge crossing.

**Recommendation Systems** use data related to users past behaviour and preferences to suggest a ranked of list of potentially interesting items to each user.

**Score** is a normalized quantity used within a recommendation system to measure the extent to which a given uncollected object is of potential interest to a specific user. Sorting the scores, from the higher to the lower, allows building a ranked recommendation list of objects of each user.

**Step-Down** (or downscale extension) occurs when a company introduces a new product in its own category, but with lower price and positioning in the market.

**Step-Up** (or upscale extension) occurs when a company introduces a new product in its own category, but with a higher price and positioning in the market.

**Systemic** identifies something (e.g., an effect) relating (e.g., influencing) to the system as a whole, especially as opposed to particular parts (e.g., local effect).

# Introduction

This thesis aims to analyze the co-branding phenomenon through a Systemic lens rather than adopting the more traditional dyadic approach. In each of the essays that form the thesis, I adopt a comprehensive perspective that allows shedding light on the interplay among the actors, the strategies, and the different facets of co-branding. Specifically, I assume a Network perspective that varies according to the specific goals of the essay. Such a perspective allows providing a systemic view of the causes and consequences of the collaborations between brands within the fashion industry and, from a managerial point of view, the effects that taking such a Holistic perspective may have on the decision-making process. The thesis is structured as a collection of three essays, each one pursues a specific research goal, but they are linked by the common adoption of the network perspective and the deployment of similar tools of analysis.

In the development of the three chapters that compose this study, the heterogeneity that characterizes the system under investigation clearly emerges. Brands and the related companies are heterogeneous in dimension, sector of the industry, products, and market target. Indeed, even if the research focuses on the fashion industry, the system involves brands from other industries that refer to various products. Moreover, the brands and companies involved in the network of Co-Branding Campaigns under scrutiny have markets that range from local to worldwide extensions. However, the analysis conducted in this thesis indicates the presence of universal factors and scale independence within this context. Extant studies still lack a unique theory able to explain all the factors involved in co-branding. In the second chapter, I draw an empirically grounded model of co-branding alliance formation, further developed in the third chapter. The model proposed is developed through the lens of the signaling theory and complex systems studies and merges together the main factors and facets of co-branding campaigns interpreted as an evolutionary complex system (Miller and Page, 2007).

## Theoretical perspective underlying the systemic view of co-branding

### Marketing as a complex system

*Marketing* refers to identifying and reaching human and social needs (Kotler and Keller, 2015). As the American Marketing Association has defined it, marketing represents all the processes, actions, and institutions that create, communicate, and exchange products (or services) for society as a whole, and in particular, for consumers and partners (Kotler and Keller, 2015). In this perspective, it is possible to see marketing as a complex structure that links consumers and companies and generates information flows between them.

Companies affirm that one of the most significant assets in an organization is the brand and its association with products (Keller *et al.*, 2011). Since we are assisting to a rapid growth of complexity that characterizes the economic world, people and companies have to make more decisions in less and less time (Keller *et al.*, 2011). Thus, a strong brand, together with the associations that it carries, makes the decisions simpler and reduces risks for both consumers and companies. (Keller *et al.*, 2011).

The association between a brand and specific products represents the core of the brand concept itself. The exploitation of this association process may be a signal not only from companies to consumers but also a signal shared between companies in their decision-making process, able to influence their choices. It is possible to represent a given industry (for example, the fashion industry in the case of the present study) as a complex system composed of many heterogeneous actors that interact to form a network. Actors influence others in the system, and the actions taken by a single may affect not only the evolution of surrounding actors but the whole system's evolution.

In the present thesis, I start by assuming that brands share their own associations with other entities, products, concepts, etc., to leverage secondary associations from the other brands in the system. According to the theory of complex systems, the system's evolution at a given level of aggregation is described by laws that cannot be inferred even assuming one had a perfect knowledge of microscopic behavior. The identification of the logics that generate emergent structures, such as communities and their characteristics, represents a key element to draw a comprehensive model of the system. Therefore, in both chapter 2 and chapter 3, particular attention is dedicated to the identification and characterization of communities, as well as to the logics and consequent interactions underlying their formation. Indeed, "*complexity emerges when the dependencies between elements become important*" (Miller and Page, 2007), as they are in the present case. The effect of removing or impairing the activity of a single actor in a complex system may have an impact that goes beyond the direct ties the actor has formed, reaching a point in which it can influence the entire system (Miller and Page, 2007). Therefore, the present analysis also aims to identify the key actors in the network of co-branding campaigns at both the level of the whole network and the level of single components.

Moreover, in the context of social systems – like the one under investigation in this thesis – the characteristics that distinguish one element from the others are liable to produce complexity. Indeed, each social element is involved in a web of connections through which it interacts with many other elements in the system and influences their behavior (Miller and Page, 2007). The system actors always make decisions influenced by social contagion, besides their own expectations. The choices made by all the actors generate an implicit sum of forces that determines the evolution of the system.

In the present analysis, it is possible to observe how the system under investigation presents characteristics that define it as a complex system in evolution. Brands show a strong interdependence that comes from the attempt to leverage other brands to reach specific benefits. Results show how some actors in the system play a very central role (hubs) so that by removing them, the network connectivity would be severely impaired. The co-branding system is composed of a web of connections between brands, in which a single brand take decisions regarding their own strategies and, unintentionally, affect other brands as well. Thus, to reach its goals, a Company must predict and take into consideration the decisions taken by the other actors in the system, *adapting* its choices and *selecting* its interactions to achieve its goals.

These considerations draw attention to the necessity of analyzing the co-branding phenomenon from a systemic perspective to understand and manage co-branding choices adequately. Indeed, interpreting decisions by looking at single brands and the single dyadic interactions between them may produce incomplete results since it is unable to capture the role of emergent structures and social influence.

### The Brand and Branding Strategy

A *Brand* is a symbol, name, or any other element that identifies a specific product or a specific seller and distinguishes that product or seller from all the others in the market[1]. For marketers, creating a strong brand is a crucial strategy. Indeed, creating a brand requires a company to design an ensemble of reputation and image elements (Keller, 2003) in such a way that the brand can convey a distinctive image and consequently create associations in consumers' minds[2].

To establish a brand with the right point of parity and difference with competitors, the company can leverage on other elements–such as a person, place, things, other brands, events, and so on (Keller *et al.*,2011). Given the link of a brand with other entities, consumers can deduce that associations characterizing other entities are also valid for the brand under consideration (Keller *et al.*, 2011). Researchers refer to leveraging secondary association as the indirect process that occurs in these situations. Specifically, this process forms additional associations in consumers' minds when consumers do not possess information or knowledge about a specific brand; thus, consumers make a decision based on secondary associations represented by the linked things, place, other brands, and so on (Keller *et al.*, 2011).

Brands can use different elements to leverage upon in order to establish a connection in the consumers' minds (Keller *et al.*, 2011).

For example, it is worth mentioning Brand Extension[3] as a potential source of brand knowledge that exploits the leveraging process. Brand extension occurs when a company uses a well-established brand name to introduce a new product (Keller *et al.*, 2011).

However, this study focuses on co-branding, which exploits the leveraging process by linking two brands together. Co-branding is a specific branding strategy occurring when two completely separate brands appear together to create and launch a product (Washburn *et al.*, 2000). It is a widely used strategy since it carries different benefits to the company, such as penetrating another market target or increasing the number of consumers (Washburn *et al.*, 2000). Cobranding can also transfer brand image and reputation or grow perceived brand value (Rodrigues *et al.*, 2011). Moreover, it can generate a spillover

[1] Definition from American Marketing Association

[2] Definition from American Marketing Association

[3] There are two different types of brand extension: i) Line Extension, that concerns using the parent brand for a new product to reach a new segment within the same product category the brand already serves, and ii) Category Extension, that concerns using the parent brand to enter in a different product category (Keller *et al.*, 2011). A brand extension offers various advantages that span from facilitating new products' acceptance to providing some benefits to the parent brand (Keller *et al.*, 2011).

effect in the surrounding system (Simonin and Ruth, 1998).
This study focuses on the mechanisms that companies may use to leverage secondary associations from other companies, looking at the brand network of co-branding campaigns as a whole system. In this thesis, I demonstrate how co-branding includes in itself most of the ways to leverage association (for example, companies, places, things, and so on). Furthermore, it is worth underscoring that such a system shows the typical marks of a complex system: the heterogeneity of actors, goals, strategies, products, and market targets; indirect influences; and emergent structures. Thus, to better identify and evaluate the opportunities it faces and finally reach its goals, a company has to consider the entire system and identify direct and indirect brand ties to envision the different possible paths of evolution of the system and the corresponding benefits.
Furthermore, previous studies highlight how consumers' minds store brand information in the form of a network, facilitating Brand Association (Henderson *et al.*, 1998). Marketing studies have also developed a mental map to highlight all the main brand associations in consumers' minds to identify a specific target (Keller *et al.*, 2011). Moreover, the Brand Concept Map is a tool that, starting from a single brand, allows to draw out the network of brand-concept associations in consumers' memory.
In the present thesis, the units of analysis are the brands, which may become mutually connected through co-branding relationships. This study assumes that the same connection mechanism that links brands with concepts in consumers' memory can determine an association between brands that allied in a co-branding campaign (direct ties) and between brands that share the same partners (indirect ties). In other words, there is the assumption that a brand may trigger the recall, in consumers' memory, of all the associated brands of its previous co-branding partnerships together with their indirect connections.

## Positioning the three chapters

### Chapter one

Chapter one reports the results of a systematic literature review on co-branding carried out to summarise the current state of the art on the topic and find gaps that allow drawing the main lines of future research. The analysis reported in this chapter produced three main results.

First of all, the analysis allowed to map the relationships between all the theories used to analyze the co-branding phenomenon. I built this map by linking together the theories that have been used together in at least one paper. The presented map, and the disposition of the theories within it, underscores a flow that starts from the right side of the map with the signal perception and, through the signal processing in the center of the map, ends with the signal evaluation on the left side. Besides showing the interplay between theories, this map also underlines the interdisciplinarity that characterizes the topic under investigation.

Second, I draw a conceptual framework that summarises all the Inputs, Moderators, Mediators, and Outputs that occur in implementing a co-branding strategy. I also include in this map all the variables that influence the partner selection process. Furthermore, I embed such variables into the meso and exo contexts to include the exogenous factors that influence the process.

Finally, I structure a detailed research agenda that shows the gaps in the current literature and envision future investigation paths.

### Chapter two

In the second chapter, a systemic perspective is adopted to analyze the co-branding phenomenon in contrast to the traditional dyadic perspective by drawing the network of co-branding campaigns. The empirical analysis is conducted on an original dataset regarding co-branding campaigns in the fashion industry and uses network analysis. The research shows how switching from a dyadic to a network perspective allows to better interpret co-branding strategies. Additionally, it is possible to highlight three specific results reported in this chapter.

First, the hypothesis that the network structure is predictive of future co-branding partnerships is tested using recommendation methods. The analysis shows that the portfolio of previous partnerships of each brand and its position in the network are predictive of future alliances.

Second, the previous result is used to develop a theoretical model of partner selection. Specifically, the model interprets the brand's portfolio of previous partnerships and its position in the network as a relevant signal in the partner selection process. The theoretical model, developed by adopting the lens provided by Signaling Theory, assumes a "company - to - company" exchange of information in the partner selection process. In this context, the portfolio of previous partnerships represents a signal the companies use to reduce information asymmetry. In our assumption, the signal (implicitly) carries messages of trust and reputation that a company can interpret through different logics; for example, the ones I empirically reveal in the analysis of network's communities, which appear to reflect company reasons rather than consumer oriented ones. Indeed, four main logics underlying the partner selection process are revealed: i) Geographic co-branding: a collaboration to exploit proximity advantages; ii) Chain co-branding: a collaboration to exploit specific supply chain advantages; iii) Coopetitive co-branding: a collaboration in which two similar brands join forces to obtain a strategic advantage with respect other individual direct competitors; iv) Identity co-branding: a to stress partners identity and heritage. Based on these logics, a brand can build its signal to share in the system and, eventually, establish a partnership with another brand with compatible logics.

### Chapter three

In the third chapter, the extent to which and how consumers' minds recall the network of co-branding campaigns is scrutinized, and it moves a step forward towards the prediction of future partnerships by including the product categories of the campaigns in the prediction model and by exploiting brands' association in consumers' mind.
Specifically, I quantify brands' association in consumers' minds by downloading brand-search time series from Google-Trends and calculating the linear pair correlations between time series. Then, the network of associations is built by applying the method of Statistically Validated Networks to the correlation matrix obtained from Google-Trends. This network is compared to the network of co-branding campaigns, concluding that the two networks carry complementary information. Indeed, the network of co-branding campaigns mostly reflects company logics of link formation, while the network from Google-Trends mainly reflects different types of consumers and their corresponding needs and tastes.
To provide a first improvement of the partner selection model proposed in chapter two, in the third chapter the information contained in the two networks are put together by calculating brand similarity, through a shrinkage of the similarity provided by both the network of co-branding campaigns and the association network based on Google-Trends data. The value of the shrinkage parameter that provides the best performance of the recommendation system is 0.30 that further supports the hypothesis that consumers' preferences weigh

less than companies' logics in the partner selection process. The recommendation system uses the (optimal) shrunk similarity matrix to provide a joint prediction of partner brands and co-branded products.

Specifically, the proposed recommendation system provides a suggestion list composed of triplets $brand - brand - product$ that represents a methodological innovation within the Recommendation Systems. Indeed, it does not only suggest items (co-branded products) to users (brands) but also suggests the potential partner together with the co-branded product.

Finally, the results of this analysis allow us to identify the variables with the strongest influence on the recommendation system's performance. Specifically, by performing a Logistic Regression analysis, it is possible to identify the Degree of co-branded product[4] as the variable that mostly affects recommendation systems' performance in predicting partnerships.

## Overall Contribution

This thesis presents theoretical, methodological, and empirical contributions.

The literature review developed in chapter one allows summarising the current state of the art on co-branding. The study provides a comprehensive description of all the theories (and their interplay) used to analyze co-branding and an overview of the dimensions involved in co-branding strategies. Moreover, the broad research agenda proposed in this chapter identifies various and interesting directions for future research.

The network analysis reported in chapter two provides a systemic view of the co-branding phenomenon. The network itself represents a map of the relationships developed between brands in the fashion industry. Furthermore, results suggest that the portfolio of previous partnerships and the brand's position in the network are predictive of future collaborations. This result makes it possible to draw a theoretical model based on Signaling Theory that uses the portfolio of previous partnerships as a signal shared between the brands in the process that leads to new co-branding alliance establishment.

Finally, the consumers' Brand-to-Brand Recall Map constructed in chapter three using data from Google-Trends shows that this network carries complementary information

[4] The Degree of a co-branded product corresponds to the number of campaigns in which the given type of product has been proposed.

with respect to the network of co-branding campaigns constructed in chapter two. Indeed, the network of co-branding campaigns mostly reflects companies' logics, whereas the consumers' brand-to-brand recall map mainly carries information about the different consumer types.

In this study, the information contained in both networks are used to implement a recommendation system that provides a ranked list of triplets brand-brand-product, that represents an innovation with respect to typical recommendation methods in that it suggests to a given brand (the user) both the product to co-brand (the item) and the partner brand in the campaign. The analysis also underscores that a feature that strongly influences the performance of the recommendation is the Degree of the co-branded product. Accordingly, the theoretical model proposed in chapter two may be improved by including the portfolio of co-branded products, together with the portfolio of previous partnerships, in the signal shared between brands.

# Chapter 1

# Birds of a Feather. Co-Branding Research: where we are and where we could go from here.

**Abstract**

*A critical decision in marketing is the association of two brands in a joint product, namely the formulation and the implementation of a co-branding alliance. Correspondingly, the inputs of co-branding alliances, the differences in performance between the paired brands, and the emergence of "spillover effects" have been pillars of the marketing research agenda for almost three decades. The extensive number of studies on co-branding alliances, combined with multiple theoretical perspectives and empirical approaches informing extant literature, calls for the summary of the state of the art of this research. We develop a map of theories used to investigate co-branding alliances and build a conceptual framework linking inputs, co-branding alliance implementation, and outputs. Finally, based on the synthesis of existing research on co-branding, we propose a structured research agenda.*

## 1.1 Introduction

Business practice provides many examples of the association of two brands in a single product, namely co-branding alliances. In co-branding alliances, two brands are combined in a joint product to exploit the potential synergies between them (Newmeyer *et al.* 2014; Rao and Ruekert 1994). For instance, recently, co-branding alliances have involved U.S. Bank and BMW Financial Services in the finance industry, Milka and Philadelphia-Kraft in the food industry, and H&M and Moschino in the fashion industry.

The increasing importance of co-branding in practice has led to a parallel growth of research in the field of marketing. Since Rao and Ruekert's (1994) pioneering contribution, existing studies have extensively focused on the conditions under which two brands can produce a stronger signal by acting together than each could have done alone. These alliances lead to different outcomes for the allied firms. According to prior literature, the performance of co-branding alliances varies substantially (Washburn *et al.* 2000) and may become asymmetrical for the brands involved (Simonin and Ruth 1998). One reason that explains the variety of outcomes obtained is that co-branding alliances support the achievement of multiple goals, such as gaining access to a new target market, developing a global brand, increasing sales, and building brand equity (Aaker and Keller 1990; Barwise and Robertson 1992; Kotteman *et al.* 2017; Washburn *et al.* 2000). Moreover, allied brands may take advantage of the "spillover effects" in different ways and degrees (Simonin and Ruth 1998), and numerous variables influence the relationship between co-branding alliances and performance. For instance, consumers' perception and brand-recall through the memory's association network (Henderson *et al.* 1998) appear to lead to variability and asymmetry of brand performance.

By adopting a bird's eye view to look at co-branding research, we can observe that multiple theoretical perspectives (Signaling Theory, Information Integration Theory, Associative Learning Theory, etc.) and numerous empirical approaches (e.g., experiments, survey, and case studies) inform extant literature.

Twelve years after a first review of the research constructed on co-branding alliances (Helmig *et al.* 2008), the fragmentation of literature linking inputs-cobranding alliance implementation-outputs of co-branding makes it challenging for scholars to have a clear and comprehensive understanding of co-branding phenomena. Additionally, the variety of theories and empirical approaches used to study the co-branding phenomenon render the definition of future research directions arduous for scholars (Durand *et al.* 2017). Recent reviews only partially address this drawback. For instance, Chiambaretto and Gurău (2017) offer a rich taxonomy of co-branding types and their benefits and risks. However, they are exclusively focused on a crucial input, such as the “fit” between partners and/or products in co-branding alliances (Chiambaretto and Gurău 2017). From a complementary perspective, Besharat and Langan’s paper (2014) analyzes how co-branding alliances benefit or harm consumers’ perception and how brands share consumers’ associations (Besharat and Langan 2014).

This chapter aims to provide a broad picture of the theories and dimensions involved in co-branding research in the current state of the art. In so doing, we contribute to the extant literature in three ways. First, we provide a comprehensive theoretical description of different facets of the co-branding alliance and the interplay between the theories that scholars have adopted and the different fields of research involved. Second, we build a conceptual framework linking inputs, co-branding alliance implementation, and outputs. We attempt to reduce the fragmentation of “what we know” on co-branding alliances as a necessary step to offer a set of insights helpful to marketing managers. Finally, drawing on our conceptual framework, we find gaps in existing research and propose an organized agenda for future research.

## 1.2 Method

To develop a systematic literature review of co-branding research, we search for papers indexed in two databases: Scopus and Web of Science. The choice of these two databases guarantees the overall quality of the selected papers. Generally, Scopus and Web of Science databases provide high-quality data, with comprehensive coverage of many research fields. Journals indexed by Scopus and/or Web of Science are published regularly, have an ISSN, and meet minimum criteria of quality such as, for example, peer-reviewed articles and internationally oriented content. Additionally, the choice to consider both databases is appropriate to guarantee the comprehensiveness of the constructed sample. For instance, in the Scopus database, “Journal of Consumer Research” and “Journal of Marketing” show temporal gaps till 1993 and 1995, respectively.

We selected articles that include the terms “co-brand*”, “co brand*”, “cobrand*”, “brand alliance*”, “joint branding”, “dual branding”, “co-marketing alliance”, “ingredient branding”, “multiple branding” in their title, abstract or list of keywords. Our search incorporates papers published until December 2019. In the Scopus database, we selected 580 papers. Following Dagnino *et al.* (2020), we refined our search based on the following criteria. First, we selected the papers that received at least ten citations. The 10-citation threshold allowed us to select the top 33% of papers according to the overall number of citations (excluding self-citations). A total of 187 selected papers satisfy this criterion. Second, we also included all the papers published in marketing journals with 3 and 4 stars, according to the U.K. Academic Journal Guide 2018[1], even if they showed less than ten citations[2]. Therefore, the final sample extracted from SCOPUS includes 205 papers. Our criteria allowed us to select the most influential papers on co-branding. On the one hand, setting a threshold for the minimum number of citations per paper guarantees the inclusion of the most important articles in the ongoing academic debate. On the other hand, since such a threshold penalises the most recent publications, we compensate for such drawback by selecting papers on the topic published in top journals, despite the number of citations.

We repeated the same collection procedure described above on the Web of Science database. We found 32 papers in addition to the ones already selected from the Scopus database.

At the end of our data collection procedure, our sample was composed of 237 papers. Abstracts of such articles were analyzed one-by-one and, after removing papers that regard a different topic or touch co-branding research marginally and one corrigendum, the final sample included 190 papers. Figure 1.1 summarises the main steps of the data collection procedure.

We analyzed the 190 papers on co-branding alliances following three main steps. First, we built a table to summarize extant studies on co-branding. For each paper, we reported the title, the year of publication, the authors' names, the title of the journal, the number of citations, the research questions, the methodological approach (quantitative and/or qualitative), the theoretical perspective(s) employed, and the contributions. Additionally, for quantitative papers, we add a column for the list of variables considered (by distinguishing

[1] These journals are: Journal of Consumer Psychology; Journal of Consumer Research; Journal of Marketing; Journal of Marketing Research; Journal of the Academy of Marketing Science; Marketing Science; International Journal of Research in Marketing; Journal of Retailing; European Journal of Marketing; Industrial Marketing Management; International Marketing Review; Journal of Advertising; Journal of Advertising Research; Journal of Interactive Marketing; Journal of International Marketing; Journal of Public Policy and Marketing; Marketing Letters; Marketing Theory; Psychology and Marketing; Quantitative Marketing and Economics.

[2] A total of 45 papers in the sample were published in marketing journals with 3 and 4 stars 34 of them with more than 10 citations.

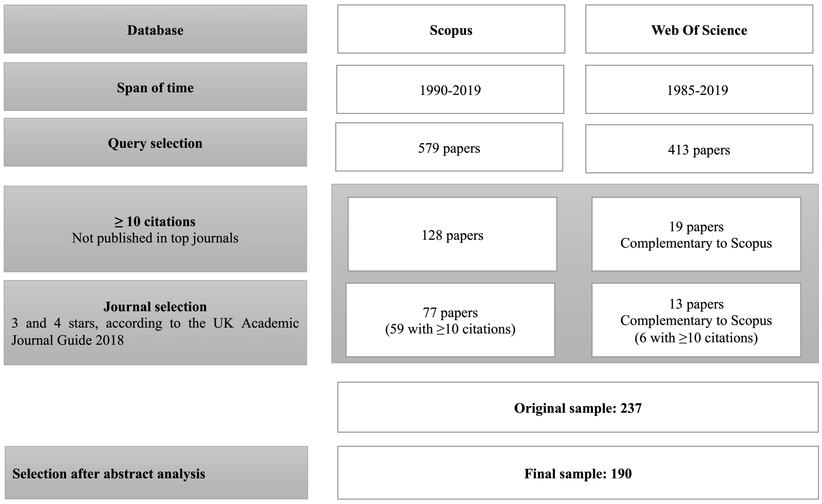


**Figure 1.1:** Data collection procedure

among dependent, independent, mediator, and moderator variables) and a column for the associated measures provided.

Second, to portray a picture of the theories informing co-branding research and how each theory is related to the others, we built a map of theories using a network approach. In this map, the Nodes represent the theories used to analyze co-branding over time. When two theories are jointly used in one or more papers, a connection between them is established. The width of the link is proportional to the frequency with which two theories are used in conjunction in the same study.

Third, and finally, we built a conceptual framework that summarizes the concepts and variables used in co-branding research. Figure 1.4 reports the conceptual framework that emerges from the current state of the art on the topic. The initial version of the framework was modified after an in-depth analysis of the papers' contents, which allowed to shrink some dimensions and reduce its complexity. We scrutinized each element in the framework and the connections among the considered elements.

## 1.3 Descriptive analysis

Our sample is composed of 190 papers. The largest portion of the papers in our sample use a quantitative approach, specifically 138 out of 190 papers. The most influential contribution is the article by Simonin and Ruth (1998), which, according to SCOPUS, received 585 citations.

Although our sample includes studies on the co-branding phenomenon published in the time period 1990-2019, looking at the distribution of papers by year of publication, we notice a spike in 2014 (i.e., 19 papers in our sample).

Furthermore, the number of journals that have published articles on co-branding is 76. The wide range of journals interested in this phenomenon reflects the impact of co-branding alliances in marketing. The five journals that have published most articles on co-branding are: Journal of Business Research (16), Psychology & Marketing (12), Journal of Product and Brand Management (12), European Journal of Marketing (10), and Industrial Marketing Management (9).

Table 1.1 shows the papers included in our sample by journal and publication year. Finally, our sample is composed of 190 papers that use 63 different theories overall. Among these papers, 73 do not mention any specific theory at all, 83 papers employ only one theory, and 34 analyse co-branding through at least two theories.

**Table 1.1:** Papers in the sample by journal and publication year

| Journals / Periods | 1992-1995 | 1996-1999 | 2000-2003 | 2004-2007 | 2008-2011 | 2012-2015 | 2016-2019 |
|---|---|---|---|---|---|---|---|
| 20TH AMERICAS CONFERENCE ON INFORMATION SYSTEMS AMCIS 2014 | - | - | - | - | - | Wang and Hajli (2014) | - |
| ADVANCES IN CONSUMER RESEARCH VOL XXII | Hillyer and Tikoo (1995) | - | - | - | - | - | - |
| BRITISH FOOD JOURNAL | - | - | - | - | - | Ponnam S and Balaji (2015) | - |
| BRITISH JOURNAL OF POLITICS AND INTERNATIONAL RELATIONS | - | - | - | - | - | Pamment (2015) | - |
| BUSINESS HORIZONS | - | - | Prince and Davies (2002); Abratt and Motlana (2002) | Farrelly and Quester (2005) | - | - | - |
| CLOTHING AND TEXTILES RESEARCH JOURNAL | - | - | - | - | - | Myers *et al.* (2012) | - |
| CORNELL HOTEL AND RESTAURANT ADMINISTRATION QUARTERLY | - | Boone (1997) | - | DiPietro (2005) | - | - | - |
| CORPORATE REPUTATION REVIEW | - | - | - | - | Kahuni *et al.* (2009) | Heslop *et al.* (2013) | - |
| EUROPEAN JOURNAL OF MANAGEMENT AND BUSINESS ECONOMICS | - | - | - | - | - | - | Melero and Montaner (2016) |
| EUROPEAN JOURNAL OF MARKETING | - | - | - | Uggla (2006); Seno and Lukas (2007) | Delgado-Ballester and Hernàndez-Espallardo (2008) | Samuelsen and Olsen (2012); Lanseng and Olsen (2012); Bignè *et al.* (2012); Gammoh and Voss (2013); Xiao and Lee (2014); Guerreiro *et al.* (2015) | Roosens *et al.* (2019) |
| EUROPEAN JOURNAL OF OPERATIONAL RESEARCH | - | Henderson *et al.* (1998) | - | - | - | - | - |

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Table 1.1 – continued from previous page

| Journals / Periods | 1992-1995 | 1996-1999 | 2000-2003 | 2004-2007 | 2008-2011 | 2012-2015 | 2016-2019 |
|---|---|---|---|---|---|---|---|
| EUROPEAN MANAGEMENT JOURNAL | Barwise and Robertson (1992) | - | - | - | - | - | - |
| EUROPEAN SPORT MANAGEMENT QUARTERLY | - | - | - | - | - | Bodet and Lacassagne (2012) | - |
| FASHION BRANDING AND CONSUMER BEHAVIOURS SCIENTIFIC MODELS | - | - | - | - | - | Shen *et al.* (2014) | - |
| HUMANITIES AND SOCIAL SCIENCES REVIEWS | - | - | - | - | - | - | Desfiandi *et al.* (2019) |
| INDUSTRIAL MARKETING MANAGEMENT | - | - | - | Bengtsson and Servais (2005) | Erevelles *et al.* (2008); Besharat (2010); Leek and Christodoulides (2011) | Kalafatis *et al.* (2014); Helm *et al.* (2015) | Chiambaretto *et al.* (2016); Cao and Yan (2017); Mohan *et al.* (2018) |
| INTERNATIONAL JOURNAL OF ADVERTISING | - | - | - | - | - | Chang (2012); Tsiotsou *et al.* (2014) | - |
| INTERNATIONAL JOURNAL OF CONTEMPORARY HOSPITALITY MANAGEMENT | - | - | - | - | Cornelis (2010) | Lin (2013) | Moro and Rita (2018) |
| INTERNATIONAL JOURNAL OF CULTURE TOURISM AND HOSPITALITY RESEARCH | - | - | - | - | Scott *et al.* (2011) | - | - |
| INTERNATIONAL JOURNAL OF ENTREPRENEURIAL VENTURING | - | - | - | - | Rodrigues *et al.* (2011) | - | - |
| INTERNATIONAL JOURNAL OF HOSPITALITY MANAGEMENT | - | - | - | Lee *et al.* (2006) | Tasci and Denizci (2010); Tasci and Denizci Guillet (2011) | Dioko and So (2012) | - |
| INTERNATIONAL JOURNAL OF MANAGEMENT REVIEWS | - | - | - | - | - | - | Agostini and Nosella (2017) |

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**Table 1.1 – continued from previous page**

| Journals / Periods | 1992-1995 | 1996-1999 | 2000-2003 | 2004-2007 | 2008-2011 | 2012-2015 | 2016-2019 |
|---|---|---|---|---|---|---|---|
| INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH | - | - | - | - | - | Zhang *et al.* (2013) | - |
| INTERNATIONAL JOURNAL OF RESEARCH IN MARKETING | - | - | Venkatesh *et al.* (2000) | Fernández-Barcala and González-Díaz (2006) | - | Worm and Srivastava (2014); Zamudio (2015) | Koschmann and Bowman (2018) |
| INTERNATIONAL JOURNAL OF RETAIL AND DISTRIBUTION MANAGEMENT | - | - | - | - | - | Huddleston *et al.* (2015); Arrigo (2015) | - |
| INTERNATIONAL MARKETING REVIEW | - | Robson and Dunk (1999) | - | Bluemelhuber *et al.* (2007) | - | - | Diallo and Siqueira Jr. (2017); Newmeyer *et al.* (2019) |
| JMM INTERNATIONAL JOURNAL ON MEDIA MANAGEMENT | - | - | - | - | - | Lis and Post (2013) | - |
| JOURNAL OF ADVERTISING | - | - | Ruth and Simonin (2003) | - | Bower and Grau (2009) | Rosengren and Dahlén (2015) | - |
| JOURNAL OF ADVERTISING RESEARCH | - | - | - | Lebar *et al.* (2005); Farrelly *et al.* (2005); Blankson and Kalafatis (2007) | - | Elberse *et al.* (2012) | Liljedal (2016) |
| JOURNAL OF BRAND MANAGEMENT | - | - | - | - | - | Ahn and Sung (2012); Myers *et al.* (2013); Besharat and Langan (2014); Ambroise *et al.* (2014) | Decker and Baade (2016); Burton *et al.* (2017) |
| JOURNAL OF BUSINESS AND INDUSTRIAL MARKETING | - | - | - | - | - | Kalafatis *et al.* (2012) | - |
| JOURNAL OF BUSINESS AND PSYCHOLOGY | - | - | Levin (2002) | - | - | - | - |

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**Table 1.1 – continued from previous page**

| Journals / Periods | 1992-1995 | 1996-1999 | 2000-2003 | 2004-2007 | 2008-2011 | 2012-2015 | 2016-2019 |
|---|---|---|---|---|---|---|---|
| JOURNAL OF BUSINESS ETHICS | - | - | - | - | Alcaniz *et al.* (2010) | Liu (2013); Sénéchal *et al.* (2014) | Singh (2016) |
| JOURNAL OF BUSINESS RESEARCH | - | Young *et al.* (1996) | - | Lafferty and Goldsmith (2005); Lafferty (2007) | - | Li and He (2013); Lee *et al.* (2013); Ilicic and Webster (2013); Mazodier and Merunka (2014); Lafferty and Edmondson (2014); Aarstad *et al.* (2015) | Voss and Mohan (2016); Rim *et al.* (2016); Naidoo and Hollebeek (2016); Moon and Sprott (2016); Ko *et al.* (2016); Cheah *et al.* (2016); Shen *et al.* (2017) |
| JOURNAL OF BUSINESS TO BUSINESS MARKETING | - | - | - | Dahlstrom and Dato-on (2004) | Yi *et al.* (2010) | - | - |
| JOURNAL OF CONSUMER MARKETING | Norris (1992) | - | Washburn *et al.* (2000) | James (2005) | - | - | - |
| JOURNAL OF CONSUMER PSYCHOLOGY | - | - | Levin and Levin (2000) | Votolato and Rao Unnava (2006); Basil and Herr (2006) | - | - | - |
| JOURNAL OF CONSUMER RESEARCH | - | - | - | - | - | Swaminathan *et al.* (2015); Cunha Jr. *et al.* (2015) | - |
| JOURNAL OF FASHION MARKETING AND MANAGEMENT AN INTERNATIONAL JOURNAL | - | - | - | - | Ahn *et al.* (2010) | - | - |
| JOURNAL OF FOODSERVICE BUSINESS RESEARCH | - | - | Boo and Mattila (2002) | - | - | - | - |
| JOURNAL OF HOSPITALITY AND TOURISM RESEARCH | - | - | - | - | Guillet and Tasci (2010) | - | - |
| JOURNAL OF HOSPITALITY MARKETING AND MANAGEMENT | - | - | - | - | Hjalager and Konu (2011) | - | - |

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**Table 1.1 – continued from previous page**

| Journals / Periods | 1992-1995 | 1996-1999 | 2000-2003 | 2004-2007 | 2008-2011 | 2012-2015 | 2016-2019 |
|---|---|---|---|---|---|---|---|
| JOURNAL OF INTERNATIONAL CONSUMER MARKETING | - | Voss and Tansuhaj (1999) | - | - | - | - | - |
| JOURNAL OF INTERNATIONAL FOOD AND AGRIBUSINESS MARKETING | - | - | - | - | Pinar and Trapp (2008) | - | - |
| JOURNAL OF MANAGEMENT | - | - | - | - | Parmigiani and Rivera-Santos (2011) | - | - |
| JOURNAL OF MARKETING | - | - | Desai and Keller (2002) | Kumar (2005) | - | - | Kupfer *et al.* (2018); Henderson *et al.* (2019) |
| JOURNAL OF MARKETING COMMUNICATIONS | - | - | - | Baumgarth (2004) | Wang and Muehling (2010) | - | - |
| JOURNAL OF MARKETING MANAGEMENT | - | - | - | - | Arnett *et al.* (2010) | Oeppen and Jamal (2014) | - |
| JOURNAL OF MARKETING RESEARCH | - | Simonin and Ruth (1998); Rao *et al.* (1999) | - | Monga and Lau-Gesk (2007) | - | Yang Goldfarb (2015) | Chan *et al.* (2018) |
| JOURNAL OF MARKETING THEORY AND PRACTICE | - | - | - | - | Lafferty and Edmondson (2009) | - | - |
| JOURNAL OF PRODUCT AND BRAND MANAGEMENT | - | Saunders and Guoqun (1997); Grossman (1997) | Vaidyanathan and Aggarwal (2000) | Rodrigue and Biswas (2004); Jevons *et al.* (2005); Askegaard and Bengtsson (2005); James *et al.* (2006); James (2006) | Halonen-Knight and Hurmerinta (2010); Gammoh *et al.* (2010) | Tompson and Strutton (2012) | Huertas-García *et al.* (2017) |
| JOURNAL OF PRODUCT INNOVATION MANAGEMENT | - | - | - | - | Bouten *et al.* (2011) | - | - |
| JOURNAL OF PURCHASING AND SUPPLY MANAGEMENT | - | - | - | - | - | Lienland *et al.* (2013) | - |

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**Table 1.1 – continued from previous page**

| Journals / Periods | 1992-1995 | 1996-1999 | 2000-2003 | 2004-2007 | 2008-2011 | 2012-2015 | 2016-2019 |
|---|---|---|---|---|---|---|---|
| JOURNAL OF QUALITY ASSURANCE IN HOSPITALITY AND TOURISM | - | - | - | Kim *et al.* (2007) | - | - | - |
| JOURNAL OF RETAILING | - | - | - | - | - | Desai *et al.* (2014) | - |
| JOURNAL OF RETAILING AND CONSUMER SERVICES | - | - | - | - | Ahn *et al.* (2009) | - | - |
| JOURNAL OF SERVICES MARKETING | - | - | - | D'Astous *et al.* (2007) | - | - | - |
| JOURNAL OF SPORT AND TOURISM | - | - | Sofield (2003) | - | - | - | - |
| JOURNAL OF STRATEGIC MARKETING | - | - | - | - | - | Rahman (2014) | - |
| JOURNAL OF THE ACADEMY OF MARKETING SCIENCE | - | - | - | Magid (2006) | - | Tsai *et al.* (2014); Newmeyer *et al.* (2014) | - |
| JOURNAL OF TRAVEL AND TOURISM MARKETING | - | - | - | - | - | Lee *et al.* (2014) | - |
| JOURNAL OF VACATION MARKETING | - | - | - | - | Ashton and Scott (2011) | - | - |
| MANAGING SERVICE QUALITY | - | - | - | Keiningham *et al.* (2006) | Tsantoulis and Palmer (2008) | - | - |
| MARKETING LETTERS | - | - | Klink (2003) | Voss and Gammoh (2004) | - | Swaminathan *et al.* (2012); Radighieri *et al.* (2014); Samuelsen *et al.* (2015) | Nguyen *et al.* (2018); Newmeyer *et al.* (2018) |
| MARKETING SCIENCE | - | Venkatesh and Mahajan (1997) | - | - | Geylani *et al.* (2008); Yang *et al.* (2009) | Cao and Sorescu (2013); van der Lans *et al.* (2014) | - |
| MARKETING THEORY | - | - | Van Durme *et al.* (2003) | - | - | - | - |
| OMEGA INTERNATIONAL JOURNAL OF MANAGEMENT SCIENCE | - | - | - | - | - | Karray and Sigue (2015) | - |

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**Table 1.1 – continued from previous page**

| Journals / Periods | 1992-1995 | 1996-1999 | 2000-2003 | 2004-2007 | 2008-2011 | 2012-2015 | 2016-2019 |
|---|---|---|---|---|---|---|---|
| PSYCHOLOGY AND MARKETING | - | - | - | Washburn *et al.* (2004); Lafferty *et al.* (2004); Gammoh *et al.* (2006); Walchli (2007) | Lafferty (2009); Esch *et al.* (2009) | Smarandescu *et al.* (2013) | Lafferty *et al.* (2016); Dahlstrom and Nygaard (2016); Chang *et al.* (2018); Koschate-Fischer *et al.* (2019); Fowler and Thomas (2019) |
| QME QUANTITATIVE MARKETING AND ECONOMICS | - | - | - | - | Kuksov (2009) | - | - |
| SCANDINAVIAN JOURNAL OF HOSPITALITY AND TOURISM | - | - | - | Mossberg and Getz (2006) | - | - | - |
| SLOAN MANAGEMENT REVIEW | Rao and Ruekert (1994) | - | - | - | - | - | - |
| SPORT IN SOCIETY CULTURES COMMERCE MEDIA POLITICS | - | - | - | Chalip and Costa (2005) | - | - | - |
| SPORT MANAGEMENT REVIEW | - | - | - | Xing and Chalip (2006) | - | - | - |
| STRATEGIC MANAGEMENT JOURNAL | - | - | - | Bourdeau *et al.* (2007) | - | - | - |
| TOURISM MANAGEMENT PERSPECTIVES | - | - | - | - | - | Otgaar (2012) | - |
| TRADEMARKS BRANDS AND COMPETITIVENESS | - | - | - | - | Hansen (2010) | - | - |

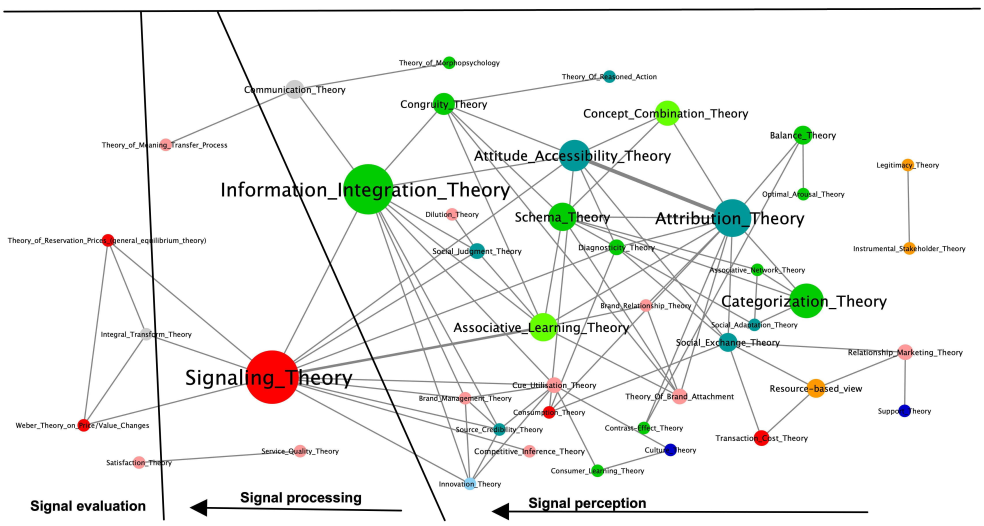


**Figure 1.2:** Map of Theories

## 1.4 Mapping the interconnections among theories

To analyze the interplay between different theories in co-branding research, we use a network approach. We build a map of theories (Figure 1.2) to show how such theories, and consequently the papers, are linked to each other by setting a link between any two theories used together in at least one paper. Thus, the map does not consider theories that never appear in combination with other theories in at least one paper of the sample (however, Table 1.2 reports the full list of theories). The colors of the theories (nodes) represent the field from which each theory originates, while each nodes' size is proportional to the frequency with which each theory is used in the papers of our final sample. Finally, the width of each link is equal to the total number of papers in which the two theories jointly appear. Among the theories considered (63 overall), 20 of them never appear jointly with another theory in any paper of the sample, whereas 43 appear in at least one combination with another theory in one or more papers of the sample.

By analyzing the map of theories, an interesting logical connection between the theories emerges. In particular, they may be seen as capturing different phases of a signaling process: from signal perception, through signal processing, to signal evaluation by the consumers. Each theory in the map contributes to explain the process that leads from signal perception to "buyer value" formation in consumers' minds. At the end of this process, if the consumer perceives that his/her "buyer value" of a product is higher than the "sale price", the transaction occurs.

The main nucleus of the described process (right side of the map) comprises psychological theories (and their branch). All these theories describe the mechanisms that generate a value in consumers' minds. However, in co-branding research, some theories are more popular than others (Table 1.3) - in particular, the ones that appear most frequently in literature are: Information Integration Theory, Attitude Accessibility Theory, Attribution Theory, Associative Learning Theory, and Categorization Theory.

**Table 1.2:** Papers clusters by theoretical approach

| Theory | Freq. | Year | Field | Main References |
|---|---|---|---|---|
| Signaling Theory | 16 | 1973 | economics | Venkateshand Mahajan (1997); Rao *et al.* (1999); Voss and Gammoh (2004); Gammoh *et al.* (2006); James *et al.* (2006); Besharat (2010); Naidoo and Hollebeek (2016); Decker and Baade (2016); Liljedal (2016); Mohan *et al.* (2018); Voss and Mohan (2016); Nguyen *et al.* (2018); Ponnam *et al.* (2015); Helm and Özergin (2015); Singh (2016); Voss (1999) |
| Information Integration Theory | 14 | 1971 | psychology | Simonin and Ruth (1998); Lafferty *et al.* (2004); Lafferty and Goldsmith (2005); James *et al.* (2006); Bourdeau *et al.* (2007); Delgado-Ballester and Hernández-Espallardo (2008); Arnett *et al.* (2010); Besharat and Langan (2014); Naidoo and Hollebeek (2016); Geylani *et al.* (2008); Lafferty *et al.* (2016); Ponnam *et al.* (2015); Helm and Özergin (2015); Singh (2016) |
| Attribution Theory | 9 | 1920 | social psychology | Vaidyanathan and Aggarwal (2000); Myers *et al.* (2012).; Newmeyer *et al.* (2014); Radighieri *et al.* (2014); Tsiotsou *et al.* (2014); Koschate-Fischer *et al.* (2019); Chang *et al.* (2018); Rim *et al.* (2016); Desfiandi *et al.* (2019) |
| Categorization Theory | 8 | 1984 | psychology | Lanseng and Olsen (2012); Thompson and Strutton (2012); Ahn and Sung (2012); Newmeyer *et al.* (2014); Samuelsen *et al.* (2015); Swaminathan *et al.* (2012); Kumar (2005); Ahn *et al.* (2010) |
| Attitude Accessibility Theory | 7 | 1986 | social psychology | Simonin and Ruth (1998); Vaidyanathan and Aggarwal (2000); Lafferty *et al.* (2004); Delgado-Ballester and Hernández-Espallardo (2008); Chang *et al.* (2018); Rim *et al.* (2016); Singh (2016) |
| Associative Learning Theory | 6 | 1980 | cognitive psychology | Alcañiz *et al.* (2010); Besharat (2010); Tsiotsou *et al.* (2014); Naidoo and Hollebeek (2016); Henderson *et al.* (1998); Heslop *et al.* (2013) |
| Schema Theory | 6 | 1984 | psychology | Alcañiz *et al.* (2010); Bigné *et al.* (2012); Myers *et al.* (2012); Cheah *et al.* (2016); Desai and Keller (2002); Ahn *et al.* (2010) |
| Concept Combination Theory | 5 | 1993 | cognitive psychology | Vaidyanathan and Aggarwal (2000); Tsantoulis and Palmer (2008); Koschmann and Bowman (2018); Swaminathan *et al.* (2015); Desai and Keller (2002) |
| Congruity Theory | 4 | 1955 | psychology | Lafferty *et al.* (2004); Heslop *et al.* (2013); Myers *et al.* (2013); Cheah *et al.* (2016) |
| Resource-based view | 3 | 1991 | management | Yang and Goldfarb (2015); Van Durme *et al.* (2003); Worm and Srivastava (2014) |
| Social Exchange Theory | 3 | 1961 | social psychology | Taek *et al.* (2010); Van Durme *et al.* (2003); Chang *et al.* (2018) |
| Balance Theory | 3 | 1946 | psychology | Basil and Herr (2006); Sénéchal *et al.* (2014); Desfiandi *et al.* (2019) |
| Communication Theory | 3 | 1948 | mathematics | Halonen-Knight and Hurmerinta (2010); Ambroise *et al.* (2014); Lafferty *et al.* (2016) |

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**Table 1.2 – continued from previous page**

| Theory | Freq. | Year | Field | Main References |
|---|---|---|---|---|
| Game theory | 3 | 1944 | mathematics | Rodrigues *et al.* (2011); Kuksov (2009); Karray and Sigue (2015) |
| Diagnosticity Theory | 2 | 1988 | psychology | Voss and Mohan (2016); Chang *et al.* (2018) |
| Transaction Cost Theory | 2 | 1981 | economics | Taek Yi *et al.* (2010); Yang and Goldfarb (2015) |
| Relationship Marketing Theory | 2 | 1994 | marketing | Wang and Hajli (2014); Van Durme *et al.* (2003) |
| Cue Utilisation Theory | 2 | 1972 | marketing | Diallo and Siqueira Jr (2017); Ponnam *et al.* (2015) |
| Cognitive Consistency Theory | 2 | 1957 | social psychology | Lafferty (2009); Cao and Sorescu (2013) |
| Social Judgment Theory | 2 | 1961 | social psychology | Ilicic and Webster (2013); Naidoo and Hollebeek (2016) |
| Institutional Isomorphism Theory | 1 | 1983 | sociology | Rahman (2014) |
| Holistic Consumption Theory | 1 | 1936 | marketing | Chang *et al.* (2018) |
| Source Credibility Theory | 1 | 1940 | psychology | Ponnam *et al.* (2015) |
| Brand Management Theory | 1 | NA | marketing | Ponnam *et al.* (2015) |
| Innovation Theory | 1 | 1978 | NA | Ponnam *et al.* (2015) |
| Attachment Theory | 1 | 1969 | psychology | Cheah *et al.* (2016) |
| Theories of the self | 1 | NA | NA | Monga and Lau-Gesk (2007) |
| Weber's Theory on Price/Value Changes | 1 | 1908 | economics | Venkatesh and Mahajan (1997) |
| Utility Theory | 1 | 1970 | economics | Kim *et al.* (2007) |
| Two-Sided Matching Theory | 1 | 1990 | mathematics | Zamudio (2016) |
| Theory of Reservation Prices (general equilibrium theory) | 1 | 1877 | economics | Venkatesh and Mahajan (1997) |
| Theory Of Reasoned Action | 1 | 1975 | social psychology | Myers *et al.* (2013) |
| Theory of Morphopsychology | 1 | 1930 | psychology | Ambroise *et al.* (2014) |
| Theory of Meaning Transfer Process | 1 | 1989 | marketing | Halonen-Knight and Hurmerinta (2010) |
| Theory Of Brand Attachment | 1 | 2006 | marketing | Tsiotsou *et al.* (2014) |

In the center of the map, "Signaling Theory" area labels the mechanisms through which the signal is processed. Specifically, it explains why consumers absorb a signal. Then, the consumers' "buyer value" is formed, and the transaction eventually occurs if the consumers' "marginal utility" is positive. In other words, Signaling Theory appears to bridge psychological theories concerning signal perception and economic theories that describe how such a signal is evaluated in a consumer's mind to generate consequential behavior.

On the left side of the map, economic theories model the mechanisms through which consumers transform a "buyer value" signal into a purchase action. Such cluster of theories includes: Theory of Reservation Prices (general equilibrium theory) and Weber's Theory on Price/Value Changes. It is worth noticing that marketing theories typically appear more heavily linked to psychological theories rather than economic theories.

In general, there is a continuous comparison between "buyer value" and "sale price." Psychological theories explain the mechanisms that may contribute to "buyer value" formation. Then, a signal between firms and consumers is transferred and diffused according to the rules set by Signaling Theory. Finally, economic theories model how the consumer evaluates the signal. In this model, co-branding signals eventually lead to a purchase activity if the consumer's "buyer value" is higher than the "sale price" of a specific product.

Although the map structure represents a general process of perceived buyer value formation, it is worth mentioning that it results from the analysis of studies explicitly focused on co-branding. Accordingly, the fundamental logic underlying the process of "buyer value" formation of a co-branded product appears to be the same as the one underlying the perception of the value of any single branded product. Indeed, a co-branding alliance is the merging of two elements (two brands), that also represent a specific characteristic, among the others, of a product. There is a specific and intentional value transfer (and "buyer value") in a co-branding alliance. Indeed, this alliance aims to generate a condition where the partners' joint product has a higher perceived value than the same product branded by only one of the partners.

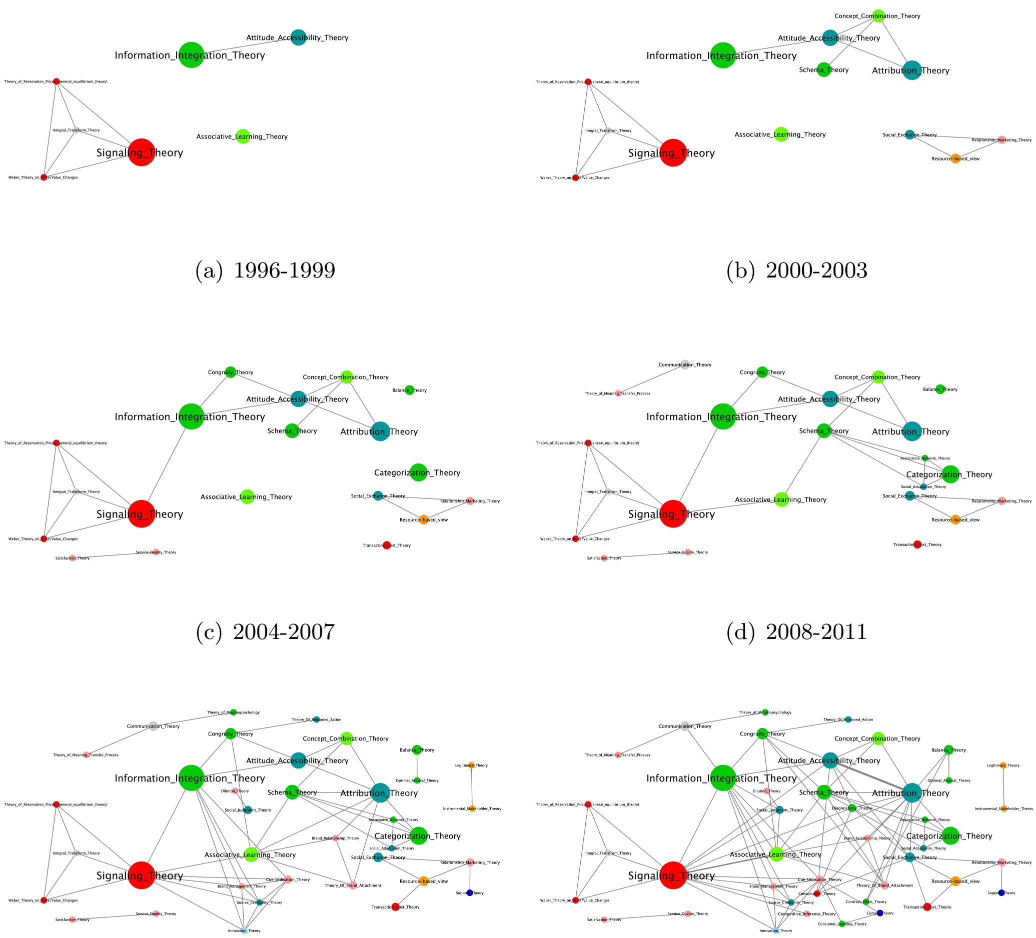
Among the possible effects of a co-branding alliance, there is the possibility of reaching a broader market target thanks to the modification of the "perceived buyer value". For example, consumers who thought that the value of a single branded product was lower than its price may perceive the value to be higher than its price when co-branded. Besides, there is the possibility to reach different market targets. Thanks to the collaboration between two brands, the new joint product often manages to reach a different market target (different for one or both the partner brands) that could hardly be reached through a single branded product.

Moreover, identifying pair relationships between theories used as interpretative lenses in co-branding research allows one to evaluate better each theory's contribution concerning the phenomenon under investigation. Specifically, looking at Figure 1.2, we observe that the Signaling Theory plays a central role in co-branding analysis. Indeed, despite the strong connection among psychological theories and economic theories, Signaling Theory represents the unique bridge between these two branches.

Furthermore, the disposition of the theories in the map naturally highlights a process in the description of the co-branding phenomenon, namely from signal perception, through the signal processing to signal evaluation by the consumers, representing a key finding of this chapter. Indeed, the relationships and processes that appear in the map of theories epitomize a fresh lens to interpret co-branding alliance literature and highlight the interdisciplinarity that has characterized studies in this field to deeply understand the phenomenon. Such interdisciplinarity in this field is also supported by many papers in our sample that jointly use two or more theories to investigate the co-branding phenomenon.

**Table 1.3:** Description of the main theories in the map

| Theory | Main theoretical insight | Foundational source | Applications to co-brand |
|---|---|---|---|
| **Information Integration Theory** | It describes how people receive information from different sources and, by adding and integrating such information, make a judgment and decide how to behave (Anderson, 1962) | Anderson, N. H. (1962). Application of an additive model to impression formation. Science, 138(3542), 817-818. | Simonin and Ruth (1998); Lafferty *et al.* (2004); Lafferty and Goldsmith (2005); James *et al.* (2006); Bourdeau *et al.* (2007); Delgado-Ballester and Hernández-Espallardo (2008); Arnett *et al.* (2010); Besharat and Langan (2014); Naidoo and Hollebeek (2016) |
| **Attitude Accessibility Theory** | It indicates that peoples' behavior is a function of their attitude toward a signal. The attitude guides a judgment only after the memory recall process occurs. The accessibility of the attitude in memory acts as a key determinant in the judgment (Fazio *et al.*, 1989) | Fazio, R. H., Powell, M. C., and Williams, C. J. (1989). The role of attitude accessibility in the attitude-to-behavior process. Journal of consumer research, 16(3), 280-288. | Simonin and Ruth (1998); Vaidyanathan and Aggarwal (2000); Lafferty, *et al.* (2004); Delgado-Ballester and Hernández-Espallardo (2008) |
| **Attribution Theory** | It analyzes the cognitive processes through which people deduce the cause of other peoples' behavior (Calder and Burnkrant, 1977) | Calder, B. J., and Burnkrant, R. E. (1977). Interpersonal influence on consumer behavior: An attribution theory approach. Journal of Consumer Research, 4(1), 29-38. | Vaidyanathan and Aggarwal (2000); Myers *et al.* (2012); Newmeyer *et al.* (2014); Radighieri *et al.* (2014); Tsiotsou *et al.* (2014); Koschate-Fischer *et al.* (2019) |
| **Associative Learning Theory** | It analyzes the circumstances in which people create connections between events in a specific context and environment (Washburn *et al.*, 2004) | Washburn, J. H., Till, B. D., and Priluck, R. (2004). Brand alliance and customer-based brand-equity effects. Psychology & Marketing, 21(7), 487-508. | Alcañiz *et al.* (2010); Besharat (2010); Tsiotsou *et al.* (2014); Naidoo and Hollebeek (2016); Washburn *et al.* (2004). |
| **Categorization Theory** | It describes how people organize their thoughts by categorizing people, situations, events, objects, etc, with the aim to process and better understand complex information (Ahn and Sung, 2012) | Ahn, H., and Sung, Y. (2012). A two-dimensional approach to between-partner fit in co-branding evaluations. Journal of Brand Management, 19(5), 414-424. | Lanseng and Olsen (2012); Thompson and Strutton (2012); Ahn and Sung (2012); Newmeyer *et al.* (2014); Samuelsen *et al.* (2015) |
| **Signaling Theory** | It describes people's behavior in a situation characterized by asymmetrical information. Analyzes the behavior when the subjects in a relationship have access to different levels of information. The sender decides how to communicate the signal, i.e., the information, and the receiver decides how to interpret that information (Connelly *et al.*, 2011). | Connelly, B. L., Certo, S. T., Ireland, R. D., and Reutzel, C. R. (2011). Signaling theory: A review and assessment. Journal of Management, 37(1), 39-67. | Venkatesh and Mahajan (1997); Rao *et al.* (1999); Voss and Gammoh (2004); Gammoh *et al.* (2006); James *et al.* (2006); Besharat (2010); Naidoo and Hollebeek (2016); Decker and Baade (2016); Liljedal (2016); Mohan *et al.* (2018) |
| **Theory of Reservation Prices and general equilibrium theory** | It indicates that the "right" price of a good exchanged in a market is the one at which supply equals demand, by taking into account all the market interactions and the reservation prices of both suppliers and demanders (Starr, 2011). The reservation price of a demander, e.g., a consumer, is represented by the maximum price that the consumer is willing to pay for a specific product. The reservation price of a seller, e.g., a firm, is the minimum price the firm is willing to accept for a specific product (Simonin and Ruth, 1995) | Starr, R. M. (2011). General equilibrium theory: An introduction. Cambridge University Press; Simonin, B. L., and Ruth, J. A. (1995). Bundling as a strategy for new product introduction: Effects on consumers' reservation prices for the bundle, the new product, and its tie-in. Journal of business research, 33(3), 219-230. | Venkatesh and Mahajan (1997) |
| **Weber's Theory on Price-Value Changes** | It argues that people perceive and evaluate change of product prices/values in proportional terms (Venkatesh, and Mahajan, 1997). | Venkatesh, R., and Mahajan, V. (1997). Products with branded components: An approach for premium pricing and partner selection. Marketing Science, 16(2), 146-165. | Venkatesh and Mahajan (1997) |




(a) 1996-1999

(b) 2000-2003

(c) 2004-2007

(d) 2008-2011

(e) 2012-2015

(f) 2016-2019

**Figure 1.3:** Map of theories evolution

Finally, we report the evolution of the map of theories over time in figure 1.3. The theories (nodes) tend to be scattered in early periods (1996-1999; 2000-2003), with links clearly forming communities homogeneous by macro-field of studies. Then, bridges between communities appear in the following periods (2004-2007; 2008-2011). Lately (2012-2015; 2016-2019), interconnectivity increases significantly, without a corresponding increase in the number of theories proposed to describe the phenomenon.

In table 1.4, we provide some descriptive statistics of the map evolution over time. Specifically, we report the number of theories used in papers published in each period and before (cumulative number of nodes), either including ($N^*$) or excluding ($N$) the theories *only*

**Table 1.4:** Map evolution: descriptive statistics

| Period | All theories ($N^*$) | Theories in the map ($N$) | Links ($E$) | $(\frac{2E}{N})$ | $\frac{2E}{N^*}$ |
|---|---|---|---|---|---|
| 1996-1999 | 7 | 7 | 7 | 2.00 | 2.00 |
| 2000-2003 | 13 | 13 | 14 | 2.15 | 2.15 |
| 2004-2007 | 21 | 20 | 18 | 1.80 | 1.71 |
| 2008-2011 | 29 | 23 | 27 | 2.34 | 1.86 |
| 2012-2015 | 53 | 37 | 57 | 3.08 | 2.15 |
| 2016-2019 | 63 | 43 | 84 | 3.90 | 2.67 |

used alone, i.e., isolated nodes in the overall map. We also report the number of links that appeared in each period and before (cumulative number of links), as well as two simple measures of network connectivity, i.e., the average degree $2\,E/N$, and $2\,E/N^*$.

Looking at the descriptive statistics reported in table 1.4, a tipping point is apparent. Indeed, both the number of theories and the number of links significantly increase in the last two periods. Specifically, in period 2012-2015, we witnessed a burst of theories used–either alone or in connection with others–for the first time to explain co-branding. Finally, in the period 2016-2019, the proportion of "new" theories is much smaller than in the previous time periods, whereas the usage of multiple theoretical approaches skyrocketed. This evidence suggests that analysing co-branding through an interdisciplinary perspective has become the prominent tendency in the last time period.

The evolution that characterises the map is also informative about the tendency of scholars to combine theories from different fields in a given paper. Indeed, figure 1.3 shows that, typically, a theory (node) tends to be used jointly with another theory (establish a connection) if it has already been used in the past to investigate the phenomenon.

This dynamic may reflect a mild innovation process, in which already used theories are joined together to explain a facet of the phenomenon, whereas it is more unlikely that theories appear in connection with others if they were not already used before.

## 1.5 Conceptual Framework

To summarize extant literature on co-branding alliances, we build a conceptual framework as represented in figure 1.4. The conceptual framework begins with the rectangle inputs of a co-branding alliance, whereas the possible consequences of a co-branding alliance are reported in the outputs section, distinguishing between positive and negative

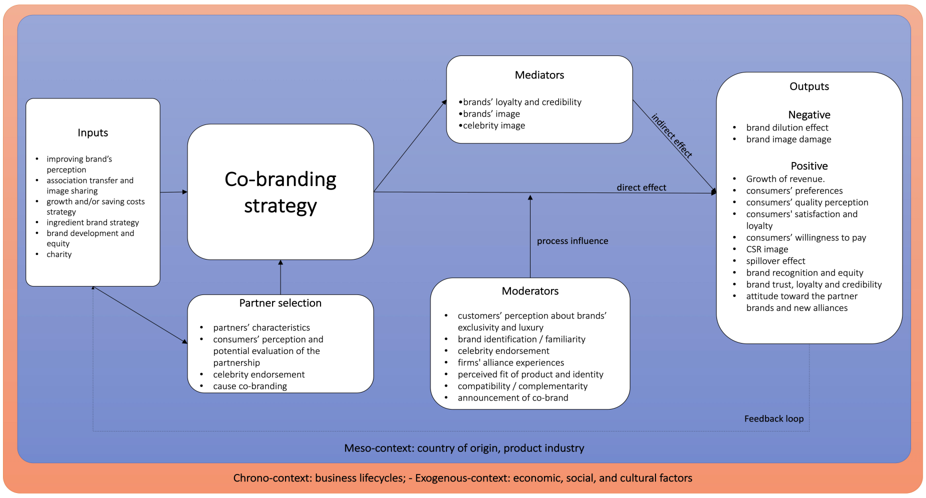



**Figure 1.4:** Conceptual Framework

effects of co-branding. Lying in between, there is the co-branding alliance from which stem the direct and indirect effects of the analyzed alliance. Specifically, we disentangle both mediators and moderators in the relationship between a co-branding alliance and outputs. Furthermore, a specific rectangle of the conceptual framework considers the variables that are also related to partner selection. It is also important to notice that any positive consequence of co-branding that can be naturally seen as input variables in the following period (feedback loop). Furthermore, we call attention to the role of contexts. Specifically, drawing on Kotlar *et al.* (2018) on strategy formulation, we consider three levels of context: (a) the meso-context that epitomizes part of the bricks that frame the firm's nature and scope; i.e., the elements in the meso-context represent a condition that stands from the birth of a firm; (b) the exo-context that considers the economic, social, and cultural factors; and (c) the chrono-context that mainly focuses on the business life-cycle of a brand.

### 1.5.1 Inputs

By analyzing extant literature, we untangle the reasons that lead firms to formulate a co-branding alliance. First, extant literature considers co-branding as an alliance to improve consumer perception of the brand(s). Abratt and Motlana (2002) highlight that each partner's evaluation in a co-branding relationship is affected by the other partner's characteristics in the alliance. This means that one of the reasons that leads brands to collaborate in a co-branding alliance is this kind of transfer mechanism that allows the consumers to perceive brands differently. Moreover, the single partners' judgment affects the alliance itself (Abratt and Motlana 2002).

Second, very interesting inputs for co-branding alliances are association transfer and image sharing. Specifically, Levin (2002) shows that a bi-directional transfer of influence might emerge as an effect of co-branding, and the consumers' attitude towards a well-known brand might be transferred to the less-known partner in the alliance. Furthermore, the positive image (of one or of both partners) can be transferred to the co-branded product (Park *et al.* 1996; Washburn *et al.* 2000). Generally, a partnership between two high-equity brands endows a highly positive image to the co-brand, and the initial equity perception of each brand implies a more positive image of the co-brand in consumers' minds. Thus, pairing two brands may increase positive brand image in consumers' minds (Washburn *et al.* 2000). Firms implement a co-branding alliance to improve brand image (Geylani *et al.* 2008). However, the selection of a partner to ally with should not only be driven by its performance or brand image, since brand uncertainty may even increase as a consequence of the alliance (Geylani *et al.* 2008).

Third, co-branding represents a growth and/or cost-saving strategy (Blackett and Russell 1999). Specifically, a brand alliance allows firms to reach new market targets and consumers (Blackett and Russell 1999) and support portfolio diversification (Barwise and Robertson 1992) that firms also use to reach the goal enlarging their market.

Fourth, a driver to establish a co-branding alliance is resource combination. In more detail, it appears to be crucial in a specific type of co-branding, namely in ingredient branding. In this case, a branded product is a key and material component of another different branded product (Desai and Keller 2002). Ingredient co-branding may lead to advantages, such as price premium and profit increase, which can be seen as critical factors to identify the best partner (Venkatesh and Mahajan 1997).

Fifth, co-branding alliances support brand development since they can improve the value of a co-branded product (Washburn *et al.* 2004) and generate brand value (Oeppen and Jamal 2014). Additionally, one of the most effective ways to leverage brand equity is to enter a co-branding alliance with a brand that already has an established name (Gammoh *et al.* 2006). The result aimed for is that a high-equity brand affects consumers' evaluation of new co-branded products (Besharat 2010).

Finally, a significant segment of the studied literature (Lafferty *et al.* 2004; Lafferty and Goldsmith 2005; Lafferty 2007; Lafferty 2009; Lafferty and Edmondson 2009; Bignè *et al.* 2012; Myers *et al.* 2013; Lafferty and Edmondson 2014) has analyzed cause-related and charity co-branding alliances. A common practice is partnering brands for charitable causes (Lafferty *et al.* 2004). This type of co-branding aims to improve consumers' attitudes toward both the brands and the alliance if the brand alliance is perceived favorably (Lafferty *et al.* 2004). This practice might be positioned in the Corporate Social Responsibility alliance of participating firms.

### 1.5.2 Partner Selection

A characterizing feature of any co-branding alliance is partner selection. Thus, it is not surprising that many papers in our sample focus on partner selection and use different concepts and variables to address the problem regarding "which partner to choose" in the formation of a specific brand alliance. Our review of extant literature recognizes four key aspects.

First, we consider the partner's characteristics. Newmeyer *et al.* (2014) frame the partner selection problem by focusing on the role of three key characteristics of the potential partners, such as the complementarity between the functional attributes of the partners, the consistency of brand image attributes, and the level of diversification between the partners in terms of product portfolios (Newmeyer *et al.* 2014). Focusing on ingredient co-branding, in which each partner offers its own key ingredient to the partnership (Desai and Keller 2002), the "ingredient" appears to be one of the most important aspects underlying partner selection Ingredient co-branding is based on sharing the most important and recognizable characteristics of the partner brands. In this context, Venkatesh and Mahajan (1997) study how to select the most suitable partner brand by choosing between well-known branded components and an unbranded component. Focusing on co-branding alliances aimed to reach new market segments in terms of price and products, Thompson and Strutton (2012) analyze the distinctive way in which a brand alliance can influence consumers' evaluations when it is implemented for the sake of brand extension. In this context, a brand characterized by high fit with the new market target represents a key aspect of the partner selection process. In this way, the brand alliance can help the parent brand to obtain a stronger position than the one it would have reached alone. Thus, the fit between the alliance and the extended product is crucial for the selection of a suitable partner (Thompson and Strutton 2012).

Second, previous studies on co-branding alliances show that partner selection might reflect the projection regarding consumers' perceptions and evaluations of the specific partnership. In detail, the "between-partner congruity" (which identifies the congruity between two or more brands involved in a partnership) may influence the evaluation of the co-branded product by the consumer and, consequently, may guide the process of partner selection (Walchli 2007). Furthermore, the concept behind the partnership, in particular the conceptual coherence of brands' personality-which is a predictor of the consumers' attitude toward the alliance (Van Der Lans *et al.* 2014), may play an important role in the choice of the "best" brand to partner with.

Finally, celebrity endorsement and cause co-branding play a crucial role in partner selection. Specifically, Seno and Lukas (2007) and Halonen-Knight and Hurmerinta (2010) investigate the celebrity endorsement phenomenon. Seno and Lukas (2007) analyze how partners can generate equity for each other and conclude that the partners' image (of both the celebrity and the brand) plays a mediator role in the process of equity creation. In their findings, the authors aim to suggest a mechanism of celebrity-endorser selection (Seno and Lukas 2007). Halonen-Knight and Hurmerinta (2010) treat celebrity endorsement as a particular type of brand alliance. The authors show the implications of image, meaning, and value transfer between partners and the necessity to see the celebrity as a real brand partner (as in a traditional brand alliance) to better manage the process of forming the partnership. Indeed, some elements of brand-alliance management should consider the celebrity-endorsement management, especially in the selection of the most appropriate celebrity in terms of congruity with the brand image (Halonen-Knight and Hurmerinta 2010).

In cause-brand alliances, extant studies show that fit between cause and brand does not significantly affect consumers' attitudes and purchase intentions, and this result is not affected by the level of firm credibility (Lafferty 2007). On the contrary, by analyzing fit as a criterion to select a partner cause in an alliance, the importance of the cause itself turned out to play a key role in shaping consumers' attitudes and purchase intentions more than the cause-brand fit (Lafferty 2009).

### 1.5.3 Moderators Variables

In the next two sections, we consider the variables (i.e., moderators and mediators) that may influence qualitatively and quantitatively the outcomes of a brand alliance. First, we focus on moderator variables; i.e., factors that change, in intensity and direction, the relationship between a co-branding alliance and its outcomes (Baron and Kenny 1986).

A variable that plays a moderating role is exclusivity. Its moderating effects might be different depending on the case in which the (exclusive) brand in the alliance is the host or the ally part (Rodrigue and Biswas 2004), and the exclusivity may be strongly related to the perception of luxury (Moon and Sprott 2016).

Second, brand familiarity appears to be one of the most explored moderators. As Simonin and Ruth (1998) show, brand familiarity in a brand alliance causes a limited spillover effect and has a partial contribution to the alliance's success. However, if the brands involved in a partnership are familiar to consumers, they contribute equally to the alliance's performance, and spillover effects may emerge (Simonin and Ruth 1998).

Third, Ambroise *et al.* (2014) empirically show how a celebrity's personality transfer influences the consumer's behavior and how such a mechanism's effectiveness depends on the celebrity's profile and brands' reputation (Ambroise *et al.* 2014). Generally, we refer to a celebrity endorsement.

Forth, the perceived fit is another factor that acts as a moderator of the effects of a brand alliance. Indeed, brand fit affects the consumers' evaluation of the alliance (Lin 2013). In this regard, Simonin and Ruth (1998) show that the attitude of consumers towards the product of an alliance is affected by individual brand fit, and the fit of both brands with the product (Simonin and Ruth 1998). From the firm's perspective, attention has been paid to compatibility and complementarity. Indeed, some brand characteristics, such as the perceived compatibility between partner brands and partner complementarity, moderate the spillover effect (Tasci *et al.* 2011). Among them, previous partnerships and strategic-alliance capabilities also play a significant role (Gammoh and Voss 2013).

Finally, a moderating effect may be produced by the co-branding alliance's announcement (Cao and Sorescu 2013). Indeed, after an announcement of a new product in co-branding, a firm stock price tend to increase more than if it was announced a single branded new product (Cao and Sorescu 2013).

### 1.5.4 Mediator Variables

Mediators are variables that occur between stimulus and response: they address how or why an effect occurs (Baron and Kenny 1986). Mediators allow us to specify the indirect effects of a co-branding alliance and, therefore, to set a clear borderline between direct and indirect effects.

A prominent example of a mediator is credibility (Bignè *et al.* 2012). Alcaniz *et al.* (2010) analyze firm credibility's mediating role as composed of two dimensions: trustworthiness and expertise. The authors analyze the relationship between altruistic attributions and brand-cause fit on the firm's social responsibility image. Specifically, Alcaniz *et al.* (2010) argue that image fit and functional fit may affect the two dimensions of firm credibility and the consequent effects on corporate social responsibility image (Alcaniz *et al.* 2010).

Furthermore, extant literature indicates that brand image and celebrity image can act as mediators in the equity-creation process of celebrity product endorsement (Seno and Lukas 2007). By exploiting brand and celebrity image, the authors show that celebrity endorsement produces equity for both the branded product and the celebrity herself.

### 1.5.5 Outputs

As the final point of the output of co-branding alliances, we refer to Rodrigues *et al.* (2011) and Chiambaretto, Gurău, and Le Roy (2016) that consider co-branding alliance as a potential situation of co-opetition. As any co-opetitive alliance, co-branding campaigns lead to the variability of the outcomes, compared to the zero-sum outcome of the competition and the fixed positive outcome of cooperation (Nalebuff and Brandenburger 1997). For instance, according to Simonin and Ruth (1998), consumers' attitude towards an alliance affects the evaluation of single partners; it means that the attitude a consumer has regards the alliance can be transferred to the single partner brands, through a spillover effect. The authors also show that the allied brands are not equally affected by the spillover effect (Simonin and Ruth 1998). Arguably, the variability of outcomes may depend on different inputs, partner selection, and moderators and mediator variables. To understand the composition of outcome variables, we distinguish between positive and negative effects. However, some (expected) positive effects of co-branding can turn into negative ones, depending on the alliance's characteristics and on the moderators' impact.

Among the negative consequences, the Brand Dilution Effect represents a typical risk that damages the brand image. Specifically, establishing an alliance with the wrong partner can result in brand dilution, adverse spillover effects, and erosion (Cornelis 2010). Furthermore, when there is information mismatching (and irrelevant information) between the partners, co-branding may negatively affect consumer purchase intentions (Ilicic and Webster 2013).

The expected positive consequences appear to be also relevant. First, the co-branding alliance may lead to the growth of preferences and choices; for example, cause-related marketing is used to encourage purchase intentions (Lafferty 2009). Therefore, amongst the positive consequences of co-branding, the most important is probably an increase in revenues. Indeed, a co-brand alliance might be beneficial to both partners in terms of profit maximization (Shen *et al.* 2017).

Second, a co-branding alliance may also affect the quality perception of a brand and its products. Indeed, especially when one of the partners has some unobserved attributes and allies with a well-known brand, consumers' quality perception increases (Rao *et al.* 1999).

Third, previous studies also show that co-branding can help build customer satisfaction and brand loyalty (Kim *et al.* 2007). Additionally, a brand alliance might be a key tool that firms use to improve their corporate social-responsibility image (Alcaniz *et al.* 2010). Indeed, many papers in the sample analyze the cause-related co-branding (one for all the previously mentioned Lafferty *et al.* 2016).

Fourth, a directly positive consequence of a co-branding alliance may be related to the consumers' willingness to pay (Chang *et al.* 2018). A brand alliance might be viewed as a key element to address consumers' purchase intentions. Specifically, previous studies indicate that the attitude towards the partner brands affects the attitude toward the alliance, and, in turn, such an attitude affects consumers' purchase intention and willingness to pay, beyond the quality of the alliance itself (Rodrigue and Biswas 2004).

Fifth, co-branding may improve brand recognition (Rodrigues *et al.* 2011). As previously mentioned, co-branding might improve or worsen brand equity, depending on whether the single partner has low or high equity, respectively (Washburn *et al.* 2000). Additionally, co-branding can lead to increased brand trust and loyalty (Delgado-Ballester and Hernàndez-Espallardo 2008; Shen *et al.* 2017), and credibility (Rodrigues *et al.* 2011).

Finally, another consequence variable is the attitude toward the partners and the alliance (James *et al.* 2006). Indeed, pairing two brands that alone produce a positive attitude allows the alliance to obtain a positive attitude (James *et al.* 2006).

### 1.5.6 Contexts

Contexts represent events and conditions that exist before or logically precede co-branding actions and are associated with the firms' deep nature. Previous literature appears to consider only the business life-cycles (Blankson and Kalafatis 2007) as a relevant chrono-context. Additionally, extant literature considers the exo-context, specifically related to the cultural context in which a co-branding alliance is established (Diallo and Siqueira 2017). Indeed, the outcomes of a co-branding alliance are moderated by the country's cultural context in which the alliance is applied (Diallo and Siqueira 2017). Cultural attributes (language, norms, beliefs) influence consumers' choices and, in the process of image association when the alliance involves partner brands that come from countries with high cultural differences, this aspect may significantly influence the performance of the campaigns (Decker and Baade 2016). Previous studies show that associating two brands in a brand alliance transmitting the message that the two partner brands share the same values and cultural context (Chiambaretto *et al.* 2016).

Moreover, when the cultural context is strongly related to the corporate brand resource, it may become a key factor for the success of the brand (Uggla 2006). Furthermore, the cultural context is also an important factor in consumer-oriented experiments, since it may substantially influence the results (Baumgarth 2004). Other variables to include in the exo-context are related to the social context. Indeed, the social context can produce brand-specific information in consumer minds (Chan *et al.* 2018). Finally, we should consider the meso-context related to the firms' characteristics: country of origin, product industry, and co-branding contract specificities. For instance, in the presence of a low brand-familiarity in consumer minds, a positive influence of the brands' country of origin has been demonstrated to shape the attitude of consumers toward a brand alliance, an influence which is even stronger than the one produced by brand fit (Bluemelhuber *et al.* 2007). Country of origin may play an important role in ingredient branding, since it can positively influence consumer perception (Cheah *et al.* 2016). Lee *et al.* (2013) confirm that country of origin fit between two allied brands is a key element that affects consumer perception since the country of origin fit may represent a cue to form the attitude toward brands (Lee *et al.* 2013). The country image influences the evaluation of related products but also may be transmitted to unfamiliar products and, also, is able to activate some concepts and knowledge that affect consumer interpretation (Ahn *et al.* 2009). The country of origin may facilitate collaboration between brands due to their proximity, that is not only geographic but also cultural and social (Agostini and Nosella 2017). This latter consideration allows to link the meso- and the exo-context in our conceptual framework. As Decker and Baade (2016) show, in a brand alliance, signals represented by the partner image dissimilarity regarding country of origin, size and industry affect the perception of the brand fit negatively and, in turn, influence purchase intention (Decker and Baade 2016). Accordingly, within the meso context, there is the product industry. Indeed, for example, the product industry is important because, when the partnership focuses on brand extension, partnering with a well-known brand, and also well established in the extended product category, may lead to obtain more favorable results than the ones that would have been obtained by acting independently (Thompson and Strutton 2012). Previous studies do take into consideration context factors, but they seem to not consider their simultaneous presence, by overlooking the actual contextual nature of factors such as country of origin, product industry, etc., which goes beyond the single variable impact.

Finally, Newmeyer *et al.* (2014) call attention to the co-branding contract specificities, and among other factors, posit that exclusivity (intended as single or multiple partnerships, i.e., number of partners a focal brand engages with) influences brand evaluation and consideration by consumers (Newmeyer *et al.* 2014).

## 1.6 Discussion

### 1.6.1 Main findings and Contributions

This chapter summarizes the current state of the art of co-branding literature and provides a comprehensive description of the theories and dimensions involved. More in detail, the study contributes to the extant literature in three ways. First, we draw a map of the theories involved in co-branding analysis that shows how theories are related to each other in describing, interpreting, and modeling the co-branding phenomenon. In the map of theories, we identify all the fields of study involved in the co-branding alliance and the relationships among theories. The process that emerges from the analysis of the map of theories suggests that theory represents the process underlying a co-branded product's perception, elaboration and evaluation on behalf of consumers as following the same phases of a traditional single branded product. Nevertheless, the wide use of this alliance indicates that two brands together can produce greater results and implications for both brands than the single brand can obtain on its own. Furthermore, the map of theories can be used to identify the position of a given paper in relation to extant literature from a theoretical point of view.

Second, we provide a conceptual framework that summarizes the phases and variables involved in co-branding alliance formulation and implementation. Our contribution is to show an updated and broader conceptual framework of the phases and variables involved in a co-branding alliance. It provides a useful tool in both managers' and scholars' hands since it proposes an organized summary of the key factors involved in the launch and implementation of a successful co-branding alliance. Such factors are organized in the framework to underline their position in the process and their mutual relationships. An exciting implication that comes from the conceptual framework is the possibility for a firm to select the appropriate factors, including mediators and moderators, to implement a co-branding alliance that intentionally fits with specific goals.

Third, stemming from the conducted analysis, in the next section, we propose a structured research agenda that may help to orient future research. We build our research agenda based on two pillars. First, we consider Figure 1.2, and we envision the opportunities of leveraging theory intersections. Second, we propose future research lines mainly as a mirror image of the structure of the conceptual framework reported in Figure 1.4. Arguably, we identify some directions for future research by juxtaposing the contents of our conceptual framework and the most advanced of literature on strategic alliances. Strategic alliances research is an interesting starting point because while co-branding alliances represent a type of strategic alliance, co-branding alliances and strategic alliances are phenomena explored by two different academic communities. Thus, we address the opportunities that arise from the interaction between studies from different fields. In particular, on one hand, studies from the marketing field that focus on the consumers' perspective and, on the other hand, studies from the management field regarding the firms' perspective and the aspects related to the management of alliance conflicts.

### 1.6.2 Agenda for Future Research

***Leveraging Theory Intersections***

This chapter shows that a multi-disciplinary background informs co-branding literature; indeed, we observed a high connectivity of theories from different fields in the map in Figure 1.2. Such a map can also be used to envision which theories (from the same or different research traditions) may be fruitfully combined, and, mostly, which ones should not (since they belong to regions of the map that are far away from each other), to obtain new insights for co-branding research. A second cue that emerges from the map in Figure 1.2 suggests it may be of interest to relax the strong rationality hypotheses underlying consumer evaluation processes deriving from the adoption of theories whose foundations are in orthodox economics (on the right side of the map) and leverage theories from the field of psychology not only to represent the way consumers perceive co-branding campaigns initially, but also the way they evaluate the signals they perceive. This shift in the theories adopted to interpret the evaluation process underlying consumer purchase decisions would have two specific benefits: (a) it would allow theory building to represent agents in a more coherent way relative to all phases of the co-branding campaign perception, processing and evaluation; and (b) it would consent biases and heuristics that specifically emerge in consumer evaluation of perceived and processed co-branding signals to be identified and comprehended. We believe that scholars may extend co-branding literature by employing inquiry and exploiting the heuristic potential of theories from other fields that do not necessarily need to be immediately near or connected to the theories have informed research in this field until today (Zahra and Newey 2009), for example, the field of neuroscience (Lee *et al.* 2007) and the evolutionary complex systems field (Miller and Page 2009). Neuroscience may inform studies on testing the brand association map, and this study enriches marketing managers' knowledge on the formulation and implementation of co-branding alliances. Instead, evolutionary complex systems studies allow to capture and interpret the role of the position of a brand in the overall network of a given industry. Within the co-branding phenomena, such an analysis may inform research regarding direct and indirect effect obtained through brands' portfolio of previous partnerships and the relationships between such portfolios.

***Inputs***

According to our review, the bulk of literature considers the inputs of co-branding alliances as a set of consumer-oriented factors. However, it seems necessary also to enquire more deeply on the logics that undergird firm partner selection choices (in addition to increasing sales, saving costs, and product diversification strategy). A qualitative analysis that carefully considers the firms' logics may reveal potential problems that may emerge in practice and needs that are not captured by previous studies. Echoing recent literature regarding strategic alliances, we underscore the importance for managers to have a well-defined understanding of why partners enter an alliance (and precisely a co-branding alliance), as a crucial factor to downgrade the risk of alliance failure and, more generally, improve the effectiveness of this alliance (Franco and Haase 2015).

Second, a fertile research approach is to provide a comprehensive vision of firms' evolution that recursively engage in co-branding alliances. This appears a necessary step to have a comprehensive view that considers both viewpoints simultaneously - both of the firms and of the consumers - to investigate the interplay between the specific dimensions involved in each perspective. For example, we call for qualitative studies that consider in dept interviews of managers of firms involved in cobrand alliances and, at same time, surveys to investigate customers' perspective.

Third, we call for inquiries, both qualitative and quantitative, to estimate how and to which extent the interplay between the firm and the consumer perspectives influence the outcome of co-branding alliances. This research could be useful to understand better how to produce positive consequences and avoid negative ones. Specifically, we call for studies that, drawing on the recent study of Niesten and Jolink (2020), investigate what stimulates partners to focus on social and environmental values (in addition to the economic ones) and what consequences may occur for both partners brands.

***Partner Selection***

First, we observe that most of the literature considered avoids exploring several dimensions involved in co-branding alliances jointly and, in particular, they disregard systemic effects. For example, previous studies either take into account only dyadic relationships between brands or consider only one brand with its history of relationships (Shen *et al.* 2017). From this perspective, an analysis of the co-branding portfolios each firm has established in time and the interactions between different portfolios may be a helpful tool to inform co-branding decisions, specifically in the partner selection process. From a more general perspective, one might consider co-branding as one of the components of alliance portfolios and assess how the diversity of alliance portfolios - in terms of partners, function, and governance (Jiang *et al.* 2010) – explains the decision of partner selection in co-branding alliances.

Second, extant literature focuses on partner selection based on expected consumer reactions. However, we believe that the brand's portfolio of previous partnerships (as a kind of heritage of the brand) may represent a variable that influences partner selection and the results of a co-branding alliance itself. Indeed, given any two brands, the common types of previous co-branded products or previous common partners can be used to introduce a similarity measure between the two brands, and used to suggest new potential partners; specifically, two brands with high similarity may have the same interest to engage in a collaboration. Such an approach would also open to the possibility of operationalizing the partner selection process, and make it automatic, for instance, by developing a recommendation system—a method widely used in other fields such as the financial market (Adomavicius and Tuzhilin 2005).

Third, our analysis shows an initial interest in the network approach to explore a co-branding alliance (Aarstad *et al.* 2015). However, this approach explores the process of consumers' associations between brand and concept related to it (Henderson *et al.* 1998). From a complementary perspective, a possibility that may be worth exploring is to take a holistic perspective in a given market segment, specifically, taking into consideration that the parts (dyadic interactions) may actually be mutually interconnected. Thus, the co-branding alliance results may be better understood by analyzing the network of co-branding relationships in a given industry or in multiple industries.

#### *Moderators and Mediators*

Our review shows an extensive interest regards the relationship between co-branding alliance and performance; however empirical results are still ambiguous. Given the large number of factors included in our conceptual framework, it is unfeasible and perhaps useless to consider all of the possible potential paths connecting the variables identified earlier. However, we try to envision studies regarding some specific paths as an example of fruitful future research. First, a reason that represents a driver to establish a co-branding alliance is image sharing, especially when the partnership links two brands with different market targets, that can be interpreted as a Step-Up or Step-Down brand extension strategy (Kim *et al.* 2001). A variable that may act as mediator might be partner brands' exclusivity linked to the luxury perception (both or just one of them) and the related products. The consequences of image sharing may be the growth of the consumers' willingness to pay (positive) or brand image dilution (negative). The consequences depend on the partner brands' specific characteristics and the nature of the co-branding alliance itself.

Second, while authors consider the importance of brands in terms of loyalty, credibility, and image, the specific characteristics of the product and the most recognizable elements of each brand may play a major role. For example, in the "Tiffany x GLOBE-TROTTER" alliance, partner firms decided to integrate their most recognizable elements in the final co-branded product (the traditional GLOBE-TROTTER luggage with the traditional Tiffany color). Drawing on Zha *et al.* (2020, p. 307), we believe that co-branding alliance "meanings enhance or impair the experience of a brand." We, therefore, suggest that studies exploring whether the impact of a co-branding alliance on consumers' willingness to pay (or other outputs of co-branding alliances) is moderated by the most recognizable elements that characterize individual brands could reveal interesting insights.

Third, our literature review shows that all the variables used as moderators in the relationship between co-branding alliances and outcomes are brand-related. Differently from studies on strategic alliances (e.g., Das and Teng 2001), co-branding research substantially neglects to consider the formal and relational mechanisms (such as trust, commitment, and so on) underlying the management of the alliance between the two partners firms (Hoetker and Mellewigt 2009). Thus, we call for studies that focus on social mechanisms within co-branding alliances: how does the level of trust between firms affect a co-branding alliance's effectiveness? Furthermore, how does the co-branding alliance's past performance inform the future level of trust between the two firms? Finally, how does the interplay between formal and relational mechanisms affect cobranding performance? We believe that studies on mechanisms (especially the social ones) in the co-branding alliance may help integrate research on the life-cycle of co-branding alliances.

Furthermore, it seems worth analyzing whether brand loyalty may act as a mediator that determines indirect effects of a co-branding alliance on the final outcome (see Figure 1.4). A credible hypothesis is that loyalty of consumers to one or both brands in the partnership may influence the final outcome of the co-branding campaign, in particular, it may generate spillover effects. Therefore, we suggest that future research should test such hypothesis through experiments on consumers (Gammoh *et al.* 2006). Such a methodological approach allows the researcher to directly inquire about consumers' perception of image sharing and willingness to pay (Lafferty and Edmondson 2014). Experiments also allow to untangle the moderator and mediator effects of the luxury perception and of the consumers' loyalty.

Finally, the proposed conceptual framework describes in detail the most traditional co-branding structure. However, the recent market dynamics suggests to extend the co-branding phenomenon to other types of campaigns. Indeed, we are witnessing a proliferation of campaigns where a key role is played by the celebrity endorsement of a product, or by influencer activity, and so on. As a future research, we can imagine to analyzes how these phenomena act as new kinds of brand alliances, and the strategy by which brands create their image and meaning in "co-creation", together with consumers. These studies may be carried out effectively through case studies, and through survey or experiments on consumers.

***Outcomes***

First, our review of extant literature shows that studies linking co-branding alliance and outputs usually do not distinguish between the short- and long-term effects. Thus, we call for studies to analyze how long a co-branding alliance affects consumers' perception and to study how, in the long run, a co-branding alliance may modify the interest of consumers towards the single partner brands. Specifically, in this way, it should be possible to isolate a direct effect (in the short run, by analyzing the effect of a co-branding alliance on individual brands' performance and consumer perception) and an indirect effect (in the long run, by analyzing how long such effects of a co-branding alliance persist). Each one of the variables introduced above, may influence not only the outcomes of a co-branding alliance and its success, but also may explain some firms' behavior, such as, for example, the recursive engagement in co-branding alliances. Thus, as a methodological suggestion, considering case studies may help better investigate some specific characteristics and direct effects of the variables described above. In contrast, repeated experiments on consumers may help identify the time scale at which such effects display themselves.

Second, and in a complementary way to the previous research direction, it seems interesting to pursue studies on the contribution of co-branding to the quest for competitive advantage by untangling short- and long-term effects (Dagnino *et al.* 2020). While our review of extant studies mainly considers multiple positive consequences of co-branding, as any strategic alliance, an intrinsic instability (and hidden tensions) may characterize co-branding alliances. From this perspective, we call for studies on the cause-effect relationships between single co-branding alliances and the quest of a temporary competitive advantage and between co-branding portfolio alliance and the emergence of a chain of temporary competitive advantages (Ferrigno 2017; Dagnino *et al.* 2020).

***Contexts***

We recognize that, despite some important advancements, co-branding literature does not offer particular attention to the contexts in which co-branding alliances emerge. First, we note that the bulk of literature considers the meso-context as the condition that stands from a firm's birth; however, business decisions appear to be framed by theories that implicitly rest on a strong notion of agent rationality. We call for studies that investigate the nature of agent rationality underlying the managerial process in formulating co-branding alliances. Are these decisions made in such a rational fashion? Alternatively, are they driven by heuristic and cognitive bias, as suggested by the studies on psychological foundations of management (Powell *et al.* 2011). This theme may also be of particular interest in the context of family firms in which brand name and family surname concur. This circumstance leads to a unique chemistry of family identity and business identity with significant consequences from a psychological perspective (Picone *et al.* 2021). Therefore, we infer that studies regarding variables that affect the family firm's decision to formulate and implement a co-branding alliance could prove very revealing.

Second, a potentially interesting future study would start from an antecedent, namely the country of origin of partner brands, which is assumed to be the same for both brands in the partnership. The hypothesis to be tested is whether or not sharing the same country of origin may increase the recognition of both brands. Cultural context may act as a moderator, and celebrity image (from the same country of origin too) may mediate the effect of the brand alliance. This second study may be developed through experiments on consumers.

Shifting our attention on the exo-context, we observe that, differently from strategic alliance research (Gomes *et al.* 2016), co-branding research has until today devoted a very limited attention to the macro-context. We call for empirical studies based on experiments on consumers in order to investigate these aspects. A specific variable of interest may be the impact of the host-country's governmental and economic policy (Gomes *et al.* 2016), as well as the competition in the post-COVID-19. Indeed, public policy adopted through the health emergency and the solution each firm has implemented to face it, may have an impact on the firm performance and image, and in turn, may produce an effect on consumer perception.

Furthermore, as regards the chrono-context, extant literature in this field has principally considered business lifecycles. Accordingly, we propose to define research lines that can enrich the comprehension of the role of time in co-branding alliances. In particular, aspects of interest include: are cobranding alliances and their outcomes influenced by the age of a "brand"? Is co-branding alliance used to move from a mature to younger industries? How does duration of top management teams limit (or enforce) the marketing offices' inclinations to pursue a co-branding alliance?

Additionally, we call for studies on the cobranding alliance evolution. Strategic management literature recognizes multiple drivers for the emergence of alliances. For example, moving from the resource-based view, Tsang (1998, p. 207) finds the following four drivers: "expansion of resource usage, diversification of resource usage, imitation of resources and disposal of resources." Such drivers can be overlapped with some drivers that we have traced in the literature on brands: growth and/or cost-saving alliance and the association transfer and image sharing. However, while strategic alliance literature shows that "the resources deployed in an alliance undergo transformation either intentionally in order to adapt to the alliance requirements or unintentionally as a result of co-evolution with the alliance" (Madhok *et al.* 2015, p. 92), how the co-brand alliance changes relationships between involved brands is not explored. Accordingly, we call for studies that explore the co-evolution of allied brands and, in such a way, illuminate the chrono-context of co-branding research. Drawing on Madhok *et al.* (2015), we argue that a temporal consideration of brand characteristics will explain the emergence of distinctive configurations of co-branding alliances over time.

Finally, the simultaneous consideration of the chrono-context and the meso-context would allow us to investigate aspects such as: (a) the role of past partnership portfolios in the definition of new co-branding relationships; (b) the reasons and the role in shaping the market of the simultaneous presence of firms that recursively implement co-branding alliances and firms that only sporadically implement such alliances in time; (c) the role of co-branding portfolios (or passed co-branding partnerships) on consumer perception; (d) the time persistence of a co-branding campaign in the consumers' memory.

**Table 1.5:** Agenda for future research

| POSITION | RESEARCH QUESTIONS | METHOD | THEORETICAL APPROACH | DATA |
|---|---|---|---|---|
| Leveraging intersections | • Which theories may be fruitfully combined, and which ones should not, in order to obtain new insights for co-branding research?<br>• Would it be possible to relax the strong hypothesis of rationality underlying consumer evaluation theories? Would it be appropriate to leverage upon psychology theories to represent how consumers evaluate the signals they receive? | Qualitative | Interdisciplinary: borrowing, adapting, and mixing theories from several fields | Co-branding previous research database |
| Inputs | • What are the company-oriented logics underlying partner selection?<br>• How is company performance dynamics influenced by recursively engaging in co-branding alliances?<br>• How does the interplay between companies and consumers perspectives influence the outcome of a co-branding alliance? | Qualitative; Qualitative: both companies and consumers perspectives; Qualitative and quantitative | Management theories | Database of previous co-branding alliances; In-depth interviews and surveys; Results of interviews, surveys, and companies' performance measures. |
| Partner Selection | • Do the portfolio of alliances a brand established in time and the interactions between different brands' portfolios inform co-branding decisions?<br>• Does the brand's portfolio of previous partnerships (as a proxy of the brand's heritage) influence partner selection?<br>• Are co-branding alliance outcomes better understood by analysing the network of co-branding campaigns instead of the single alliances? How does such holistic perspective help to understand the whole industry dynamics? | Quantitative | Network theory; Signaling theory | Database of previous co-branding alliances. |

Continued on next page

Table 1.5 – continued from previous page

| POSITION | RESEARCH QUESTIONS | METHOD | THEORETICAL APPROACH | DATA |
|---|---|---|---|---|
| Moderators and Mediators | • Are there potentially interesting paths in the presented conceptual framework yet unexplored?<br>• Do the product's specific characteristics and the most recognisable elements of a brand play a major role in establishing an alliance?<br>• Focusing on the social mechanisms underlying co-branding alliances: how does the level of trust between companies affect a co-branding alliances' effectiveness? How does the co-branding alliances' past performance influence the trust between the two companies? How does the interplay between formal and relational mechanisms affect co-branding performance?<br>• Is it possible to analyse how phenomena such as celebrity endorsement of a product and influencer activity act as new kinds of brand alliances? What are the outcomes when companies use a strategy through which they "co-create" brand image and meaning together with consumers? | Qualitative and quantitative | Psychology theories | Results of in-depth interviews to company managers and experiments on consumers about actual and potential co-branding campaigns. Case studies. |

Continued on next page

**Table 1.5 – continued from previous page**

| POSITION | RESEARCH QUESTIONS | METHOD | THEORETICAL APPROACH | DATA |
|---|---|---|---|---|
| Outputs | • For how long a co-branding alliance affects consumers' perception? How, in the long run, does it modify the interest of consumers towards the single partner brands? Which are the direct and indirect effects (direct: the impact of a co-branding alliance on individual brands' performance and consumer perception; indirect: how long such effects persist)?<br>• What is the contribution of co-branding to the quest for a temporary competitive advantage or a chain of temporary competitive advantages? | Qualitative and quantitative | Economic theories; Management theories | Case study and experiments |
| Contexts | • Are co-branding decisions made in a rational way? Are they driven by heuristic and cognitive bias?<br>• What is the impact of the macro-context? How do political and socio-economic variables affect co-branding decisions and outcomes?<br>• Are co-branding alliances and their outcomes influenced by the stage of brand life cycle? Is co-branding alliance used to move from a consolidated to a younger industry? How does the duration of top management teams limit (or reinforce) the company inclination to pursue a co-branding alliance? | Qualitative and quantitative | Management theories | Case studies, survey, and experiments on consumers |

### 1.6.3 Managerial Implications

Co-branding phenomena have increasingly spread in the last years, and contemporaneously it attracts significant managerial and practical interest. Our analysis of the state of the art allows us to identify some implications for managers.

First, technological change and the explosion of different types of brand alliance lead managers to envision and implement strategies that more and more involve consumers as stakeholders, in such a way that firms and consumers can express themselves with only one voice. Firms need to attract consumers' loyalty and trust. At the same time, consumers want to identify and share a given message and become part of the product development and brand storytelling. In this context, managers should consider that the borderline between consumers and producers tends to weaken. Moreover, our analysis shows how firms need to trust each other to implement such strategies, to gain competitive advantages, such as improving their image and meet the tastes of a wider market target. The bottom line of this analysis is that trust—in consumers and other firms—has become fundamental to build reputation.

Second, managers can use the conceptual framework proposed in Figure 1.4 to identify the variables and dimensions involved in a brand alliance. Specifically, looking at the scheme, a manager can identify the appropriate variables to use in defining a co-branding campaign, given her specific goals. Furthermore, a manager can exploit the elements in the framework to exploit and develop brand's strengths and moderate brand's weaknesses. Moreover, according to the expected outputs of a campaign and brand specific characteristic, managers can use the presented maps to facilitate the process of partner selection in the definition of an alliance.

Third, the contexts in which a firm is embedded may guide the identification of the most suitable strategies to improve brand positioning in the market, considering the whole system, with all its elements, facets, and contexts, as it stands at a given time. Such strategies and the use managers can make of the conceptual framework reported in Figure 1.4 may also vary depending on the stage of brand life cycle. In other words, our conceptual framework represents a tool for managers that can incorporate and help to respond to social, economic, and market changes (exogenous dynamics), as well as to the evolution of a brand and the corresponding firm (endogenous dynamics).

Finally, managers can think in terms of single company strategies as well as joint company strategies, to reach specific goals. Along this line of thinking, they can influence and be influenced by co-branding campaigns in both direct and indirect ways.

## 1.7 Limitations

This study presents some limitations. First of all, we do not analyze in deep the temporal dimension, in particular, the evolution of studies and theories over time, which might be important to explain the burst of the co-branding phenomenon over the last few years. Second, besides the wide spread of the phenomenon, the study of co-branding should take into account and deeply understand the effects of other types of alliance that showed a similar burst, for example, celebrity endorsement, featuring, and so on. Admittedly, the present study only marginally touches on these aspects. Finally, it is advisable to consider a more global vision of the whole market to deepen our understanding of the dynamics and the associated variables involved in the co-branding phenomenon. Specifically, taking into consideration all the brands that characterize a given market, and concentrate on the evolution of the connections among such brands, as represented by alliances, may provide a better understanding of the whole market and its evolution.

## 1.8 Conclusions

The large extension of research, combined with multiple theoretical perspectives and empirical approaches, confirms the interest in co-branding alliances. We hope this chapter serves as a trigger to orient and stimulate new studies on the topic. Indeed, co-branding alliance may have a powerful impact on brands' and firms' development, other than the market as a whole and, consequently, may also have a wide spreading in academic marketing literature. The present study helps to draw and summarize findings so far. Specifically, it highlights how co-branding is embedded in different contexts and dimensions of both firms and consumers. The two maps presented in this study underly the interdependence among such dimensions, which needs to be carefully considered in the brand management process, as it suggests the presence of a mutual dependence among firms and between firms and consumers already at the stage of envisioning a new campaign.

# Chapter 2

# A Network Perspective on co-branding campaigns: evidence from the fashion industry

**Abstract**

*Co-branding strategies have attracted increasing attention in the academic community over the last decades. Previous research privileged the analysis of co-branding campaigns by studying dyadic relationships between brands. Here, we take a network view to highlight the influence of the single companies' co-branding portfolio on partnership formation. From a theoretical perspective, the studies on co-branding analyze the process through which partner brands send a "signal" to consumers. Here, instead, we propose to look at partner selection as a process in which a signal, namely, the portfolio of previous co-branding campaigns, is sent from one brand to the others. In particular, we focus on the network of co-branding campaigns in the fashion industry, and look at the system through the lens of Signaling Theory. Indeed, we demonstrate that brand portfolio and network structure are predictive of further partnerships, and therefore, they exert a significant influence on the partner selection process.*

## 2.1 Introduction

The *brand-leveraging process* is one of the most interesting topics in branding research (Keller 2003a). It analyses how consumers react to a brand strategy when a brand is related to other entities, e.g., another brand (Keller 2003a). When researchers talk about co-branding, they refer to a specific marketing strategy in which two brands create a new product together that will carry the specificities and names of both brands in the partnership (Washburn *et al.* 2000). In this chapter, we analyze the brand-leveraging process from the companies' perspective and adopt a holistic approach to analyze co-branding alliances to infer the logics underlying partnership formation. In particular, we inquire whether the portfolio of partnerships a brand has constructed in time influences the formation of new co-branding partnerships. The position of a brand in the overall co-branding network is not only descriptive of such a portfolio but also accounts for indirect brand relationships due to the alliances between brands from different portfolios.

Furthermore, we aim to understand whether such information about brands is predictive of the formation of new partnerships. Such a predictive power would imply a significant change of perspective in the investigation of co-branding strategies. Indeed, extant studies typically analyze co-branding campaigns in dyads (Geylani *et al.* 2008, Ahn *et al.* 2010, Motion *et al.* 2003), a perspective that does not take into account the portfolio of co-branding alliances each company established in the past and the position each brand has within the overall network of co-branding partnerships. Studies on brand partner selection (Venkatesh and Mahajan 1997; Walchli 2007; Newmeyer *et al.* 2014; Van der Lans *et al.* 2014) investigate brand relationships in pairs and do not take into account network effects. Furthermore, several studies regarding partner selection in co-branding campaigns implicitly or explicitly interpret partner selection as a consequence of firm conjectures regards the effects of branding partnerships on consumer perception and do not take into account possible alternative logics, especially the ones that originate from the company's perspective. For instance, Venkatesh and Mahajan (1997) analyze consumers' perception related to ingredient branding by analyzing how consumers perceive a product with branded or unbranded components (Venkatesh and Mahajan 1997). Van der Lans *et al.* (2014) study how several dimensions associated with brand perception (such as Sincerity, Competence, Excitement, and Sophistication) influence the consumers' perception of an alliance. Then, the results of the analysis are used to build a model of partner selection (Van der Lans *et al.* 2014). Instead, Thompson and Strutton (2012) focus on using a co-branding strategy for the sake of brand extension. Specifically, they explain that partnering with a company with a higher perceived fit to brand extension positively influences the outcome (Thompson and Strutton 2012). Our approach integrates these two aspects by considering the company's perspective through the role played by the portfolio of partnerships each company has established in time on the formation of new co-branding relationships. The portfolio of historical partnerships of each brand has in the network indirectly includes information about the consumers' perception and feedback (indirect effects and hubs). In the present study, following Signaling Theory, we interpret the brand's portfolio as a signal sent from a brand to another that may lead to the establishment of a new co-branding partnership. The adoption of a network perspective in the present analysis is supported by previous studies on the factors that influence the capability of companies to attract potential partners that identify the companies' experience in alliances, i.e., the portfolio of previous partnerships, as a crucial factor (Gammoh and Voss 2013). Although this has not been the focus of previous studies on co-branding strategies, the study of interfirm alliances has underscored that alliance experience is a strong attractor for prospective partners. Consequently, the portfolio of previous co-branding alliances may be interpreted as a signal of the degree of alliance experience a company has at any given point in time.

Adopting a complementary approach to previous research that focused on the systemic view of alliances from the perspective of consumers (Henderson *et al.* 1998; Jevons *et al.* 2005; Uggla 2006), here we also take a systemic vision, but from the companies' point of view. Specifically, we adopt a network perspective that allows us to reveal and analyze how the structure and properties of the whole co-branding network (i.e., the brands' portfolio and position in the overall system) influence partnership formation.

The present study contributes to leverage signaling theory (Spense 1973) in marketing literature by proposing a model of partnership formation to shed light on the effects of signals emitted by the companies in the system (network view). Indeed, in our approach, the partnership portfolios of two brands act as trust signals for both companies in the negotiation phase of a potential co-branding campaign, reducing information asymmetry. The implementation of a recommendation system on the network shows that the portfolio of previous partnerships and the position of the brands in the network actually do influence a cobranding campaign in the formation of new co-branding alliances.

Finally, connectivity measures of nodes, both direct and indirect, in the network of co-branding campaigns can be informative about the logics that underlie the formation of partnerships. Specifically, they reveal: i) the central role of some brands in the network (hubs) and their "broker" position; ii) that a limited number of local logics underlie the formation of clusters within the overall network (for instance, country collaboration, competition effects); and iii) the specific brand position in the whole network and its portfolio of relationships may be used to identify new potential partnerships.

The chapter is structured as follows. In the next section, the conceptual framework is presented. Then, the research objectives, the methods, and data collection procedure are explained. After that, the chapter presents the inferential analysis and a descriptive analysis of the network of cobranding campaigns, which are followed by a discussion section. Finally, we draw our conclusions, describe the limitations of the study, and indicate potentially interesting followup research.

## 2.2 Conceptual Framework

One of the most important assets of a company is its brand name and the consumers' association of the brand with its product (Keller 2003b). The "consumer brand value" can be defined as the combined effect of brand knowledge, attitude, and behavior that affect the consumers' preferences and purchase intention, and it represents an attempt to quantify the consumers' perception of the brand itself (Pansari and Kumar 2017).

A positive brand image is one of the most relevant elements at the basis of the competitive advantage of a company because it allows consumers to associate specific product elements to it (Rodrigues *et al.* 2011). As shown by Alcañiz *et al.* (2010), brands are typically used as signals to identify the position of both the products and the associated companies in the market (Erdem *et al.* 2006). Thus, companies need to create a brand with high value and identity to differentiate their products from those of competitors (Alcañiz *et al.* 2010).

An increasingly used strategy is co-branding, which determines a bidirectional transfer of reputation between two brands, and aims to generate products with higher perceived value (Rodrigues *et al.* 2011). Indeed, a *co-branding strategy occurs when two brands jointly appear on the logo and/or package of a new product* (Grossman and Till 1998; Besharat 2010). Notice that, within the scope of the present study, the concept of co-branding involves an alliance of at least two brands that jointly propose one or more products (including a whole line of products) to the market with a limited or unlimited time horizon.

Therefore, in this study, we do not consider *composite branding*, which occurs when two brands create a new compound brand name (Tsai *et al.* 2014).

Chiambaretto *et al.* (2016) show how co-branding might be beneficial to both partners from the perspective of penetrating (new) market segments. Such an effect is favored by brand image transfer, which is due to the brand-association resulting from the co-branded product in consumers' minds. With a co-branding relationship, brands send a specific signal communicating that the partners share the same value and quality level (Chiambaretto *et al.* 2016).

Co-branding is also a strategy that companies use to build brand equity by leveraging the association with the partner brand, to expand their position into a new market (Kottemann *et al.* 2017). These effects can generate competitive advantage (Kottemann *et al.* 2017). As occurs for brand extension (DelVecchio and Smith 2005), co-branding can be a strategy used to produce a premium price and as a tool to reach a stronger position in the market (Bengtsson and Servais 2005).

It is worth highlighting that brand representation is a collection of brand attributes that reside in the consumers' long-term memory, and specific activation cues can trigger such representation in a particular moment (Cornelis 2010). The process of recalling the information linked to the brand name in the consumers' mind produces a brand association (Cornelis 2010). Furthermore, Keller (2003a) underscores the relevance of the brand-leveraging process in brand research, as it analyses how the formation of a connection between a brand and another entity (a brand, a place, a person, etc.) affects consumers' perception of the brand itself (Keller 2003a).

Despite the benefits of co-branding, this strategy can also produce adverse effects on partner brands (Geylani *et al.* 2008). The prominent risk of co-branding is to ally with a brand that can decrease the products' brand equity (Washburn *et al.* 2000) or produce brand dilution and adverse spillover effects (Cornelis 2010). The adoption of a network approach to investigate co-branding, as the one adopted in the present study, is supported by Henderson *et al.* (1998). Indeed, they show that brand effects of alliances, such as dilution, can be detected through suitable network property indicators, such as density (see, for instance, Newman 2011).

The approach proposed in this study highlights the relevance of the historical portfolio of partnerships that each brand has created in time to forecast new alliances. In this way, we argue that the system as a whole is more informative than single dyads (Miller and

Page 2009) and that portfolios of partnerships represent signals shared by the companies during the partner selection process.

Stemming from Spence (1973), signaling theory has become a widely used theoretical approach in situations characterized by information asymmetry–i.e., when the two parties have access to different information (Connelly *et al.* 2011) or when there is incomplete information in the system (Brunner and Baum 2020). The process considered in signaling theory involves two parties (the sender and the receiver) and a shared signal (information). The sender chooses if and how to send information (the signal) to the receiver who decides how to interpret it (Connelly *et al.* 2011). The signals sent (asynchronously) by the parties also represent the critical information that can generate the mutual "trust" between the parties (Brunner and Baum 2020). Both the signal transmission process and the asymmetrical information between potential partners that characterize the interactions of the present study lead us to choose signaling theory as a suitable framework to model the partner selection process in co-branding alliances. Previous research in marketing has used signaling theory to describe signal transmission from a brand to consumers (Gammoh *et al.* 2006; Rao and Ruekert 1999) and to investigate how the experience gained from previous alliances influences the quality of a new partnership (Gammoh and Voss 2013). In this study, instead, we analyze the impact of the portfolio of previous partnerships on partner selection in a co-branding campaign, where the portfolio represents the *signal* shared by the brands.

Previous research highlights that the product brand portfolio can also be a key element in creating organizational attractiveness to potential employees in the recruitment process (Brunner and Baum 2020). In their study, however, Brunner and Baum (2020) consider the product brand portfolio of a corporate brand, whereas, here, the brand portfolio has a different connotation, as it indicates the list of previous partnerships of a given brand. However, similarly to their study, multiple signal exposure and consistency are relevant themes in the present research (Brunner and Baum 2020). Indeed, the portfolio of the brands' previous partnerships carries information about its reputation and may also influence the trust of the receiver brand, that is, a potential partner brand. Indeed, on the one hand, the quality and consistency of previous partnerships can be used by the receiver brand to assess the reputation of the sender brand. On the other hand, the presence in the receiver's portfolio of one or more brands from the sender's portfolio can win the *trust* of the receiver (Easley and Kleinberg 2010). Signaling theory has mostly been applied to investigate the interaction between companies and consumers, where, for instance, the organizational characteristics of a company can represent the signal received and used by consumers to inform their purchase decisions. However, a similar mechanism can also be envisioned to occur between two companies. Indeed, by assuming the company's perspective, some brand attributes can reflect the reasons that lead companies to select a specific partner brand and establish an alliance (Decker and Baade 2016). Such motivations may include access to new geographic markets, new market targets, and different or complementary resources (Decker and Baade 2016). Differently from strategic alliances, co-branding alliances require a company to pay more attention to the risks directly related to brand value, prominently, dilution effect, instead of strategic risks, such as opportunism (Decker and Baade 2016). According to signaling theory, companies can reach more favorable results by reducing the information asymmetry between companies and consumers. For instance, if a company's identity is partially unknown to both consumers and potential partners, the company can reduce such an informational gap by sending signals regarding the past and the present of its marketing strategies (Pecot *et al.* 2018). Similarly, two brands linked by a co-brand partnership implicitly launch a signal of mutual "trust" to the market. Indeed, consumers can exploit their "private" information about the single partner brands (that represent signals as well) and create an association that, overall, leads to the formation of the alliance value in their mind (Decker and Baade 2016).

In this study, we empirically observe that the brands' portfolio of previous partnerships represents a facet of the brands' heritage that acts as a signal of quality and trust to the other companies in itself (Pecot *et al.* 2018). Typically, we refer to brand heritage as "a dimension of a brand's identity found in its track record, longevity, core values, use of symbols and particularly in an organizational belief that its history is important" (Urde *et al.* 2007:4). However, the heritage of a brand may be partially unknown to consumers leading to information asymmetry. Therefore, engaging in an alliance with brands already perceived as having a coherent and robust heritage may help the brand to reinforce the perception of its origin.

One of the most relevant topics of network theory within the management domain is the process of partner selection (Beckman *et al.* 2004). From the company's perspective, the extension of its network can pursue different aims, for example, explore new opportunities by gaining access to new knowledge and resources - that is, a form of exploration. On the contrary, the concept of exploitation occurs when a company tends to reinforce an existing relationship (Beckman *et al.* 2004). A company may also create an alliance to face uncertainty. Indeed, the creation of a new partnership represents a way to face company-specific uncertainty, which means the unpredictability of the future that comes from incomplete information (Beckman *et al.* 2004), i.e., information asymmetry.

Establishing a new partnership is a signal of confidence that a company sends to the market (Beckman *et al.* 2004). This conceptual view is similar to ours in that we interpret the brand portfolio as a signal of "trustworthiness" a brand sends to another company to engage in a new co-branding alliance.

As Sarkar *et al.* (2001) notice, some structural aspects are crucial in the understanding of partnerships, especially elements such as the reasons that lead to partner selection and partnership formation (Sarkar *et al.* 2001). Nonetheless, the choice of who to collaborate with is highly influenced by the resources a partner can share and the actual benefit that a company can obtain because they are decisive elements for the alliances' success (Sarkar *et al.* 2001).

The partner selection process should identify the best (with the best resources, skills, and knowledge to share) among all the potential partners (Shah and Swaminathan 2008). In strategic alliance literature, amongst the main factors that influence partner selection and subsequent strategies, there are trust, commitment, complementarity, and economic value (Shah and Swaminathan 2008). All these factors seem to be consistent with our approach regarding the brand portfolio of previous partnerships as a signal a brand sends to other brands in the system.

In this study, we focus our attention on the process of partner selection. Previous studies have analyzed the partner selection process from different points of view, i.e., partner selection in ingredient branding (Venkatesh and Mahajan 1997), consumer perception of partners' brands (Walchli 2007), brand image similarity of partners as a driver of brand fit (Van Der Lans *et al.* 2014), brand and product attribute complementarity (Newmeyer *et al.* 2014), brand extension (Thompson and Strutton 2012), and celebrity endorsement (Seno 2007; Halonen-Knight 2010). In the studies above, signaling theory provides the framework to describe the impact of an alliance on consumers. In particular, these studies analyze how the signal emitted by an alliance towards the consumers influences the outcome of the co-branding campaign, depending on the consumers' perception itself. Spence (1973) analyzed this process through the lens of Signaling Theory (Spence 1973), and Venkatesh and Mahajan (1997) investigated the impact of an ingredient co-brand strategy on consumers, specifically the impact of choosing branded components instead of unbranded ones. Another study considered the effect of partner-brand congruity on consumers' perception of the co-brand (Walchli 2007). Furthermore, Van Der Lans *et al.* (2014) focused their attention on consumers' perception of brands' fit (Van Der Lans *et al.* 2014). Instead, in the product endorsement by a celebrity, the objective is to select the right partner to improve brand equity for both partners (Seno and Lukas 2007), for instance, by determining a meaning and value transfer (Halonen-Knight and Hurmerinta 2010).

The focus of this study is on the role played by historical and trust aspects, just marginally considered in previous research. These aspects are: i) the brand's portfolio of (previous) cobranding campaigns and ii) the indirect effect produced by the network structure surrounding potential partner brands. These aspects are different, though not mutually independent. Indeed, if one looks at the whole network of co-branding campaigns, a brand portfolio is able to provide information only about the subnetwork adjacent to the brand (first neighbors) and its (direct) effect on forecasting future campaigns. However, an enlarged subnetwork that includes second neighbors—that is, the neighbors of brand first neighbors—allows one to consider indirect effects on the formation of new alliances. In the section "Discussion," we show that such signaling mechanisms influence the process of partner selection. Indeed, the proposed procedure takes into account the portfolio of previous co-branding partnerships of each brand and the trust role represented by the most active brands in the system. Thus, while previous studies propose mechanisms of partner selection based on the characteristics of potential partners and products (dyadic perspective), we show that non-dyadic mechanisms–depending on the network topology of already established alliances–are relevant and exploitable to anticipate new partnerships. Furthermore, while previous studies analyze single dyadic cases (Venkatesh and Mahajan 1997) or a selection of alliances, even with a synthetic database (Van Der Lans *et al.* 2014), our application is empirically grounded, and it relies upon a dataset of real co-branding alliances.

## 2.3 Research Objectives

The objective of the present study is to investigate the logics underlying partnership formation to study how it is influenced by the portfolio and position of the two brands in the fashion industry co-branding network. Furthermore, our research aims to forecast new alliances by exploiting the brands' portfolio of previous co-branding alliances and the brands' position in the co-branding network. The research propositions of the study are:

i. The brands' portfolio of co-branding relationships and the brands' position in the network of co-branding campaigns are predictive of the formation of new co-branding relationships;

ii. Different logics underlying co-branding partnership formation may be identified, as well as their effect on the structure and properties of the co-branding network.

To test the first proposition, we use recommendation systems (Adomavicius and Tuzhilin 2005). These methods are computational tools typically used to provide a ranked list of objects to users in a way that potentially meets their preferences. They exploit information about users' similarity (Fiasconaro *et al.* 2015) and objects' similarity. In the present study, we use recommendation methods to suggest new potential partners to each brand by using the overlap between the partnership portfolios of two brands as a measure of their similarity. Specifically, the similarity between two brands increases as the proportion of shared previous partners increases.

The second proposition is tested by revealing and characterizing clusters of brands in the cobranding network. We determine the clusters of brands in the co-branding network through Modularity optimization, which is a method that determines communities (clusters) by maximizing the deviation of the observed number of Links within communities from the one expected in a randomly rewired network (Newman 2011). Afterwards, we study the characteristics of brands belonging to each Community to identify the logics that reflect the brands' potential intention to engage in co-branding alliances.

## 2.4 Data Collection

To reconstruct companies' co-branding portfolios and identify company positions in the overall network of co-branding alliances in the fashion industry, a network of co-branding campaigns is constructed. Such a network is obtained by linking together companies that have formed cobranding alliances at some point within the fashion industry.

The network of co-branding alliances has been built by using a specific procedure. First, we started from online brands' lists [1]. Specifically:

- Fashion united, top 100 fashion companies Index (10/2019);
- Brand Directory, Apparel 50 2019 Ranking;
- Forbes, The World's Most Valuable Brands (2019);
- Financial Times, Top 100 global brands 2019;
- Ranker, The Best Luxury Fashion Brands (10/2019);
- Ranker, The Best Italian Clothing Brands; (10/2019);
- Ranker, The Best French Clothing Brands. (10/2019);

Then, we merged these lists, and we used a Depth-First Search (DFS) method (Even 2011) to search for co-brands on Google.

Specifically, for each brand in the list, we looked for all the brand collaborations among the top 100 outcomes provided by Google to the joint queries "BRAND NAME" & "alliance," "BRAND NAME" & "co-brand." All the retrieved collaborations were included in the network of co-brand (i.e., our dataset), whereas if unlisted brands appeared, they were divided into two categories, fashion and other, and fashion brands were included in the original list to be searched as well. The procedure was repeated until all the brands included in the (expanding) list were searched for. In other words, the search procedure was performed for all new nodes (brands) that were not included in the original list, provided that they appeared in some retrieved collaboration and were classified as fashion brands. In contrast, if we found a partnership with a brand out of the fashion industry, we added the link (collaboration) in our dataset, but we did not further search the non-fashion brand on Google.

Some extra specification is needed to clarify better the process underlying dataset construction. We treated retail brands as "fashion brands" only if the retail had its product label. Another specification concerns "holding companies" that appeared in some

[1] https://fashionunited.com/i/top100
https://brandirectory.com/rankings/apparel/table
https://www.forbes.com/powerful-brands/list/
https://www.ft.com/content/3a3419f4-78b1-11e9-be7d-6d846537acab
https://www.ranker.com/list/best-luxury-fashion-brands/ranker-shopping
https://www.ranker.com/list/best-italian-clothing-brands/ranker-shopping
https://www.ranker.com/list/best-french-clothing-brands/ranker-shopping

of the original lists. Such holding companies were replaced in the original list by all the brands that compose the business group. Thus, we treated subsidiary companies as single brands. The construction process of the dataset lasted two months, November and December 2019. At the end of the data collection procedure, the dataset included 881 brands connected by 1346 links.

## 2.5 Quantitative analysis

### 2.5.1 Hypothesis testing: predicting co-branding campaigns

In this section, we investigate the possibility that the brands' portfolio and the brand positioning in the real co-brand network are predictive of future partnerships. Specifically, we demonstrate the following

**Proposition**: *the co-branding network has predicting power on deleted campaigns.*

The demonstration is done by showing that the *null hypothesis* ( $H_0$) that *the co-branding network has no predicting power on deleted campaigns* should be rejected if tested on our data.

To do so, we rely upon *recommendation systems*–a topic heavily investigated in computer science, network theory, and economics, with application to various fields (Adomavicius and Tuzhilin 2005), e.g., media-services providers, insurance companies, and investment consultants. Recommendation systems are devised to suggest *objects* of potential interest to *users* in user-object systems by processing information about previous choices made by the users. However, the apparent symmetry between the treatment of items and users in such methods (Fiasconaro *et al.* 2015), on the one hand, made it possible to devise mixed user-object methods to improve the effectiveness of the recommendation.
On the other hand, such symmetry has opened to the possibility of applying them to social and economic systems where the qualitative difference between users and objects disappears (Zhang *et al.* 2007), e.g., the friendship network. Within the scope of the present study, we use recommendation methods for the sake of partner selection. In particular, they are used to provide a ranked list of potential partners for each brand in the system, that is, a ranked list of partner-brands that a specific brand might be interested in collaborating with. The Recommendation systems construct the ranked list by processing information limited only to the brand portfolio and the surrounding network structure. Recommendation methods differ from each other, mostly depending on the metrics used

to quantify the similarity between the elements (brands, in our case) of the system (Fiasconaro *et al.* 2015). It is worth underscoring that the objective of this study is not to determine the most effective recommendation method to predict brand alliances but rather to show that the brand portfolio and network structure are predictive of future co-brands. Therefore, we consider one of the most popular recommendation methods, the Collaborative Filtering (CF) (Sarwar *et al.* 2001), in which pair similarity is calculated through the Hub Promoted Index (HPI) (Ravasz *et al.* 2002). The heuristics behind the method is that two brands that share a significant proportion of their portfolios *should have* similar "*preferences.*" Therefore, brands that belong to the portfolio of only one of the (two) brands represent potential partners of the other brand in future campaigns [2].
To test our hypothesis, we shall compare recommendation lists obtained from the analysis of a co-brand network subset (training set) with actually observed collaborations (test set). A *bona fide* assessment of recommendation quality requires that the training set and test set do not overlap. Here, we accomplish this goal by using k-fold cross-validation (Molinaro *et al.* 2005), which is a non-exhaustive cross-validation method. Specifically, we randomly split the cobrand network into ten non-overlapping sub-networks and evaluate the quality of recommendation independently for each sub-network (the test sets) by using the union of the other nine sub-networks as a training set to construct the recommendation lists. Brands that appear with only one collaboration in the co-brand network can belong to either the test set or the training set, and, therefore, they are not suitable for the present study. Accordingly, we performed the analysis of the *2-shell* of the co-brand network, which includes 330 brands connected by 823 links (collaborations). The *K-Shell* of a network (Carmi *et al.* 2007:11150) is obtained by iteratively pruning the network from the nodes with a number of connections lower than $k$, until all of the remaining nodes form a subnetwork in which each node (brand) has at least $k$ links (collaborations) with the other nodes (brands) in the shell. We study the K-Shell decomposition of the network, up to its core shell, in section “Descriptive analysis”. Here, we just focus on the *2-shell*, which is the largest subnetwork that allows us to test the predicting power of brand portfolio on future collaborations.

We evaluated the quality of a recommendation list by calculating the average R-score

[2] A known drawback of CF method is that it tends to provide recommendation lists in which the preference for network hubs is possibly overestimated. However, it’s worth to say it again, determining the most effective recommendation method for the sake of partner selection in co-brand campaign is out of the scope of the present chapter.

(Zhou *et al.* 2010) in the test set. For each brand, say $B$, in the training set, we evaluated the quality of recommendation as the average rank in its recommendation list of actually observed cobrand partners of $B$ from the test set. Such a value is then divided by the overall number of brands in the recommendation list [3] of $B$ to obtain a standardized quantity, the brand-specific R-score, which ranges between 0 and 1. Finally, the mean value of all the brand-specific R-scores can be interpreted as an overall measure of the quality of recommendations: the smaller the R-score, the better the recommendation quality. In the case of random recommendations, i.e., no predicting power, the expected value of the average R-score is 0.5. Therefore, a significant deviation from 0.5 is a mark of the predicting power of the recommendation system. We report the average R-score in figure 2.1 for each one of the ten test subsets considered in one 10-fold cross-validation, s1, s2, ..., s10. To account for the statistical uncertainty associated with the finite sample size and better clarify the implication of obtained results, the figure also shows the average R-score obtained for each specific subset after performing a random rewiring of the training sub-network (red line in the figure), which mimics the result expected under the null hypothesis $H_0$. As anticipated, the R-score associated with the prediction after a random rewiring of the network fluctuates around 0.5. Finally, error bars associated with R-score values correspond to three standard deviations (as evaluated over the brand-specific R-scores).

Figure 2.1 clearly shows that the average R-scores obtained across the ten validation subsets are significantly lower than 0.5. To associate a P-Value with the null hypothesis stated above, we repeated the cross-validation procedure 1,000 times, each time independently from the others, by randomly selecting the ten sub-networks from the 2-shell of the original co-brand network. Only in two cases out of 1,000, and for only one subset out of ten each time, the average R-score crossed the value of 0.5. Therefore, a very conservative estimate of the probability that the R-score associated with the recommendation system is consistent with the null hypothesis ($H_0$) that *the network has no predicting power on missing links* is $p$=0.002. This value allows us to reject the null hypothesis $H_0$ at 1% level of statistical significance. Therefore, we conclude that the network structure around two brands is predictive of the possibility that the two brands will engage in an alliance.
Recommendation methods show that network structure is predictive of deleted links, that

[3] This number is equal to the total number of brands in the network minus the number of brands connected to $B$ in the training set.

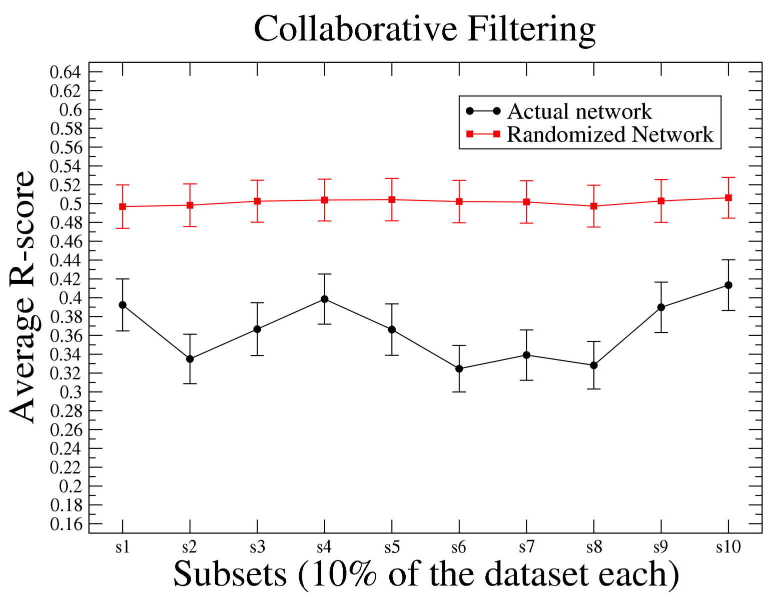



**Figure 2.1:** Average R-score

is, partnerships present in the real co-branding network but removed from the dataset. Therefore, we analyze such a structure and its characterizing features in section "Descriptive analysis" to unveil the rationale behind the demonstrated predictive power. We conclude this section by showing the outcome of running the recommendation system on the whole *2-shell* subnetwork. Indeed, on the one hand it's worth to show how this method can be used in practice to inform managers' decisions, and, on the other hand, it makes it apparent the asymmetry between brands in the recommendation lists, an asymmetry that will be further discussed in section "Theoretical implications."

### 2.5.2 Quantitative link prediction: Recommendation systems for partner selection purpose

The analysis of R-score highlights that recommendation methods, as applied to the network of co-branding campaigns, have predictive power on future campaigns. This evidence indicates that the formation of future co-branding relationships may depend on the portfolio and indirect relationships of brands in the past. Therefore, through the Score produced by the recommendation methods, we can build a (ranked) list of potential co-branding partners for each brand in the dataset.

**Table 2.1:** Potential partnerships predicted with recommendation methods

| Brand A | Brand B | Ranking of Brand B in the list of A | Ranking of Brand A in the list of B |
|---|---|---|---|
| Disney | Nike | 1 | 3 |
| Comme Des Garcons | Vans | 2 | 9 |
| Dr.Martens | Adidas | 1 | 7 |
| Emporio Armani | Izzue | 8 | 95 |
| Fendi | H&M | 6 | 109 |
| Balmain | Converse | 4 | 134 |

In Table 2.1, we report some interesting (potential) partnerships recommended by the system as applied to the whole 2-shell cobranding subnetwork.

The table shows the apparent asymmetry between brands, as naturally introduced by the recommendation system. Indeed, besides cases of symmetrical preference, that is, cases in which both brands have a good ranking position in the list of the other brand, e.g., DISNEY and NIKE, there are cases in which one brand has a high ranking position in the recommendation list of the other brand and not vice versa, e.g., FENDI and H&M. This second case is of particular interest from the theoretical point of view, since one may envision a mechanism of co-brand formation in which one of the two brands approaches the other with an alliance proposal (*initiator*), and the other one considers the request, implicitly gaining a strategic advantage in the negotiation (the *aggressor*).
The table suggests that each brand receives a signal from the other brands within the network, and such a signal might trigger a profitable partnership. However, the signal is not necessarily reciprocal, depending on the portfolio and positioning of each brand in the network. These conclusions support the theoretical mechanism of partnership formation that we propose in section “Theoretical implications.”

## 2.6 Descriptive Analysis

### 2.6.1 Network Analysis

In the analysis that follows, we consider measures from both the single node perspective and the whole network perspective. The node measures considered are reported in Table 2.2. Node "Degree" identifies the direct influence on the node from the other ones (Newman 2011): if a brand has a high degree, it can use benefits that directly come from

**Table 2.2:** Node measures used in this study

| ***MEASURE*** | ***MEANING*** | ***INTERPRETATION*** |
|---|---|---|
| ***DEGREE*** | N. of links pointing to a node. Direct influence. | Brands can exploit the image of other brands in a direct way. |
| ***BETWEENNESS CENTRALITY*** | Index of flow control. It identifies the broker and peripheral nodes. | If a brand with high value is removed, the connectivity of the network will suffer. Some brands act as brokers, and their removal will divide the network. |

**Table 2.3:** Whole network measures used in this study

| ***MEASURE*** | ***MEANING*** | ***INTERPRETATION*** |
|---|---|---|
| ***CLUSTERING COEFFICIENT*** | Number of triplets in the network that close into triangles. | A high value suggests that triadic closure might be a mechanism underlying the formation of a co-branding partnership. |
| ***DENSITY*** | Number of actual links in the network divided by the maximum possible number of links. | A high value indicates a high probability that two randomly selected brands have allied in a co-branding campaign. |

other nodes. Node "Betweenness Centrality" is a measure of centrality of a node in the network: a brand with high betweenness centrality plays a significant role in the overall connectivity of the network, suggesting that the node is either a hub or a bridge between different clusters of brands (determined, for instance, by the market target, or market sector).

Besides local measures, also global measures of connectivity may provide useful information about the properties of the system (see Table 2.3). The "clustering coefficient" is a measure of connectivity obtained as the ratio between the number of triangles and the total number of triplets in the whole network, which includes 881 brands connected by 1346 links. A high value of the clustering coefficient suggests that triadic closure (Easley and Kleinberg 2010) might be a mechanism underlying link formation, i.e., alliances, in the co-branding network. Triadic closure is a typical mechanism of link formation in social systems, in which an open triplet–three nodes connected by only two links–is closed to form a triangle (Newman 2011). The triadic closure occurs when two indirectly connected

**Table 2.4:** Node measures: top 10 brands ranked by betweenness centrality

| NAME | TYPE | DEGREE | BETWEENNESS CENTRALITY |
|---|---|---|---|
| DISNEY | OTHER | 27 | 0.155 |
| ADIDAS | FASHION | 36 | 0.130 |
| IZZUE | FASHION | 35 | 0.106 |
| NIKE | FASHION | 35 | 0.097 |
| COCA COLA | OTHER | 29 | 0.095 |
| VANS | FASHION | 28 | 0.083 |
| COMME DES GARCONS | FASHION | 22 | 0.065 |
| STAPLE | FASHION | 26 | 0.063 |
| CONVERSE | FASHION | 25 | 0.053 |
| WOOD WOOD | FASHION | 23 | 0.052 |

nodes form a link. The advantage of forming a triangle is that it reduces conflicts and negative behavior and increases mutual trust between the partners (Bergé, 2017).
Within the present study, a high value of clustering coefficient, which quantifies the extent to which triadic closure acts as a mechanism of link formation, indicates that companies can exploit the indirect influence from other brands. Specifically, it suggests that a new partnership is more likely to form between brands that share one or more companies among their former collaborations. Another network measure, which is relevant within this study, is the "density" coefficient. Network density is the ratio between the number of actual links in the network and the maximum possible number of links that may form within it (Newman 2011). A high value of density indicates a high probability that two randomly selected brands have collaborated in a co-branding campaign and, therefore, that direct effects of alliances dominate over indirect effects. Indeed, network density indicates the overall tendency of brands to form collaborations in the market, in contrast with the dyadic vision. High values of both network density and clustering coefficient indicate that companies tend to be cooperative within a specific field. In contrast, low values of both quantities suggest a high degree of competition and, therefore, a limited tendency to collaborate. Finally, a high value of density and a small value of the clustering coefficient indicate the tendency of brands to selectively form collaborations in a coopetivive context (Rodrigues, Souza, and Leitao 2011).

### 2.6.2 Findings

According to the values of betweenness centrality reported in Table 2.4, the top six fashion brands occupy a very central position in the network and act as brokers.

Concerning the properties of the whole network, the clustering coefficient is 0.013, which

**Table 2.5:** Node measures in 5-shell: top 10 brands by degree and betweenness centrality

| NAME | TYPE | DEGREE | BETWEENNESS CENTRALITY |
|---|---|---|---|
| NIKE | FASHION | 14 | 0.086 |
| WOOD WOOD | FASHION | 12 | 0.065 |
| NEW BALANCE | FASHION | 11 | 0.063 |
| ADIDAS | FASHION | 12 | 0.062 |
| VANS | FASHION | 11 | 0.060 |
| PATTA | FASHION | 11 | 0.052 |
| DR. MARTENS | FASHION | 9 | 0.045 |
| CONVERSE | FASHION | 11 | 0.043 |
| STUSSY | FASHION | 9 | 0.036 |
| KITH | FASHION | 8 | 0.032 |

is very low and suggests that the mechanism of triadic closure does not apply to partnership formation in the fashion industry. The reasons could be related to competition effects among brands within the same triplet, which may have, for instance, the same target-market. The network density is 0.004, which is also low and indicates that so is the connectivity among brands. The reasons for this could be related to the fact that: i) brands are selective in defining their co-branding partnerships; ii) companies are worried about the risks of co-branding campaigns, and iii) brands follow local logics in their co-branding campaigns.

### 2.6.3 K-shell decomposition - The core of the co-branding network

Another analysis carried out in this study is the K-shell decomposition, which identifies the core structure of the network. The k-shell decomposition is a well-known technique in graph theory, consisting of pruning *"the network down to those nodes with more than k neighbors"* (Carmi *et al.* 2007:11150). In particular, *"Nodes with low/high values of k are located at the periphery/center of the network"* (Garas *et al.* 2012:3). The deepest shell revealed in the cobranding network is the 5-shell (see Figure 2.2) that includes 42 brands connected together by at least five links per brand. We have also calculated node measures for the 5-shell (Table 2.5).

Concerning overall measures of connectivity, the clustering coefficient of the 5-shell is 0.125, which is a higher value than that of the whole network. This result means that, within the 5-shell, the mechanism of triadic closure may be hypothesized. The network density is 0.185, which is also higher than the corresponding value for the complete network. As expected, the deepest shell of the network is composed of brands that make extensive use of the co-branding strategy. Overall, the relatively large number of brands (42) involved in a deep shell (the 5-shell) and the high values of both the density and the clustering coefficients indicate that cobranding is an effective marketing strategy that brands exploit on a rather regular basis. Therefore, studying the network structure of the 5-shell might provide relevant information about the rationale behind such a strategy. Along this line of thinking, it is of particular interest to reveal and study the "communities" (i.e., clusters in a network) within the deepest shell since the rationale underlying co-branding strategies might vary across communities. By using a community detection algorithm based on modularity optimization (Newman 2011), we found four communities in the 5-shell. Figure 2.2 shows the map of revealed communities. Their characterization allowed us to identify four different logics underlying the formation of alliances that suggest different types of co-brand, each one associated with specific trust signals (which are further discussed in the theoretical implication section). Specifically, some possible logics underlying the emergence of each community arise from the following discussion.

- In community C1, the majority of brands are related to the same geographic area (5 brands out of 8 are based in the US), and a geographic proximity collaboration could be hypothesized–there are only three exceptions: OFF-WHITE, which is an Italian fashion brand with an American founder, and WOOD WOOD and END., which are both retailers, from Denmark and the UK, respectively. Geographic proximity (Bergé 2017) may be a factor that stimulates brand alliance. Indeed, for example, partner selection might be tacitly oriented by the framework a company is embedded in, such as a regional innovation network (Fritsch and Kauffeld-Monz 2010). Thanks to localized interactive learning processes and the knowledge embedded in social interaction, a territorial area with companies (brands) densely embedded provides a powerful context for the development of interbrand relationships (D'Allura *et al.* 2012). The partnerships based on geographic proximity may also be explained with the emergence of (formal and/or informal) social networks (Felzensztein *et al.* 2010). Also, the role of retailers appears to be central in this community. KITH, WOOD WOOD, and END. are retailers that are not specialized in a specific segment of the market (like sport) and, therefore, do not want to associate their image with only one or a few specialized brands. Moreover, the variety of products and target consumers of collaborations, as well as the presence of two non-fashion companies (END. and

DISNEY), further reduce the degree of competition among fashion brands, which in turn, can benefit from cooperation. In other words, brands within this community seem to compete mildly (the retailers) and cooperate mildly (most fashion brands). Therefore, such empirical evidence suggests the existence of a new type of co-branding partnership logics, which is *Geographic* co-branding.

- In community C2, we can highlight that nodes form a perfect bipartite subgraph, where the two sets of nodes are qualitatively different, and no intra-set collaboration occurs. Specifically, on one side, nodes of set 1 in Figure 2.2 are related to the same sport market target, and on the other side (set 2 in the figure), they are retailers, almost all focused on sport footwear. Among the several reasons that may lead to a brand alliance, previous studies on strategic alliances underlie the importance of the supply chain and the interaction between its different levels (Whipple and Frankel 2000). The increasing need for an integrated network within the supply and distribution chains underscores the importance of a strategic alliance between suppliers and retailers as a potential source for competitive advantage and in order to increase efficiency (Whipple and Frankel 2000).
  In this community, there is no triangle, but only triplets that likely will never close - missing links are related to competition effects among brands within each one of the brand categories. Moreover, all the partnerships propose the same product (shoes, with only one exception) to the same market target (almost all mass market).
  Therefore, community C2 appears to be characterized by intense competition among brands. Specifically, in this community, we empirically observe evidence that suggests the existence of a new logic underlying the partnership formation, which is *Chain* cobranding, and the benefits of the collaboration probably come from the strengthened interaction between different levels of the supply chain.

- Community C3 appears to be a "concept" cluster formed around "streetwear." Specifically, brands in this community form a weak tripartite network, in which two sets of brands–sets 1 and 3 in the figure–are composed of brands that do not collaborate with other brands from the same set, and a central set of three brands of streetwear, namely, BAPE, SUPREME, and NEIGHBORHOOD that collaborate directly among them and with brands from both side sets. Set 1 includes well-established brands of shoes in the low-medium target market, mainly oriented

towards young men, whereas set 3 includes clothing brands with no specific target market. Thus, the central set represents a fully cooperative sub-cluster, also strongly interacting with the other two sets of brands, which, on the contrary, show a marked intra-set competition. Such an interpretation of the community leads to the "coopetitive" concept. Coopetition occurs when two companies in direct competition also cooperate (Bengtsson and Kock 2000). According to Chiambaretto *et al.* (2016), the hyper-competition that characterizes the market today leads companies and their brands to collaborate with direct competitors. Coopetition, in this case, might be explained by the knowledge and expertise shared between the partners that better fit the market target–the same for both brands. On the one hand, cooperation allows brands to access new market targets by launching suitable products and, at the same time, gain access to crucial resources and technologies. On the other hand, competition pushes brands to stay innovative. Despite these benefits, cooperation between brands in direct competition might also have adverse effects. Indeed, the risks related to the potential opportunistic behavior of one of the two partners increase as a consequence of direct competition (Chiambaretto *et al.* 2016). Such an interpretation of the present community as a coopetitive one is also supported by an analysis of co-branded products of the alliance in the community that are strongly related to brand image, being very recognizable and even iconic in some cases.
Thus, we empirically observe a new logic that underlies the co-branding partnership formation, namely, *Coopetitive* co-branding. In this case, the benefits from partnering with a competitor brand come from the possibility that two brands together can better compete with all the other direct competitors.

- In community C4, all brands are related to only two different geographic areas: the US and Japan, with only one exception (VETEMENT - France). Besides highlighting a US-Japan collaboration, the brands from this cluster seem to share their own culture and expertise in the collaborations, e.g., streetwear (Japan) and sport (US) culture. It is interesting to note that almost all the US brands in this community show a deep American identity, are family-owned, and have introduced at least one major innovation in the past. Such a "cultural fusion" between the US and Japan and between sport and streetwear, which involves expertise and image sharing, and the variety of co-branded products make this community a fully cooperative one. In this context, the mechanism that marks this community can be found in the

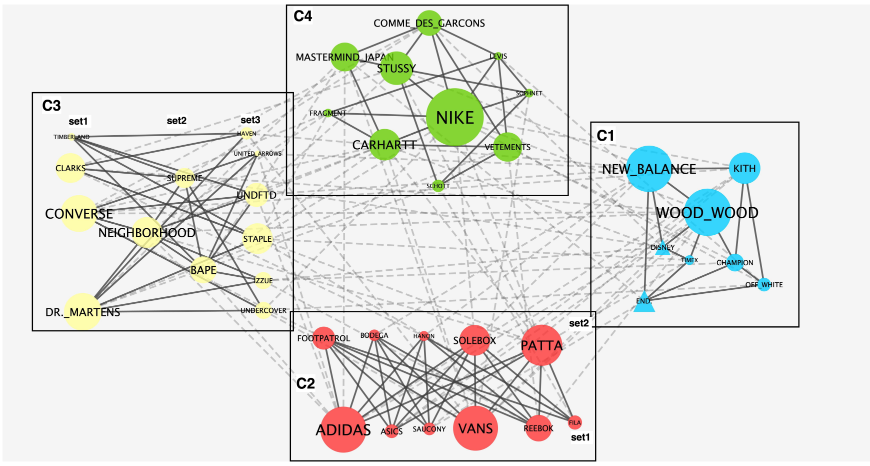



**Figure 2.2:** 5-shell and revealed communities

concepts of "trust" and "reputation." Specifically, in branding studies, the concept of "trust" refers to either "trust" as expectancy, namely the positive effect on an alliance of consumers' belief on the qualities of either brand in the partnership, or "trust" as the confidence that the relational party in an alliance will not exploit the weaknesses of the other party (Delgado-Ballester and Munuera-Alemán 2005). Instead, "reputation" represents probably one of the most important characteristics of a brand. It reflects the publics' perception of the brand (Heller 2008). Generally speaking, companies look at the positive public perception of product quality, which is also strongly related to the perception of the company itself (Heller 2008).
Therefore, here in this community, we empirically highlight *Identity* co-branding as the logic for partnership formation. Here, the partnerships can benefit from the heritage that each brand carries with it, which can implicitly strengthen the other brands in the partnership.

Additionally, we analyzed the node clustering coefficient–that is, the ratio between the number of triangles and the number of triplets that are incident in the node (Newman 2011). In this context, the node clustering coefficient (CC) may be used to quantify the tendency of a brand to participate in a collaborative group (high values of CC) or a competitive one (low values of CC). In particular, a low left-tail p-value[4] (right-tail p-value) indicates that the brand is immersed in a competitive (cooperative) sub-network since the brand is embedded in a market niche where the clustering coefficient is significantly lower

[4] P-values have been associated to node clustering coefficients by constructing 10,000 randomized replicas of the network through random rewiring (Xulvi-Brunet and Sokolov, 2004).

**Table 2.6:** Statistically significant clustering coefficients of nodes within the 5-shell

| Brand | CC | Left tail P-value | Right tail P-value | Market niche | Community |
|---|---|---|---|---|---|
| Adidas | 0.0909 | 0.0376 | - | competitive | C2 |
| Asics | 0 | 0.0155 | - | competitive | C2 |
| New Balance | 0.0364 | 0.0016 | - | competitive | C1 |
| Reebok | 0 | 0.014 | - | competitive | C2 |
| Bodega | 0 | 0.0473 | - | competitive | C2 |
| Dr. Martens | 0.0556 | 0.0297 | - | competitive | C3 |
| Footpatrol | 0 | 0.0152 | - | competitive | C2 |
| Solebox | 0 | 0.0031 | - | competitive | C2 |
| Vans | 0.0545 | 0.0065 | - | competitive | C2 |
| Wood Wood | 0.0606 | 0.005 | - | competitive | C1 |
| Fragment | 0.4 | - | 0.011 | cooperative | C4 |
| Levis | 0.3333 | - | 0.0393 | cooperative | C4 |
| Neighborhood | 0.2889 | - | 0.0169 | cooperative | C3 |
| Bape | 0.3056 | - | 0.0175 | cooperative | C3 |
| Off White | 0.3333 | - | 0.0405 | cooperative | C1 |

(higher) than the one expected in a completely random scenario.

Results reported in Table 2.6 quantitatively support the interpretation of communities as provided above. Indeed, according to the clustering coefficient, nodes from community C2 only appear as surrounded by competitive brands, nodes from community C4 only by cooperative brands, whereas both competitive brands and cooperative brands surround nodes from communities C1 and C3.

## 2.7 Theoretical Model

In this study, we adopt the Signaling Theory approach, which is widely used to model the interaction between two parties with access to different information, i.e., informational asymmetry (Connelly *et al.* 2011). In signaling theory, the process involves a sender and a receiver that exchange information (the signal).

The sender chooses to transfer the signal to the receiver that determines how to interpret it (Connelly *et al.* 2011). The sender represents the "initiator," and the receiver is the "aggressor." Likely, the initiator is the one most interested in starting a collaboration. In contrast, the aggressor is the one that, together with the signal, implicitly receives a negotiation advantage.

In our context, we assume that the two potential partners initially have asymmetrical information and preferences. Then the sender decides the suitability of other companies as possible partners in an alliance and sends the signal to those companies (the receivers). In the model, which we ground on the demonstrated predicting power of the recommendation system, the signal includes the portfolio of previous partnerships of the sending brand. The signal is received by each potential aggressor, which processes the signal (consisting in the sender brand itself and its portfolio) based on different possible logics, e.g., competition and cooperation logics, trust and reputation of the counterpart, also related to geographic proximity, supply chain deals, brand identity, as we have been able to infer from the analysis of the inner structure of the network. [5]

Once a given receiver collects the signals from the sender, together with signals from other senders in the system, it may send back its own signal (its portfolio of previous partnerships) to the sender. Such a feedback mechanism (which is outlined in Figure 2.3) can lead to establishing the new co-branding alliance.

The presented theoretical model assumes that the signaled portfolio does not include information about the temporal order of signaled campaigns-an assumption which is supported by the analysis reported in section “Quantitative analysis”. Indeed, looking at the co-brand network as an evolving complex system (Miller and Page 2009) in which collaborations form over time, one might be tempted to describe such a stochastic process as a *path-dependent* process, where the probability that a new link (co-brand) occurs between two nodes (brands) depends on the *ordered* list of past co-brands. However, our analysis disregarded the time of link formation-e.g., links in a test set could represent brand alliances occurred before others included in the training set-and the fact that the training network still has predictive power on the links in the test set, despite such a lack of information, points towards the concept of *"phat dependence."* According to Page (2006), *"path dependence"* occurs when the path of previous outcomes matters, whereas *"phat dependence"* occurs when the events in the path matter, but the order of occurrence possibly does not, which appears to fit with the results reported in this paper, and supports the signaling model introduced in this section.

In sum, we argue that the information about the environment represented by the network of previous partnerships reduces perceived risk, and the portfolio of each brand represents a signal that facilitates the establishment of an alliance depending on the logics each company follows for its brand.

[5] Later in this section, we will focus on the role played by competition and cooperation logics. However, our results do not imply that the other aforementioned logics play a negligible role, instead they could easily be included in the proposed model.

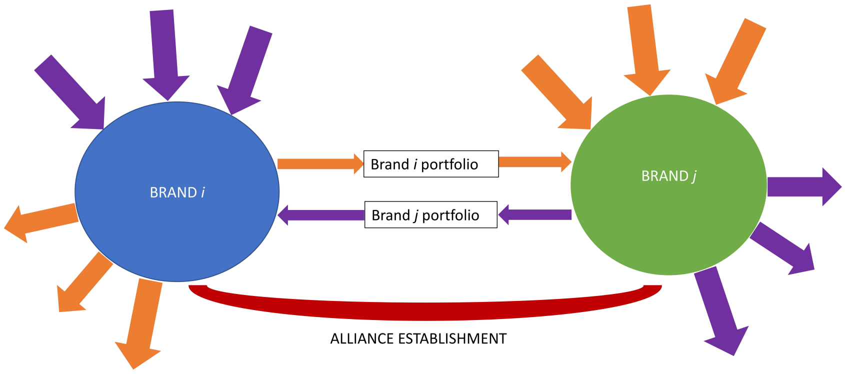



**Figure 2.3:** Signaling Theory application to the network approach

### 2.7.1 Model definition

We operationalize the concepts underlying the introduced signaling mechanism in the following way. We consider a signaling mechanism that starts when a brand, $i$, sends a signal including the list of its previous partnerships–that is, its portfolio–to the market. Brand $i$ sends such signal with a probability proportional to the sum of two terms: $N_1^i$–the size of its portfolio of previous partnerships–which is a proxy of the inclination of the brand to participate in an alliance, and $\alpha$, which is a parameter representing the typical propensity of the market to form new alliances:

$$p_i \rightarrow \propto (N_1^i + \alpha) \tag{2.1}$$

Our assumption is that each brand establishes a co-branding alliance only if it receives such signal from the counterpart. Accordingly, each brand in the market holds information about the list of previous partnerships of each one of the brands it allied with in the past, i.e., its second neighbors. Thus, a brand can exploit information about its first and second neighbors to process a new signal it receives from another brand. Specifically, the receiver brand, $j$, can evaluate the intersection between its (first and second) neighbors and the portfolio of previous partners (the signal) of the sender brand, $i$[6]. Brand $j$ may send back the signal including its own portfolio of $N_1^j$ previous partnerships to brand $i$, implicitly conveying its interest in the collaboration. The probability that $j$ sends such signal is

[6] The reason why the model focuses on first and second neighbors will be explained later in this section.

$p_{j\rightarrow} \propto (N_1^j + \alpha) \cdot (N_{1,2}^{i,j} + \beta)$, that is, the product of a term analogous to the one considered for brand $i$ (representing the overall inclination of brand $j$ to form an alliance) and a term $(N_{1,2}^{i,j} + \beta)$, which accounts for the common neighbors of brands $i$ and $j$, which will be discussed later in this section, and represents the incentive of brand $j$ to form a collaboration with $i$, to gain a competitive advantage. Parameter $\beta$ accounts for the overall degree of competition in the system, which may depend on the industry sector (e.g., fashion in this study). A high value of parameter $\beta$ indicates the fact that the number of signals received by (a generic) brand $j$ is high (see figure 2.3), and therefore the relative weight of the signal coming from brand $i$ is low.
Once brand $i$ receives the signal from $j$, it processes the signal according to its stored information (first and second neighbors), and the probability that it chooses $j$ as partner among the other brands that responded to its original signal is proportional to $(N_{1,2}^{j,i} + \beta)$–a term similar to the one already considered for brand $j$.
Based on this flow, the probability of establishing a partnership between brand $i$ and brand $j$ is:

$$p_{i\leftrightarrow j} \propto (N_1^i + \alpha) \;\cdot\; (N_1^j + \alpha) \;\cdot\; (N_{1,2}^{i,j} + \beta) \;\cdot\; (N_{1,2}^{j,i} + \beta) \tag{2.2}$$

where:

- $N_1^i$ ($N_1^j$) is the size of brand $i$ ($j$) portfolio of previous partners and represents a proxy of the overall inclination of brand $i$ ($j$) to do co-branding;
- $N_{1,2}^{i,j}$ ($N_{1,2}^{j,i}$) is the intersection between the first neighbors of brand $i$ ($j$) and the second neighbors of brand $j$ ($i$).

The rationale behind the inclusion of the terms $N_{1,2}^{i,j}$ and $N_{1,2}^{j,i}$ (i.e, the size of the intersection between brand $i$ first neighbors and brand $j$ second neighbors and *vice-versa*, respectively) in the model is that we observe a system based on alliances where, basically, cohabits brands in competition. This situation may be graphically represented through a bipartite structure[7] (an example is reported in figure 2.4). Indeed, this kind of (bipartite) sub-structure represents a high competition configuration, where brands in the same set strongly compete among them and collaborate with brands from the other set, which also

[7] A bipartite network, as the one reported in figure 2.4 , occurs when there are two distinct sets of nodes and the structure of links present all the connections between the sets but no connection within a single set.

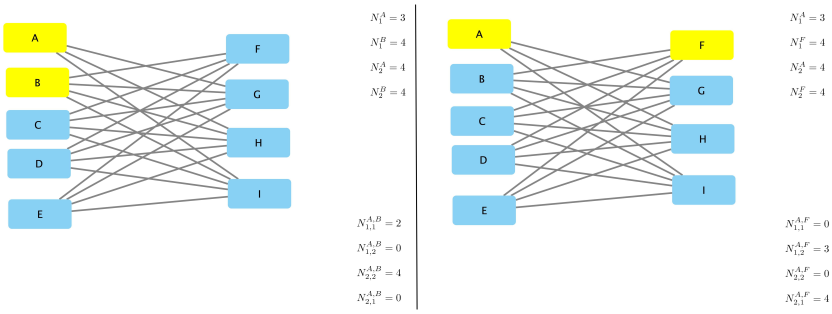



**Figure 2.4:** Example of the application of the theory model in a bipartite structure

compete among them. Following on this, in figure 2.4 brands $A$ and $B$ are members of the same set, they are in direct competition, and probably they will never ally. Instead, brands $A$ and $F$ are members of two different sets, and they may likely establish an alliance. Since our goal is to define the probability that two brands establish a partnership, we select a measure that takes low values for competing brands (such as $A$ and $B$ in figure 2.4), and, on the contrary, high values for a potential partnership between brands from different sets ($A$ and $F$ in figure 2.4).

To select a suitable measure to capture these aspects, we have three candidates: the intersection between the first neighbors of the two brands, the intersection between the second neighbors of the two brands, and the intersection between the first neighbors of one brand and the second neighbors of the other one.

If we consider the intersection between the portfolios (first neighbors) of brand $A$ and brand $B$, we obtain high values. If we consider the intersection between the second neighbors of both brands $A$ and $B$, the result is basically the same. But, in a competition environment, brands from the same set ($A$ and $B$ in figure 2.4) should not ally. If we consider the intersection between the first neighbors of $A$ and the second neighbors of $B$ (or *vice-versa*), we obtain 0, which suggests that the appropriate measure is this one. Switching the attention to brand $A$ and brand $F$ in figure 2.4, the intersection among their first neighbors is 0, as well as the intersection between their second neighbors. However, in this configuration, brands from different sets ($A$ and $F$ in figure 2.4) should ally. Instead, by considering the intersection between the first neighbors of $A$ and the second neighbors of $F$ (or *vice-versa*), we obtain a high value, which reinforces our inclination to use this measure in the model. Indeed, according to our model, the probability that $A$ and $B$ establish a partnership is very low, as compared with the probability that $A$ and $F$ establish a partnership.

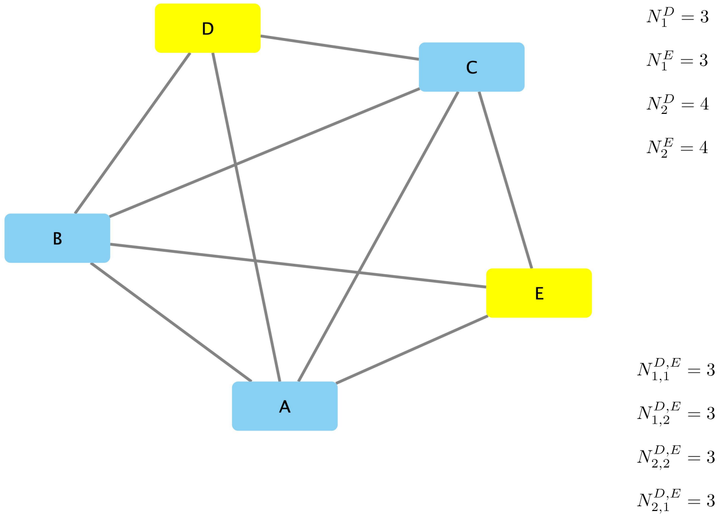



**Figure 2.5:** Example of the application of the theory model in a full cooperative structure

The intersection between first neighbors of brand $i$ and second neighbors of brand $j$ also work even in the opposite case of fully cooperative sub-structure, as the one reported in figure 2.5, where the values of the intersections are high for all the three considered measures. In this example, the probability that $D$ and $E$ establish a partnership is very high according to all of the measures.
Notice that, with this model, we take into consideration both the direct (first neighbors) and indirect (second neighbors) influences that a single brand can exploit from the network perspective.

Moreover, this assumption is supported by our results, since by either adding or replacing $N_{1,2}^{i,j}$ with $N_{1,1}^{i,j}$ (intersection between first neighbors of $i$ and $j$) or $N_{2,2}^{i,j}$ (intersection between second neighbors of $i$ and $j$) in our theoretical model, the performance of predictions tends to be lower, according to the leave-one-out procedure (explained later in this section).
It is worth mentioning that the presented model is unsupervised. Indeed, we set both parameters $\alpha$ and $\beta$ equal to 1. However, as future research, it is possible to produce a generalization of the model by optimizing the model performance with respect to $\alpha$ and $\beta$. To do this, different industry sector should be considered.

### 2.7.2 Model Performance

In this section, we use the leave-one-out cross-validation procedure to assess the performance of the model for all the co-brands in the dataset. This method is widely used in other fields (such as protein interaction networks (Yook *et al.*, 2004) where the prediction of single links is relevant.

We demonstrate that the signal represented by both direct and indirect influence is predictive of future partnerships. This is done by testing the null hypothesis that the signal represented by both direct and indirect influence is not predictive of removed links. We test this hypothesis through the *leave-one-out* procedure.

This approach consists of iteratively removing one link at a time from the network, and use the remaining links (training set) to evaluate the performance of the model in predicting the removed one. The procedure is repeated for each one of the links in the dataset.

The performance measure used to test the model is the $R - score$. In particular, the average $R - score$ of our model is 0.326 with a standard error of 0.015. It is worth underlying that 1) the proposed model outperforms the recommendation system considered in the section Hypothesis Testing, and 2) it only exploits information from the network of co-brands.

Overall, the good performance of the model indicates that the signal composed by direct ties (portfolio of previous partnerships, i.e., first neighbors) and processed by exploiting information on indirect ties (second neighbors) is predictive of future partnerships.

The test of the model presents some limitations. Specifically, our dataset does not include information about the exact sequence in time of the alliances, which makes it impossible to consider the previous partnerships of a brand at a given time in the analysis of the performance. Evaluating the model performance through the *leave-one-out* approach is equivalent to assume that the removed link is always the last one formed. In other words, at each link removal, we assume the remaining links as historical information a given brand has, without taking into account the exact sequence in time of the alliances. In a future work, we plan to include information about the time of alliances that, together with the inclusion of other industry sectors, will make it possible to estimate optimal values of the two (sector specific) parameters.

## 2.8 Discussion

### 2.8.1 Theoretical Implications

The proposed theoretical model confirms the predictive power of the network of co-branding campaigns. The model assumes that the probability of two given brands ($i$ and $j$) to form an alliance is proportional to the size of brands' portfolios of previous partners-which represents a proxy of the overall inclination of brand $i$ ($j$) to do co-branding-and the intersection between the first neighbours of brand $i$ ($j$) and the second neighbours of brand $j$ ($i$). Therefore, the model takes into account both direct and indirect influences. The environment represented by the network of previous partnerships reduces perceived risk, and the portfolio of each brand represents a signal that facilitates the establishment of an alliance depending on the logics each company follows for the success of its brand. It is worth noticing that the presented model does not involve consumer oriented logics, which is supported by some empirical findings that highlight company oriented logics underlying co-branding. Specifically, we empirically find some logics that emerge from a systemic view of the network of co-branding campaigns that better link co-branding to inter-organisational aspects than to consumers expected reactions to specific co-branding campaigns. Indeed, the signal represented by the portfolio of previous partnerships acts as a trust and reputation signal. When interpreting these signals, a limited number of logics guiding partner selection for co-branding campaigns emerge. In particular, the logics followed are:

- *Geographic* logics, where a collaboration between two brands is moderated by the possibility to exploit proximity advantages. Such a mechanism is well known in management science. Indeed, according to Boschma (2012), geographic proximity helps to reduce the transaction costs, facilitates the exchange of knowledge, in particular tacit knowledge, and fosters cooperation dynamics (Boschma and Lambooy 2012). Previous studies show that the emergent social networks, even if informal, favors the formation of relationships between companies characterized by geographic proximity (Felzensztein *et al.* 2010). Thus, by exploiting geographic proximity, companies may gain competitive advantages.

- *Chain* logics, where brands exploit collaborations to ensure their position and popularity. Indeed, brands engage in a co-branding alliance in order to gain a stronger position in the consumers' mind, besides obtaining specific distribution advantages.

This interpretation is supported by previous research on strategic alliances (Whipple and Frankel 2000) that show that companies engage in cooperative supply chain deals to reach competitive advantages by merging their strengths and resources. In this way, the partner brands should have mutual benefits (Whipple and Frankel 2000).

- *Coopetitive* logics, where both brands want to reach a broader market target. They do this by using their best and most recognizable resources and joining forces with similar/competitor brands. In contrast with previous management studies that highlight how coopetition strategy can help companies to reach new markets (Rodrigues *et al.* 2011), our empirical analysis indicates that brands may also choose this strategy simply to get a quantitative advantage, in terms of the number of potential consumers within the same market target.

- *Identity* logics: brands want to share and stress their own identity and heritage with consumers. Previous research highlights that a fundamental element to develop brand loyalty is the role of brand identification. Brand identity has an essential effect on trust and perceived value, both directly and indirectly (He *et al.* 2012). Furthermore, brand identification can have a mediation role on the effect of brand identity that consequently leads to brand loyalty (He *et al.* 2012).

To summarize, empirical findings suggest that, in the setting of co-branding alliances, the partner selection process is not only consumer-oriented, as previous studies suggest (Venkatesh and Mahajan 1997, Walchli 2007, and Van Der Lans *et al.* 2014), but also guided by company-oriented logics. These results suggest that, even in the case of co-branding strategies, aspects such as tacit local knowledge, supply chain relationships, coopetition, and identity may pave the way for new alliances. Just as literature on strategic interfirm alliances has underscored in other contexts, also in the case of co-branding strategies these aspects seem to play an important role.

### 2.8.2 Managerial Implications

The most important implication for managers is perhaps that the history of previous cobranding partnerships (i.e., the brand portfolio) represents the element that a manager has to leverage upon, in order to establish a new partnership. The target of this signal

should be potential partners that the company preliminary selects, depending on the adopted logics, as empirically revealed in our analysis. Specifically, potential partners should be selected among companies with characteristics compatible with the adopted company logics.
In particular, based on the revealed communities and their characterization, we identified four different new potential co-branding logics:

1. *Geographic co-branding: a collaboration between two brands which is moderated by the possibility to exploit proximity advantages.*

2. *Chain co-branding: a collaboration in which brands exploit specific supply chain advantages to ensure brand position and popularization.*

3. *Coopetitive co-branding: a collaboration in which two brands join forces with similar/competitor brands to obtain a strategic advantage with respect to all the other individual direct competitors.*

4. *Identity co-branding: a collaboration in which two allied brands share and stress their own identity and heritage with consumers.*

Furthermore, the demonstrated predicting power of the co-branding network can be exploited to inform managers' decisions during the partner selection process for a future co-branding campaign. Indeed, recommendation methods, which are already used by media services providers, such as Netflix, and e-commerce companies, such as Amazon, can be used by managers to receive suggestions about potential partners, or to check where an initiator partner stands in its recommendation list of companies.

## 2.9 Conclusions

The present study indicates that switching from a dyadic to a network perspective in the analysis of co-branding alliances allows to better identify, interpret, and model brand strategies. In particular, it enables to infer that partnership formation is influenced by the portfolio and position of the two prospective partner brands in the co-branding network, instead of just depending on a dyadic relationship and, furthermore, it allows to infer specific logics guiding company choices. The contribution of the chapter to the literature on co-branding is multifold as it shows that: i) the adoption of a network perspective is able to capture aspects of the partner selection process in co-branding campaigns that dyadic analyses overlook; ii) the portfolio and position of a brand in the network of co-branding campaigns are predictive of future alliances; iii) brand portfolios and brand positions in the structure of the overall network are relevant signals in the co-branding partner selection processes; and iv) there are at least four specific logics underlying co-branding partner selection.

In this study, specific measures from network theory were used to analyze brand connectivity, both direct and indirect, and to infer the different logics underlying the formation of alliances and the role played by the brands within the network of co-branding campaigns. The results obtained show that some brands play a central role in the network, and they act as brokers. Also, the presence of communities of brands in the inner structure of the network suggests that local logics may guide partnership formation. Local logics include tacit local knowledge, supply chain relationships, coopetition, and identity. This result clarifies the behavior of companies in their choices regarding partner selection for a co-branding campaign.

Through the application of a recommendation system, this study shows that the structure of the co-branding network has a statistically significant predictive power on potential partnerships. This entails that the specific brand position in the whole network and its portfolio of relationships influences the pattern of new co-branding campaigns engaged in, to the extent that they may be used to identify new potential partnerships. Beyond the aspect of prediction, this result is significant as it supports the idea that the portfolio of passed co-branding relationships undoubtedly influences the new campaigns companies activate.

The present research draws from and contributes to the Signaling theory. Indeed, in the theoretical model proposed in this study, the partner selection process considers the portfolio of previous partnerships as a signal sent from one "initiator/sender" company to another one, the "aggressor/receiver" company. Following Signaling theory, the brand portfolio is interpreted as a signal that facilitates the establishment of new partnerships. Single aspects of the signal may activate a limited number of specific logics underlying partnership formation, as we empirically observe in the analysis of the inner structure of the network. Though the logics identified are not customer-centered, as typically underscored in co-branding studies, they are not new to the management literature regarding strategic inter-firm networks. Accordingly, the proposed model of partner selection only exploits information about brands' portfolios, and it shows a rather high predicting power on removed links.

The present study highlights that, when choosing a partner for a co-branding alliance, companies are not guided only by their conjectures relative to the effect it may have on consumer reactions. Indeed, other logics may influence such a choice. In particular, logics such as tacit local knowledge, supply chain relationships, coopetition, and identity, which are empirically revealed in this study, can affect company decisions in the partner selection process.

The network perspective is not "new" in brand analysis. Indeed, micro-foundational analyses show how the memory recall process in consumer minds works as a network. In particular, Keller (1993) defines brand knowledge as a complex network of nodes and links in consumer memory, where a node can trigger the activation of linked nodes. Finally, when the number of active nodes exceeds a given threshold, the information is recalled (Keller 1993). Such an association map in consumer's mind identifies the brand value, exclusivity and image, and suggests how these concepts might be leveraged in the market (John at al. 2006). Research has shown that the brand association process is the combination of perceptions, beliefs, and preferences that are linked to specific brands in consumers' memory (Henderson *et al.* 1998). In the consumers' memory, the association between two brands is mediated by (qualitatively) different elements, such as product attributes and exclusivities, concepts, activities, and people and feelings, as well as by the presence of other competing brands (Henderson *et al.* 1998).

Therefore, the effects of each co-branding partnership are long-lasting in the memory and perception of consumers. The question remains whether the logics followed by companies, as they emerge in this study, are coherent with a careful and intentional consumers-oriented strategy.

## 2.10 Limitations and Future research

The most important limitation of the present study is the possibility to extend results to other industries and other types of alliances. Indeed, we are aware that the results of our analysis are limited to the fashion industry and may not directly apply to company alliances other than cobranding. However, the introduced methods and concepts can easily be adapted to investigate other types of alliances in other industries. Limitations also involve data quality and detail. Indeed, for the sake of deepening our comprehension of company logics and improving the performance of recommendation systems, the dataset should be complemented by including information about the type and price of the co-branded products, an estimate of performance of the campaigns, and how that varied the individual performance of allied brands over time.

Although previous research in the field of strategic interfirm alliances has identified logics such as the ones that emerge in this study as drivers for the creation of inter-firm relationships, it becomes of interest to understand the possible effects these choices may have on consumer perceptions when they involve extremely delicate strategic resources such as brands. This consideration is particularly relevant in light of the studies conducted on consumer perceptions and memory.

Given the network interpretation of the consumer recall process (Keller 1993) and the demonstrated predictive power of the co-branding network on future campaigns, it becomes relevant to investigate how the co-branding campaigns a company has established in time influence consumer perception. Also, given the role of the co-branding portfolio that emerges from this study, it would be relevant to investigate impact of indirect co-branding ties, i.e., the portfolio of partner brands, on the consumer perception and the performance of a new campaign.

Further, we envision at least two significant trajectories to build on the results of this study. In particular, it would be extremely interesting to trace the time and sequence in which new partnerships are created. The consideration of time would allow to understand whether the formation of new co-branding partnerships is not only influenced by passed co-branding campaigns of potential partners (and of the partners in those campaigns—that is, indirect relationships), but also by the sequence of partnerships formed in time. The mechanism that we envision and aim to test in the future is a limited path dependence, in which the signaled brand "portfolio" is not temporarily ordered (phat dependence), but it does not include very old collaborations, e.g., campaigns occurred more than ten years ago, which introduces temporal (path) dependence.

Finally, it seems extremely interesting to test if and how the existing co-branding network is recalled by consumers' memory, which would allow us to investigate the indirect influence of co-branding on consumers.

# Chapter 3

# Interplay Between Co-branding Network and Consumers Brand-to-Brand Recall Map: Partner Selection

**Abstract**

*Co-branding is a widely studied topic in previous marketing research. It is a specific marketing tool that occurs when two brands work together to create and launch a collaborative product. Here, by using tools from network theory, we analyze the network of collaborations within the fashion industry and the network of correlation between brands based on data from Google-Trends, which, in our assumption, reflects the brand-to-brand recall map. We focus on how the consumers associate brands and if their memories reproduce the network of co-branding campaigns. The analysis shows that the two networks carry complementary information. Based on this, we can envision how companies can integrate and use the information from both networks to establish a fruitful new partnership. Starting from the network of co-branding campaigns, we build a Bipartite Network that links two different sets: all the brands and all the products in previous collaborations. Therefore, we propose an effective method to suggest new types of co-branded products that each brand should do by implementing a recommendation system. Moreover, according to the similarity between brands' recommended lists of products, we devise an automatic tool to suggest potentially profitable partnerships to each brand.*

## 3.1 Introduction

A wide range of scientific disciplines uses Network Theory to investigate the structure and properties of a variety of systems, for example, finance (Garlaschelli *et al.*, 2007) (Mantegna, 1999), economics (Iori *et al.*, 2008) (Easley and Kleinberg, 2010), sociology (Liljeros *et al.*, 2001), and management (Dagnino, 2004) Here we propose a network analysis in marketing field (Easley and Kleinberg, 2010), specifically in brand context.
Previous studies highlight that people store brand information in memory through network mechanisms, which may facilitate the brand association (Henderson *et al.*, 1998). Thus, we begin by building a network of co-branding campaigns in which we link together couples of brands in a partnership. Specifically, co-branding occurs when two brands jointly produce and launch a new product with both brand names (Washburn *et al.*, 2000). The widely use of this strategy is because it can produce various benefits for the companies, such as penetrating new or wider market target(Washburn *et al.*, 2000) but also transfer brand image and reputation among partner brands and increase perceived brand value (Rodrigues *et al.*, 2011).
This chapter aims to test if consumers' memory reproduces at some extent the actual network of co-branding campaigns and how we can use the information contained in both the co-branding network and the brand-to-brand recall map to recommend potential company alliances. Specifically, we apply recommendation methods and –by calculating the similarity between couples of brands– we build a partner selection system that also includes a suggestion for a suitable co-branded product. This procedure represents a methodological innovation within the recommendation systems since these kinds of methods are usually applied to suggest objects of potential interest to users. Here we want to take a step forward and use the results produced in a user-object system to implement a user-user-object recommendation system.

The research questions of this study are:

(i) Is the network of co-branding campaigns reproduced in consumers' minds?

(ii) Do the network of co-branding campaigns and the consumers' brand-to-brand recall map provide the same information?

(iii) How can we combine the information from the two networks to provide a recommended list of potential co-branded products?

(iv) How can we exploit that information to suggest potential partnerships and products?

To reach the goals of this study, we first draw a "network of co-branding campaigns" by collecting data on actual co-branding strategies within the fashion industry. Then, we replicate the "consumers brand-to-brand recall map" through correlation analysis of Google-Trends index. Google-Trend index is a standardized proxy of the number of searches for a specific query (brand name, in our case) on google at a specific point in time.

By comparing the two mentioned networks, we want to test if consumers' memory reproduces the network of co-branding campaigns (at least partially).

Furthermore, by filling the co-branding dataset with information about the specificities of each co-branding campaign, we build a bipartite network (users-objects) that we will use to model partner selection.

Using the bipartite network and exploiting the information from both the network of co-branding campaigns and the brand-to-brand recall map, we can construct improved recommendation lists of co-branded products. Moreover, using a similarity measure between the recommended lists of products for each couple of brands (similarity between brands), we can build a partner selection model for potential partnerships.

## 3.2 Theoretical Background

A network representation of the purchase mechanism is a bipartite graph, which is a network composed of two sets of nodes, where one set represents the users, and the other set represents the objects. The establishment of a link occurs when a user collects an object. In this representation, recommendation methods are specific algorithms applied to bipartite networks that suggest potentially interesting objects to users. These suggestions rely on the similarity between users, usually calculated starting from the number of common past collected objects (Fiasconaro *et al.*, 2015).

Previously, recommendation systems were applied to the fashion industry, in order to improve the performance of online stores (Xing *et al.*, 2020), and better identify consumers' preferences (Kumar and Sambangi, 2019). In this chapter, instead, we use recommendation systems for partner selection purposes, in addition to (potentially interesting) co-branded products. We take into consideration, not only company perspectives, but also consumer behaviour and characteristics. Indeed, one of the most important activity in marketing field is related to the market segmentation, which allows identifying and satisfying the different consumers' needs based on consumers' characteristics (Park and Sullivan, 2009). There are many different criteria able to delineate consumer segments according to their preferences and behaviour (Sarabia-Sanchez *et al.*, 2012). Here, we do take them into account "indirectly" by considering consumers' internet searches. Specifically, we use data from Google-Trends index that, as we will show in the analysis development, allow to identify specific consumer types.

Previous research studies different types of recommendation methods (Zhou *et al.*, 2010). Indeed, we can distinguish between Content-Based methods, which are based on users' preferences and objects' characteristics; Collaborative Filtering methods suggest object based on the users' historical behavior; and Hybrid methods, as a combination (Xu, 2018). However, one of the most used is Collaborative Filtering, which produces its results –recommended list of suggestions– based on users' past behavior (Ansari *et al.*, 2000) through user (or object) similarity measures (Zhou *et al.*, 2010). Furthermore, Collaborative Filtering tries to reproduce the "word-of-mouth" procedure (Rafsanjani *et al.*, 2013), which is a very used mechanism in marketing activities because it influences customers' buying decisions (Hennig-Thurau *et al.*, 2004). Specifically, "word-of-mouth" has an important role in the spreading of market information because it exploits the diffusion of information between consumers (Goldenberg *et al.*, 2011).

In the network systems, recommendation methods can be used to predict missing links, i.e., to anticipate the interest of users and suggest potential purchase options by identifying their needs (Zhou *et al.*, 2010). Indeed, the output of a recommendation system is an ordered list of recommended objects for each user list (Zhou *et al.*, 2010). Each element of this list corresponds to a potential new link in the bipartite network users-objects (Fiasconaro *et al.*, 2015).

In the complex system field, some authors explain the importance of the concept of Path Dependence, which is the assumption that future actions strongly depend on past actions, and the "path" –as the disposition of the events in time– matters too (Page, 2006). The reasons underlying Path Dependence may be different, for example, lock-in effects, which represent the circumstance where actors make a specific decision because other similar people have already made it (Page, 2006). To build a Path Dependence, the specific structures surrounding each user, as well as recursive behavior and characteristic connections are needed (Page, 2006). We can conceptually transfer the lock-in effect in recommendation systems by looking at the similarity between users estimated according to users' past behavior, namely, brands' previous co-branding campaigns. In recommendation algorithms, the similarity is a measure that influences the scores (Zhou *et al.*, 2010). Thus, the assumptions underlying recommendation systems are that i) people tend to have the same purchase behavior over time (lock-in effect) and ii) similar people tend to display similar purchase patterns. In our application, past co-branding partnerships represent the surrounding structure of each user, that is, the path from which future choices depend, whereas not-in-common partnerships between brands may represent the target of a new partnership (tendency to emulate).

In contrast, the historical dependence of actions may rely upon past events but not upon their order. Specifically, in the decision-making process, the path of previous events may matter, but not the order of the events, which is the concept of Phat Dependence (Page, 2006). In our application, we do not consider the specific time of events. However, our analysis demonstrates that such structures are predictive of removed links. Therefore, we show how the process underlying partner selection in a co-branding campaign is (at least) phat dependent.

According to complex systems theory, interactions between elements with heterogeneous attributes are significant to explain the formation of emergent structures in the system. All the changes in the activity produce an evolution process within the network (Palla *et al.*, 2007). The interactions generated from each element can represent a signal shared with other elements within the system (spreading of information). In this context, an important aspect is synchronization, which characterizes human life in different aspects, for example, in communicating with an invisible common frame (Arenas *et al.*, 2008). Synchronization is a key factor in the "opinions formation process." Indeed, since people change their opinion influenced by other people, they generate a kind of collective behavior, keeping together a group of people with similar characteristics (Arenas *et al.*, 2008).

## 3.3 Data

In the present study, to develop our analysis, we start by building the database of the existing network of co-branding campaigns.

The network was constructed by linking together brands that established a co-branding

partnership at some point in the past within the fashion industry.
First of all, we build a unique brand list by merging prominent on-line ranked lists of fashion and luxury brands [1].
Then we used a Depth-First Search (DFS) approach (Even, 2011) to search for all the co-branding partnerships on Google. Specifically, the dataset includes all the brand partnerships among the top 100 results on Google, searched by using the queries "BRAND NAME" & "alliance"; "BRAND NAME" & "co-brand". If in these collaborations, a fashion brand not in the list appeared, we included it in the list to search for its collaborations as well. We repeat this procedure for all the brands on the list (including newly added brands). At the end of the data collection procedure, the dataset included 881 brands connected by 1346 links.
To better perform our analysis and study in deep the network, we apply the k-shell decomposition (Carmi *et al.*, (2007) to the network of co-branding campaigns, which allows us to identify its core structure. The network of co-branding campaigns comprises five shells. Thus, the deepest shell (the core structure) is the 5th. It means that in our network, we can distinguish a structure with five levels of deepness. Figure 3.1 reports the 3-shell of the network of co-branding campaigns. We choose to show 3-shell because it is the most suitable to apply recommendation systems in the present study (as reported and better explained in section "Methods").

Thus, starting from 3-shell, we built a bipartite network (brands-cobranded products). For each co-branding partnership in the database, we create the label for co-branded products by collecting information about:

- co-branded products (categories: accessories, bags, clothing, jackets, scarves, luggage, beauty, cars, scooter, food, drink, glasses, hat, hi-tech, jewellery, shoes, sport-equipments, sunglasses, t-shirt, toy, watch, other);
- co-branded product average[2] price (categorised by ranges in a logarithmic scale);
- co-branding target (categories: any, medium-high, high)
- duration of the collaboration (categories: limited, unlimited, recursive[3]).

[1] Fashion united, top 100 fashion companies Index (10/2019); Brand Directory, Apparel 50 2019 Ranking; Forbes, The World's Most Valuable Brands (2019); Financial Times, Top 100 global brands 2019; Ranker, The Best Luxury Fashion Brands (10/2019); Ranker, The Best Italian Clothing Brands; (10/2019); Ranker, The Best French Clothing Brands; (10/2019)
[2] We considered the average price in case of multiple co-branded items.
[3] including seasonal

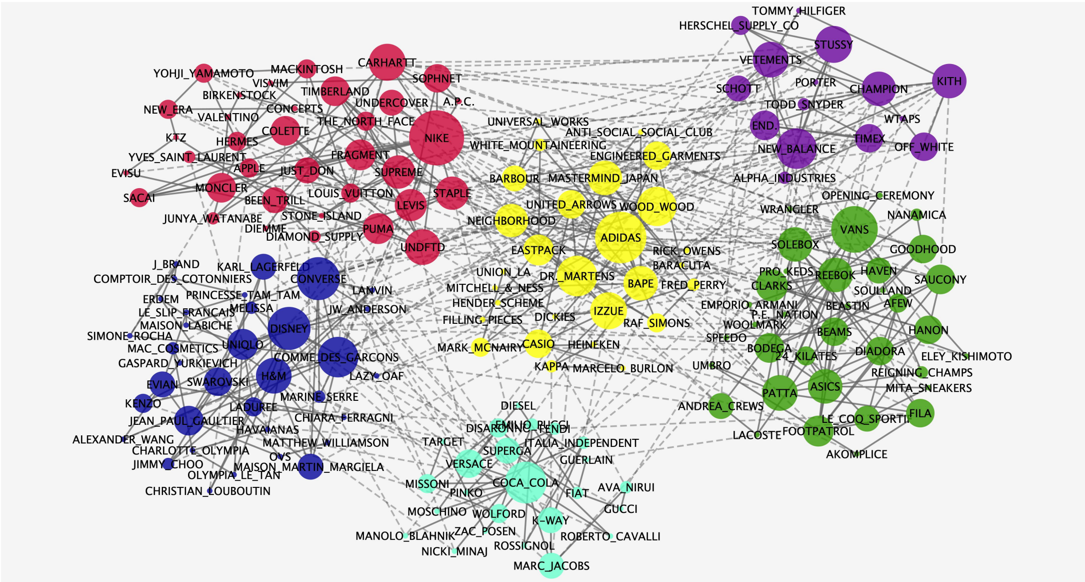



**Figure 3.1:** 3-Shell of the co-branding network

By joining together the features listed above, we produce a unique label and, for each partnership, we associate this label with both the allied brands. At the end of this procedure, we obtain a users-objects network. Specifically, a bipartite network is characterised by a structure that includes two distinct sets of nodes, in our case, namely "brands" and "co-branded products." We set a link between a brand and a product if a given product was the object of a past collaboration that involved that specific brand.

Second, again from 3-shell, we built a *Statistically Validated Network* (SVN) using data from Google-Trends. In particular, for each brand in 3-shell, we collect time series of Google-Trends index. This index counts how many searches have a specific query (in our case, the brand name) on google within a particular span of time. We download data for the last two years (from 1st January 2018 to 31st December 2019), with worldwide coverage, obtaining weekly data.

Using these time series, we calculate the correlations between each pair of brands in 3-shell. Then, we select all the statistically significant correlations to build a network, which in our assumption represent a kind of "*consumer brand-to-brand recall map*".

The choice to use 3-shell is related to the need to have a minimal history of past behavior for each brand to better perform a prediction model.

## 3.4 Methods

To test if consumers mind reproduces the network of co-branding campaigns, we build a Statistically Validated Network (SVN) (Curme *et al.*, 2015), that in our assumption represents the "consumer brand-to-brand recall map." The SVN was built through the time' series of Google-Trends index. Specifically, we calculate the Pearson Correlation coefficient between the time series of Google-Trends index for each pair of brands. Then, we select all the statistically significant correlations to build SVN. The statistical significance of correlation coefficients has been tested by doing $N$ independent data shuffling. Furthermore, we set the threshold of statistical significance at 1% corrected for multiple hypothesis testing through the Bonferroni method. Since the number of brands (vertices) in the dataset (network) is 172 and the number of tests, $T$, is equal to the total number of brand pairs in the dataset, it results that $T = \frac{172*171}{2}$. Therefore, by setting the univariate threshold at 0.01, the Bonferroni corrected threshold of statistical significance is $t_B = \frac{0.01}{T} = 6.8 \cdot 10^{-7}$. The p-value associated with any given brand pair is calculated as the proportion of realisations in which the correlation between the same two brands is higher (lower) than the empirical positive (negative) correlation. To avoid coarse-graining effects due to an insufficient number of shufflings, we set $N > \frac{1}{t_B} = 1.47 \cdot 10^6$. Therefore, a safe choice of the total number of shufflings is $N = 6,000,000$[4]. To be more specific, the data shuffling are done to broken the correlation and test the hypotheses. In our case, we fix time information and rearrange only the corresponding data by iterating this procedure for the $N$ independent tests. We prefer data shuffling with respect to the data simulation because, through the shuffling of the data already contained in the analysis, we maintain the underline marginal distribution.

Figure 3.2 report the SVN, where only the statistically significant correlations between brands are reported[5].

Furthermore, we also apply community detection algorithms based on modularity optimisation (Newman, 2011).

After that, we test if Google-Trends correlation based network (SVN) and the 3-shell of the network of co-branding campaigns are similar[6]. Specifically, by comparing the two

[4] Of course, larger values of $N$ would improve the accuracy of p-value estimates. However, that would result in increasing CPU time, and $N = 6,000,000$ appeared to be a good tradeoff between accuracy and reasonable CPU time.

[5] Empirical and Descriptive Analysis section reports a full description of this figure

[6] The choice to use 3-shell is related to the need of having a minimal history of past behaviour for each brand, to better perform a prediction model.

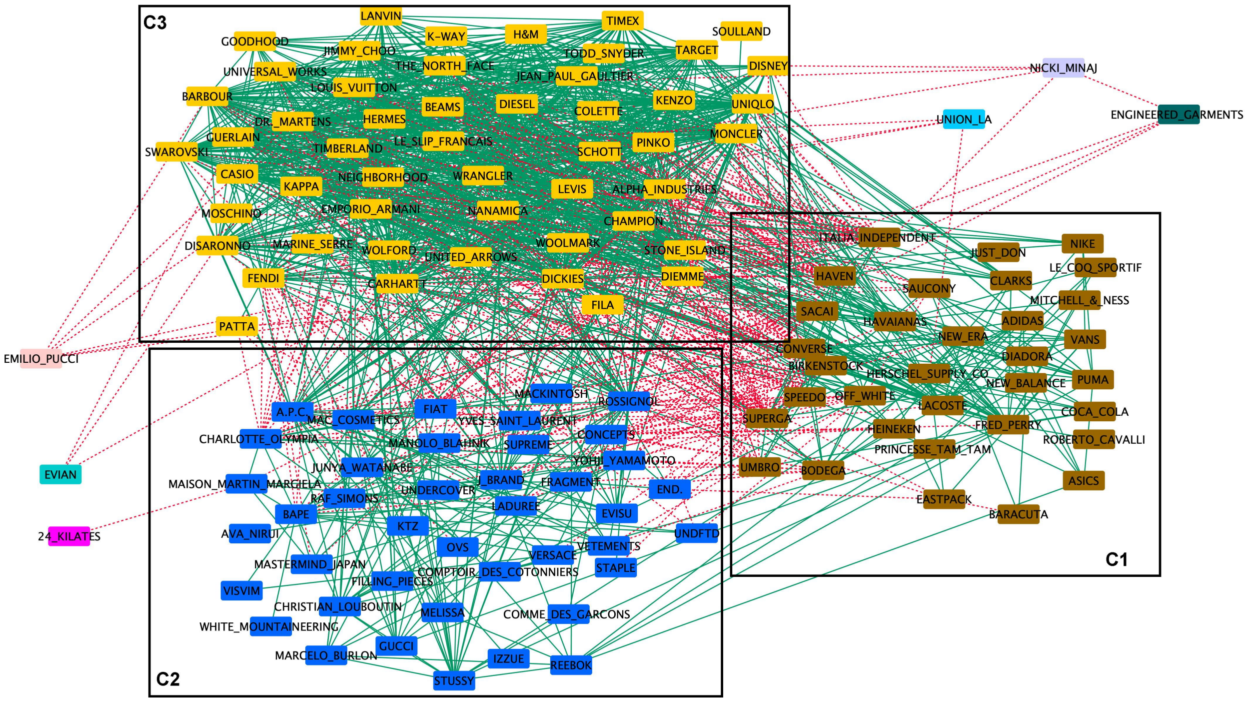



**Figure 3.2:** Google-Trends correlation based network

networks, we measure the extent to which they carry the same information. 3-Shell of the network of co-branding campaigns includes 172 brands connected through 537 links. The Google-Trends network only includes 131 brands and 1438 links. Indeed, the Google-Trends time series of 41 brands did not show any statistically significant correlation with other brands and were then removed from the network. It is worth noticing that the number of links in common between the two networks is rather small, that is 39 links (31 associated with positive correlations in Google-Trends and 8 with negative correlations). We further investigate this observation by associating a $p-value$ with the intersection between the two networks. We accomplish this goal by testing the observed outcome (39) against a null hypothesis in which the intersection is assumed to occur by chance. The considered null model assumes that links from both networks are randomly picked from a bulk made of all the possible links among the $n = 172$ vertices (which are the same in both networks, including isolated nodes in the Google-Trends network). Under such a hypothesis, the number of links in the intersection network follows a Hypergeometric Distribution. Specifically, if $T$ is set equal to the total number of possible links in the network, i.e., the bulk dimension $T = n\,(n-1)/2$, then:

$$p - value = \sum_{k=0}^{E_{int}} \frac{\binom{E_{gt}}{k}\binom{T-E_{gt}}{E_{co}-k}}{\binom{T}{E_{co}}}$$

The urn model underlying such null hypothesis is obtained by considering an urn composed of $T = n\,(n-1)/2$ links, which are divided into the $E_{gt}$ links contained in Google-Trends network and the ones that are not $(T - E_{gt})$. Then, we randomly draw from the urn a number of links equal to the total number of links in the network of co-branding campaigns, $E_{co}$, and we count the number of links contained in the Google-Trends network among the drawn ones (i.e., the intersection between the two networks). Here we show that the actual intersection of the two networks is significantly smaller in size than the expected size according to the null model. Indeed, if we calculate the probability to obtain a number of links lower or equal to the value observed, we obtain a p-value $= 0.0237$.
The $p - value$ for the whole network is 0.0237, by considering only positive links the $p - value$ is 0.0273.
These results show that the two networks are different, with a statistical significance of 5%. Thus, the two networks carry partially complementary information. The interpretation of the communities reported in section "Empirical and Descriptive Analysis" also support this conclusion.

Through this information, we develop a recommendation system that combines both networks' information to suggest objects (co-branded products) of potential interest to each brand and, then, to predict potential partnerships.
Recommendation Methods exploit the similarity between two users to produce a score, which is the final output of the procedure. Specifically, the similarity between two users, $i$ and $j$, is calculated as Zhou *et al.* (2010):

$$s_{ij} = \frac{\sum_{\alpha=1}^{o} a_{\alpha i} a_{\alpha j}}{\sqrt{k_i k_j}} \tag{3.1}$$

Where $\alpha$ is a given object, $O$ is the total list of objects, $k_i$ and $k_j$ represent the number of objects collected by user $i$ and $j$; $a_{\alpha i}$ is equal to 1 if user $i$ has collected object $\alpha$, 0 otherwise.

The previously described similarity measure (1) seeks to calculate a score for each object. In particular, for user $i$ that has not collected an object $\alpha$, the score is calculated as follows (Zhou *et al.*, 2010):

$$v_{\alpha j} = \frac{\sum_{j=1}^{u} s_{ij} a_{\alpha j}}{\sum_{j=1}^{u} s_{ij}} \tag{3.2}$$

For each user, by sorting scoring values (related to each object) in descending order (the most recommended objects are positioned higher in the list), we build the final recommendation list (Zhou *et al.*, 2010). Finally, to each score, the corresponding rank position is associated (Zhou *et al.*, 2010).

According to this, we now proceed to predict missing links.
To predict links, we use an out of sample test, specifically, 10-fold cross-validation. In particular, we divide the dataset into ten non-overlapping subnetworks. By applying Recommendation Methods, we use nine subnetworks as a training set to predict (removed) links in the test set (the tenth subnetworks).
Based on the recommended list construction, removed links should be positioned with higher ranks (Zhou *et al.*, 2010). We then calculate the ranked position for each object (removed links) as follow (Zhou *et al.*, 2010):

$$r_{\alpha i} = \frac{p}{o - k_i} \tag{3.3}$$

with $p$ = position of uncollected object (removed link), $o$ = total objects in the training set, $k_i$ = number of objects already collected by user $i$. Finally, by averaging all $r_{\alpha i}$ for removed links, we can calculate the *R-score*, which represents a quality measure of the ability of the Recommendation Method to predict links (Zhou *et al.*, 2010). The smaller is the *R-score*, the better is the quality of the method and its ability to predict removed links (Zhou *et al.*, 2010).

In this study, to use the information contained in both networks (cobranding campaigns and brand-to-brand recall map), we build a unique similarity matrix by shrinking two matrices: i) the matrix of Binary Pearson Correlation Coefficient associated with the bipartite network of brands and cobranded products, and ii) the correlation matrix of time' series Google-Trends index.
Using 10-fold cross-validation on the network of cobranding campaigns, we calculate the

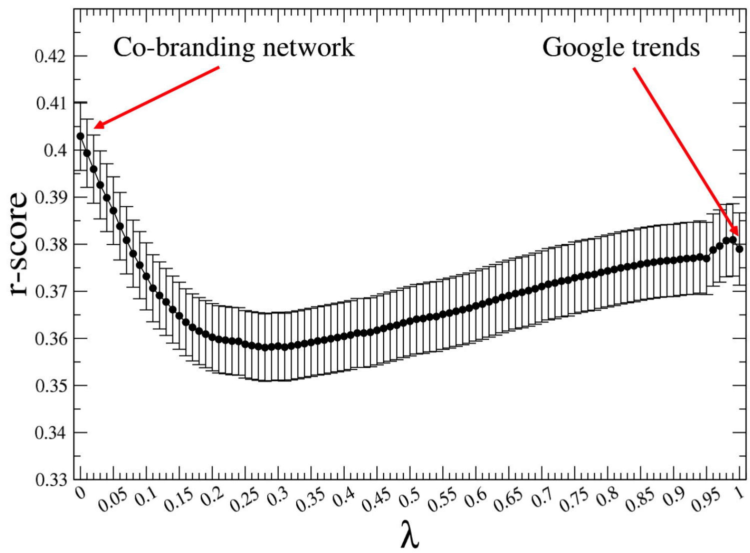



**Figure 3.3:** 10-fold to determine optimum $\lambda$

optimum shrinkage parameter to build the unique similarity matrix (Figure 3.3).

$$S(\lambda) = \lambda C_{GT} + (1 - \lambda) C_{CB} \tag{3.4}$$

Where $C_{GT}$ is the matrix reporting the Google-Trends correlation based network, and $C_{CB}$ is the matrix reporting the correlation from the brands-products network.

In Figure 3.3 the *R-score* for each level of $\lambda$ is reported. The figure shows that $\lambda$=0.3 is the optimum value of the shrinkage parameter, that is, the one that minimizes the *R-score*. This result suggests that company logics underlying partner selection tends to be more influenced by managerial/company factors than by consumers' expected impact.

Through this similarity matrix, we can apply Recommendation Methods on the bipartite network to obtain:

- a ranked list of suggested co-branded products

- a ranked list of suggested future partnerships

To reach the first goal, we apply the Recommendation algorithm to the bipartite network. For each user (brand), we calculate a score associated with each object (co-branded product) and produce a ranked list of recommendations. Indeed, the final result of this step is a ranked list of recommended objects (co-branded products) for each user (brand). Table 3.1 reports an example of a sublist of recommended objects.

| BRAND | PRODUCT | PRICE-RANGE | TARGET | DURATION | SCORE | RANK |
|---|---|---|---|---|---|---|
| FENDI | SHOES | 100-200 | ANY | LIMITED | 0.746282 | 1 |
| FENDI | CLOTHING | 100-200 | ANY | LIMITED | 0,493675 | 2 |
| FENDI | SHOES | 200-300 | MEDIUM-HIGH | LIMITED | 0,337089 | 3 |
| FENDI | DRINK | 20-30 | ANY | LIMITED | 0,242285 | 4 |
| FENDI | SHOES | 300-400 | MEDIUM-HIGH | LIMITED | 0,159999 | 5 |
| FENDI | CLOTHING | 200-300 | MEDIUM-HIGH | LIMITED | 0,151159 | 6 |
| FENDI | JACKET | 300-400 | MEDIUM-HIGH | LIMITED | 0,097611 | 7 |
| FENDI | CLOTHING | 60-70 | ANY | LIMITED | 0,093471 | 8 |

**Table 3.1:** Example of a recommendation output

The second goal was to suggest a (ranked) list of potential partners to each user. Thus, first of all, we switch from a *user-object* environment to a *user-user* environment. To do this and produce a ranked list of partners for each brand, we can compare the lists of recommended objects for each brand in partnership. In this way, we can obtain a similarity measure between brands through the lists of recommended products needed to produce a list of recommended partners. In doing this, we can follow two directions:
First, for each couple of brands in the dataset, we can compare the entire ranked list of co-branded products and calculate the *Spearman Correlation*.

Second, according to the $HIT(L)$ methods, traditional recommendation systems (applied in user-object networks) show to users only the first $L$ results, where $L$ is a fixed threshold applied to the output list. Some websites generally use this procedure, for example, "Netflix" or "Amazon Prime," and the assumption underlying this procedure is that people's mind has not the ability to process a large quantity of information. Thus, these websites show users only a reduced list with the top results.
The reason why we also try to use the entire list is that the target of the present study is the company that should have a higher ability to process a large quantity of information than a single user.
However, the results lead us to conclude that the $HIT(L)$ method was the most performant, likely because it reflects the fact that also companies process limited information (though larger than users in other systems).
Our analysis grounds on an out-of-sample test, namely *leave-one-out*. The reason to use this method instead of the 10-fold cross-validation depends nature of the analysis, since,

in this way, removing only one link from the network of co-branding campaigns means removing the two correspondent links in the bipartite network, i.e., the two brands of the removed partnership linked to the corresponding co-branded product. Indeed, in this way, we are sure to investigate each part of the network structure, while using a 10-fold approach may not guarantee to cover each edge of the network.

Thus, to produce the list of potential partners, the procedure carried out is the following. First, we remove one link from the network of co-branding campaigns (brand $B_i$ linked to brand $B_j$). Thus, we remove the two corresponding links from the bipartite network as well (each partnership in the network of co-branding campaigns corresponds to two links in the bipartite network, specifically, $B_i$ and $B_j$ both linked to their co-branded product, i.e., the object of their collaboration).

Second, we apply the recommendation method on the bipartite network to produce the ranked lists of recommended products for each brand. In this step, for each brand, we obtain a list of recommended products sorted by the scores, from the higher to the lower. After that, we set a threshold, $L$, on the ranked lists of recommended products, and we calculate the overlapping between the list of brand $B_i$ with the list of recommended products of all other brands in the network, obtaining in this way a ranked list of potential partners (of $B_i$) through the measure of overlapping, ranked according to the binary Pearson's correlation coefficient, as reported in equation (5). From the list of potential partners, we remove the links related to the partnerships already established in the past by $B_i$ and, according to the categorisation of the brands, some links of incompatible partnerships.

We repeat this procedure for brand $B_j$.

For the removed link ($B_i$ linked to $B_j$ in the network of co-branding campaigns), we calculate the position of $B_j$ in the list of potential partners of $B_i$ and $vice-versa$, calculating the *R-score* for both brands. Then, we calculate the average *R-score* between them.

We repeat this analysis for all the links in the network of co-branding campaigns (i.e., the leave-one-out procedure), and, finally, we calculate the global average *R-score* as the mean between all the average *R-scores* obtained for all the couples of brands in the network of co-branding campaigns.

We repeat this procedure by varying the value of the $L$ threshold.

Specifically, we determine the best threshold level of $L$ (as figure 3.4 shows) as $L$=35, since it is the threshold that minimises the global average *R-score*. However, each value between 30 and 40 can be acceptable as well. The fact that different levels of the thresh-

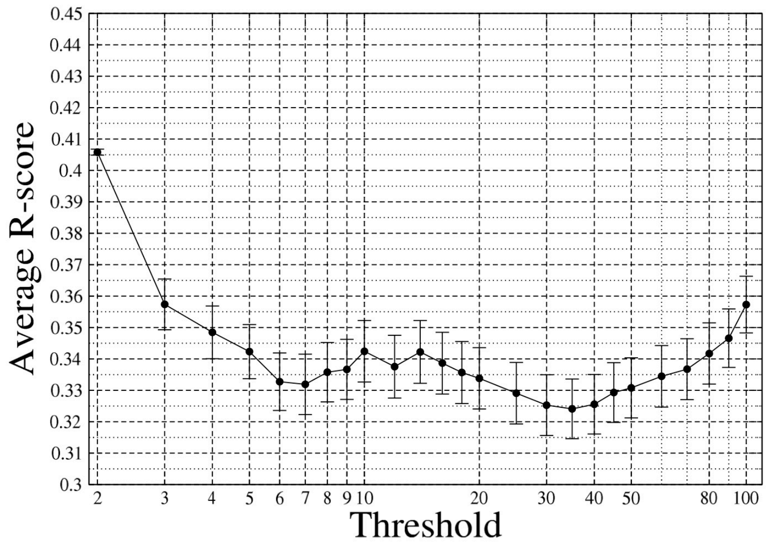



**Figure 3.4:** R-score as a function of the threshold level $L$.

old provide similar outcomes in terms of performance (average *R-score*) likely reflects the heterogeneity of firms with respect to their portfolio and main-production, which would suggest that different thresholds may apply to different brands. However, such an analysis is out of the scope of the present chapter.

It may happen that for some brands couple, the *R-score* is strongly different between the two partners brand, meaning that this potential partnership is not statistically significant (this case occurs when, in a couple of brands, one partner brand is not high positioned in the list of potential partners of the other).

Thus, the methods discussed so far assume symmetry between the brands that may not represent well the actual structure of the system.

To tackle this problem, we can hypothesise to perform the procedure by introducing a kind of weight, depending on the popularity (degree) of each brand in the whole system, which is, however, out of the scope of the present analysis.

The similarity measure between the recommended lists of co-branded products, through the overlapping of the lists, is calculated as follows:

$$\rho(n_{ij}|L) = \frac{n_{ij} - \frac{L^2}{N}}{L \cdot (1 - \frac{L}{N})} \tag{3.5}$$

where, besides the threshold level $L$, $n_{ij}$ is the overlapping between the top $L$ product categories of brand $B_i$ and brand $B_j$, and $N$ is the total number of brands in the network. We test the statistical significance of the lists correlation as follows:

$$p - value(n_{ij}|L) = \sum_{x=n_{ij}}^{L} \frac{\binom{N}{x} \cdot \binom{N-L}{L-x}}{\binom{N}{L}} \tag{3.6}$$

The score measures associated with all the potential partners are calculated and ranked through equation (3.5).

## 3.5 Empirical and Descriptive Analysis

In both our networks, we apply a community detection algorithm to show the clusters inside them. Thus, first of all, we can provide a qualitative description of the networks.

In Google-Trends correlation-based network, as Figure 3.2 shows, the different colors of the links are related to the positive/negative correlation. Specifically, green links identify positive correlations, and red links identify the negative correlations. Instead, the different colors of the nodes identify the different clusters. Here, the correlation is interpreted as:

- if positive: consumers search for the two given brands at the same time, meaning that they associate the two brands, even if these associations may be related to different reasons.

- if negative: consumers do not search for the two given brands at the same time, meaning that they do not associate the two brands; again, this evidence may be related to different reasons.

Accordingly, we can first observe how the network presents negative correlations between the communities and positive correlation within the communities. This characteristic leads to the conclusion that people tend to search for two brands in the same community simultaneously, associating the two brands in their mind, and they do not associate brands from different communities. Nonetheless, the positive correlations that link brands in different communities exist and are mainly related to the association between brands related to different market targets (brand extension) or brands in direct competition (substitute products).
Moreover, the three main communities have a specific interpretation since they identify three different types of consumers. Specifically:

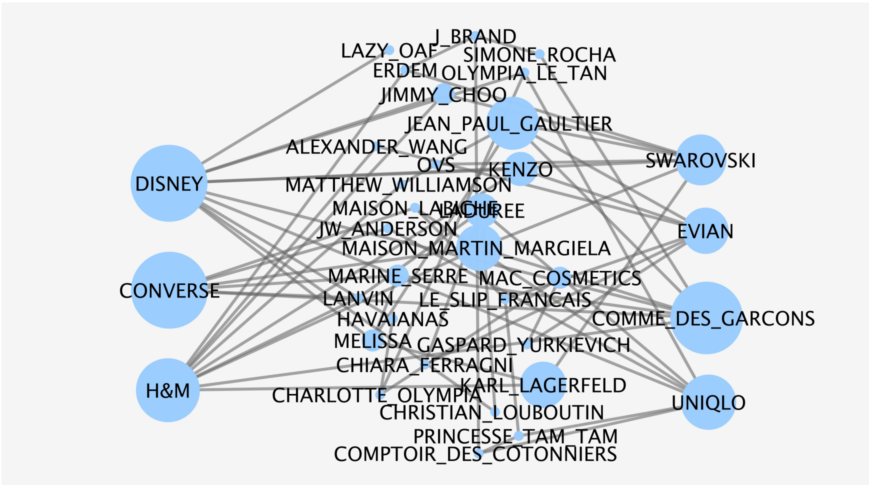



**Figure 3.5:** Comm.1 Clash of the Titans

- C3 (the yellow cluster) identifies Mass Consumers (70% of mass brands),
- C2 (the blue cluster) identifies Luxury Consumers (65% of luxury brands),
- C1 (the brown cluster) identifying Sport Consumers (64% of sports brands).

In 3-shell of the network of co-branding campaigns, the community detection algorithm shows six clusters, and in figure 3.1 are identified with the different colors of the nodes. In the Figure, the dash links connect brands in two different communities (i.e., link external to the single community). First of all, we can highlight that almost all the communities present a tripartite structure.

Specifically, figure 3.5 shows the community one. In this community, we can observe how the brands with a higher number of connections (node dimension indicate the degree) compete with each other to obtain a collaboration with the small ones.

In community 2 (figure 3.6), the Italian luxury brands compete with each other Italian brand and collaborate with all the other brands in the community.

As shown in figure 3.7, community 3 shows a fusion between two different (opposite) market targets. Even if the figure does not show, either this community presents a tripartite structure. This community displays the use of a co-branding strategy to apply step-up (down) brand extensions.

Community 4 (shown in figure 3.8) presents brands from basically two countries. It may represent a kind of heritage sharing between the culture of the two Country of origin,

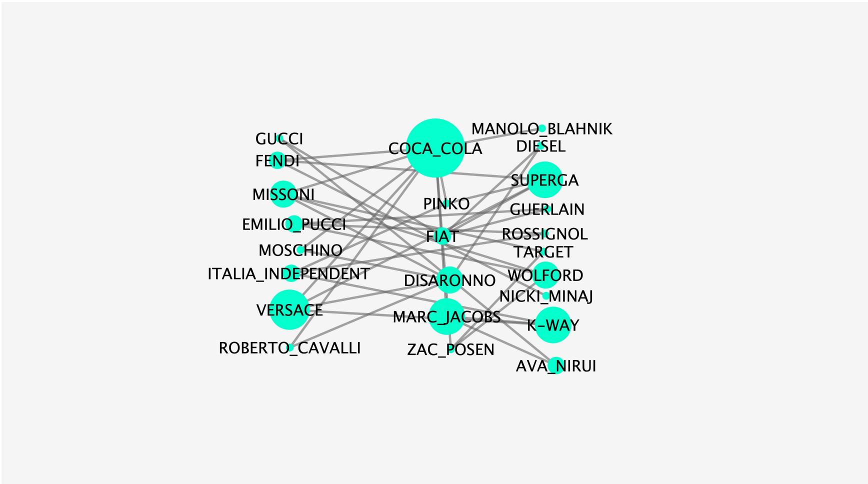



**Figure 3.6:** Comm.2 Italian luxury brands vs other brands

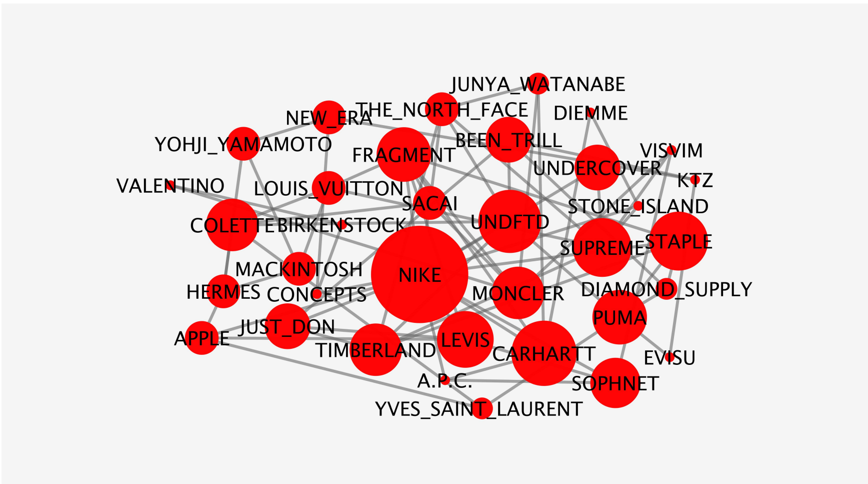



**Figure 3.7:** Comm.3 Fusion between market target

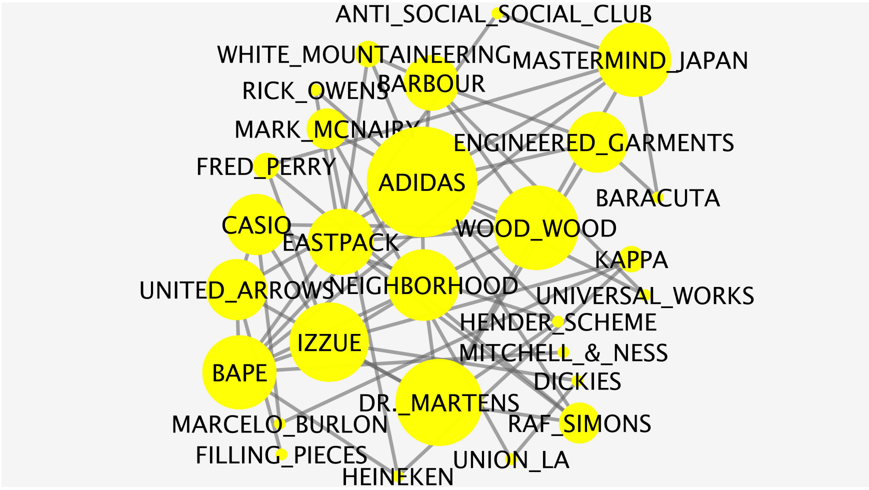



**Figure 3.8:** Comm.4 Geographical heritage fusion

exploited through the brands' collaborations.

Figure 3.9 shows a planar subgraph. In this community, all the brands come from the same Country of origin (USA), and the only cross within the links connect brands from different Countries (links in red color in the figure). Thus, proximity advantages may be hypothesised.

In Figure 3.10, the interpretation of the bipartite structure highlights strong competition effects. Indeed, in this community, it is possible to observe on one hand sports brands, and on the other hand, retail brands (mainly sport targeted). The nodes in the two sets strongly compete within the set and cooperate between the sets, representing a form of collaboration based on supply chain advantages.

Finally, we provide some descriptive statistics for both the networks. About 3-shell of the network of co-branding campaigns, we summarise the main results in table 3.2, and we provide a graphical representation of the degree distribution in figure 3.11. As results show, a Log-Normal Distribution well describes the tail of the degree distribution ($k \geq 8$). We test the distribution through Anderson-Darling (p-value=0.5278), Cramér-von Mises (p-value=0.5707), and Pearson $\chi^2$ (p-value=0.2263), and conclude that, according to the performed tests, the Log-normal distribution hypothesis cannot be rejected.

Finally, table 3.3 provides the top ten hubs in 3-Shell, and table 3.4 shows the main hub for each community. As the tables show, the main hub of each community corresponds to an hub of the whole 3-shell.

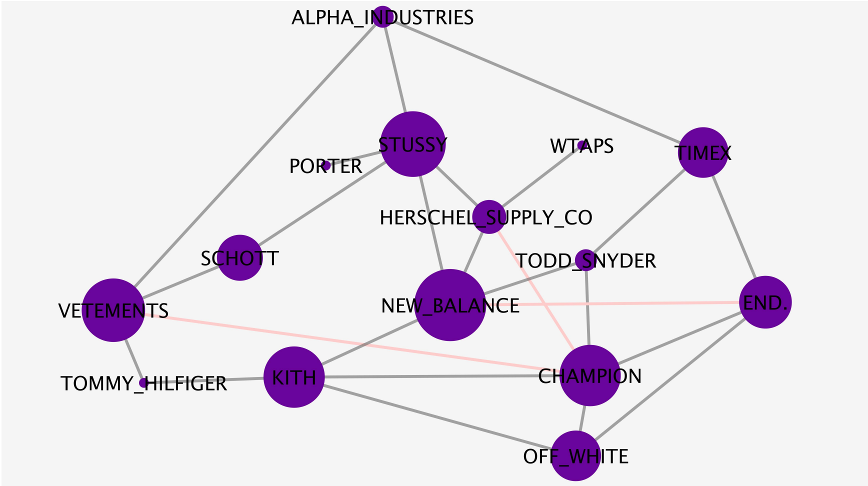



**Figure 3.9:** Comm.5 Planary geografical community

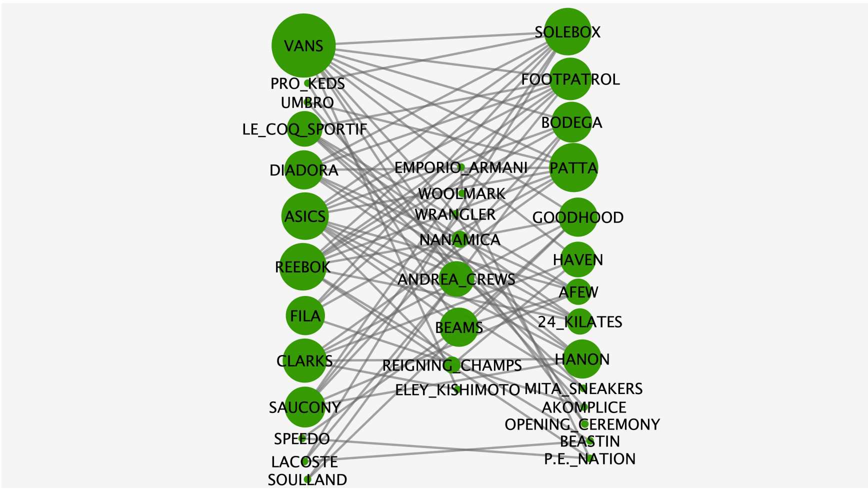



**Figure 3.10:** Comm.6 Brands strong competition

**Table 3.2:** 3-Shell: descriptive statistics

| MEASURE | VALUE |
|---|---|
| Numbers of Nodes | 172 |
| Numbers of Links | 537 |
| Clustering Coefficient | 0.072 |
| Network Density | 0.037 |
| Network Diameter | 5 |
| Average N. of Neighbors | 6.244 |

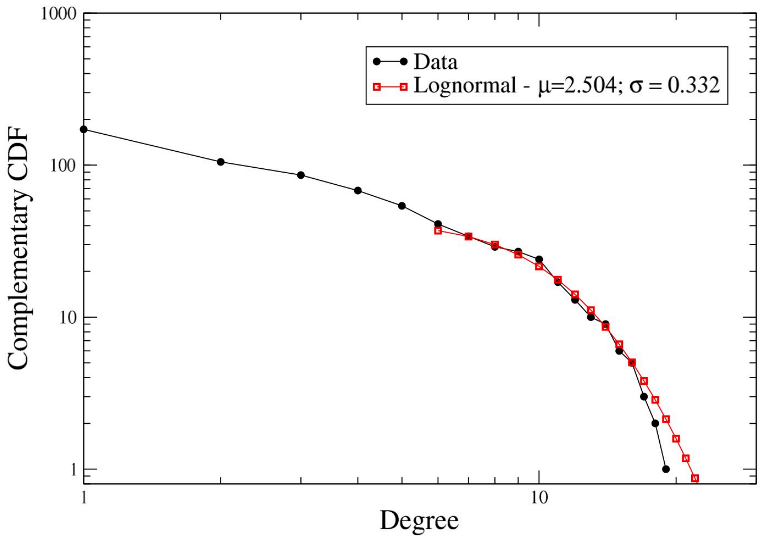



**Figure 3.11:** 3-Shell degree distribution

**Table 3.3:** Top ten hubs in 3-shell

| BRAND | DEGREE |
|---|---|
| NIKE | 29 |
| ADIDAS | 26 |
| VANS | 22 |
| CONVERSE | 19 |
| DISNEY | 19 |
| COCA COLA | 18 |
| DR. MARTENS | 17 |
| NEW BALANCE | 17 |
| COMME DES GARCONS | 17 |
| WOOD WOOD | 16 |

**Table 3.4:** Main hubs for each community in 3-Shell

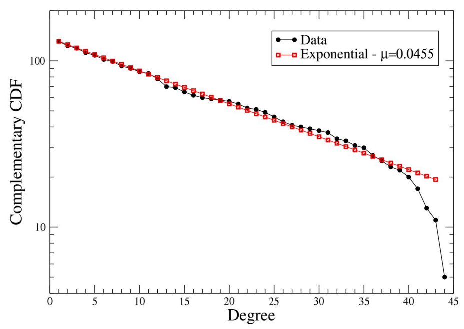
| COMMUNITY | BRAND | DEGREE |
|---|---|---|
| COMMUNITY 1 | DISNEY | 10 |
| COMMUNITY 2 | COCA COLA | 9 |
| COMMUNITY 3 | NIKE | 13 |
| COMMUNITY 4 | ADIDAS | 13 |
| COMMUNITY 5 | CHAMPION | 6 |
| COMMUNITY 6 | VANS | 10 |

Switching on the analysis of the statistics on Google-Trend network, we summarise the main results in Table 3.5, and we provide a graphical representation of the degree distribution in Figure 3.12. As results show, an Exponential Distribution well describes the degree distribution. We test the distribution through Anderson-Darling (p-value=0.1007), Cramér-von Mises (p-value=0.2039), and Pearson $\chi^2$ (p-value=1.73393*$10^{-6}$). Furthermore, in Figure 3.12, we also show the degree distribution of the Planar Maximally Filtered Graph (PMFG) associated with the Google-Trends correlation matrix. Though we provide an in-depth description of the Google-Trends PMFG in appendix 2, here we show the degree distribution of this graph to help interpret the result concerning the good fit of the exponential distribution to the empirical Google-Trends network degree distribution. Specifically, previous research (Aste *et al.* 2012; Aste *et al.* 2012b) shows that the degree of a Planar Graph, which is a graph that can be embedded on a sphere (genus=0), follows a power-law distribution. However, at growing surface genus, the degree distribution tends to an exponential distribution. Since the density of the Google-Trends network is pretty high, which likely corresponds to a high value of the genus, the analysis reported in Aste *et al.* (2012) and Aste *et al.* (2012b) may provide an explanation of the results reported in Figure 3.12.
Finally, Table 3.6 provides the top ten hubs in the Google-Trends network, and Table 3.7 shows the main hub for each community. Different from the results in 3-Shell, in Google-Trends network the hubs of the communities do not correspond to the hubs in the whole network.

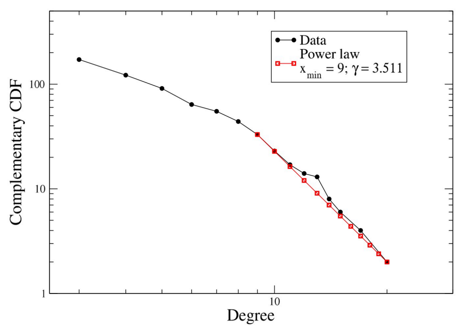
Another notable element is the difference in connectivity within communities in the Google-Trends network. Indeed, communities C1 and C2 in Figure 3.2 present a lower connectivity (density measure is 0.165 and 0.135, respectively) than the connectivity in community C3 (density=0.580). This result mainly shows that in community C3 lot of the correlations between the couples of brands are statistically significant; thus, the recall process between the brands may be stronger than in the other communities. From a consumers' point of view, this result has an interesting meaning since it seems to represent the association in consumers' minds due to the brand extension.

**Table 3.5:** Google-Trends network main measures

| MEASURE | VALUE |
|---|---|
| Number of Nodes | 131 |
| Number of Links | 1438 |
| Clustering Coefficient | 0.547 |
| Network Density | 0.169 |
| Network Diameter | 5 |
| Average N. of Neighbors | 21.954 |




(a) Google-Trends SVN




(b) Google-Trends PMFG

**Figure 3.12:** Google-Trends degree distribution of the SVN network and PMFG

**Table 3.6:** Top ten hubs in Google-Trends network

| BRAND | DEGREE |
|---|---|
| MONCLER | 57 |
| CARHARTT | 55 |
| DICKIES | 53 |
| DIESEL | 53 |
| BARBOUR | 53 |
| GUERLAIN | 52 |
| EMPORIO ARMANI | 52 |
| TIMBERLAND | 52 |
| THE NORTH FACE | 52 |
| SCHOTT | 52 |
| KENZO | 52 |

**Table 3.7:** Main hubs for each community in Google-Trends network

| COMMUNITY | BRAND | DEGREE |
|---|---|---|
| COMMUNITY 1 | LACOSTE | 11 |
| COMMUNITY 2 | BAPE | 17 |
| COMMUNITY 3 | MONCLER | 46 |

### 3.5.1 Intersection interpretation

Another interesting analysis comes from the overlapping between the two networks, i.e., the links in common in the two networks, i.e., the links actually object of a brand alliance that also present a significant association in Google-Trends.
Indeed, since our analysis demonstrates a (significantly) small overlapping between the two networks, it seems interesting to analyse it in deep.
The links in common in the two networks are 39 (see table A1 in appendix) and present both negative and positive correlations (from the statistically validated network of Google-Trends).

The highest positive correlation links the brands "THE NORTH FACE" and "TIMBERLAND," both belonging to community C3. A positive correlation means that consumers search for these brands on google simultaneously, and this may depend on the fact that consumers see both brands as a way to identify themselves. Indeed, this collaboration seems to show the need to sharing a specific message that identifies a kind of consumer, as our interpretation of the communities in the Google-Trends network reveals. Thus, a collaboration between these brands (that actually exists) concerns a product with an intrinsic meaning and specific characteristics, such that consumers perceive the collaboration product better than the one offered by the single brand because it may satisfy better consumers' needs and tastes. On the other hand, for example, if we look inside community C1 in figure 3.2, the google-trend correlation between "NIKE" and "ADIDAS" is positive and very high as well, though we cannot observe an actual brand alliance between these brands. Indeed, despite the two brands insist exactly on the same market target, in this case, consumers perceive them as substitute products Within the Google-Trends network, the positive correlations connecting brands from different communities are mainly related to direct competition brands (consumers look for the same substitute product) or brands from another market target (highlighting the brand extension links in consumers' minds). Meanwhile, for example, "KAPPA" and "K-WAY" (community C3) present a positive correlation in consumers' minds, they are targeted basically to the same sports market segment, and they have actually established a co-branding alliance, probably due to the specialisation that characterises each one of the brands. This case highlights a coopetition logic that occurs when two companies compete and cooperate at the same time (Bengtsson and Kock, 2000). This kind of logic can be easily interpreted as a mechanism of balancing in a signed network. Specifically, two companies implement a coopetition alliance to obtain an advantage by working together and facing the single direct competitors (especially the strongest in the market). On a signed triangle, if we look at the structure (three nodes in relationship between them), where each edge has a label, "+" or "-", to identify cooperation or friendship and competition or animosity, respectively, we have four different triangle *motifs*, two stable (balanced) and two not stable (not balanced) (Easley and Kleinberg, 2010):

1) Each edge is classified as "+". In this case, each node cooperates with the others. This situation is stable and balanced situation.

2) Two edges are classified as "-" and one edge as "+". This situation is also stable (balanced): two nodes cooperates to compete with the third one.

3) Two edges are classified as "+" and one as "-". In this configuration, node $A$ cooperates with both $B$ and $C$, but $B$ and $C$ compete among. This situation is unstable (unbalanced), since it is a source of stress for node $A$, and the tendency is to stabilize by transforming a "+" in a "-", and therefore, become configuration (2).

4) Three edges are classified as "-". This situation is a mildly unstable configuration, since each element is in a competition with the others, and, therefore, an alliance between two competitors, i.e., a "-" that becomes a "+" may improve their ability to compete with the third node. Thus, this configuration can also transform and become configuration (2).

Based on the description above (Easley and Kleinberg, 2010), the coopetition alliance can be associated with the stable configuration "- - +", that is, configuration (2), which results as an evolution of a condition in which each element compete with each other, i.e., configuration (4).

Another interesting example comes from the collaboration between "CHRISTIAN LOUBOUTIN" and "LADUREE" (positive correlation and same community, C2). In this case, both the brands have a luxury market target, and the collaboration is probably related to maintaining this image of exclusivity. Indeed, in this case, the consumers' target is the same, but they exploit the image of each other to obtain advantages. This case seems to reproduce a kind of identity logic, which is a derivative of the broader concept of "*homophily*", a mechanism that we recognize among the reasons underlying some consumption patterns and reflect in brand strategies, such as this one.

As network theory shows, one of the most important and fundamental mechanisms in social networks is *homophily*, i.e., the concept that each person tends to be more similar to his own friends (Easley and Kleinberg, 2010). There are two mechanisms underlying homophily (Easley and Kleinberg, 2010):

- *Selection*: the tendency to form a link between people based on immutable characteristics. People choose and select friends with similar characteristics. From the consumers' point of view, this mechanism may be associated with reasons related to the social and educational status.

- *Social Influence*: when people adapt and modify the behaviour to become more similar to their family or friends. From the consumers' point of view, this mechanism may be associated with the need to be part of a group.

These two concepts are two faces of the same medal. In particular, the mechanism of selection describes how people (nodes) and their characteristics guide the link formation, while the social influence mechanism highlight how the extant links within the network tend to shape people (nodes) characteristics (Easley and Kleinberg, 2010).

In our case, we interpret the collaboration between "CHRISTIAN LOUBOUTIN" and "LADUREE" as the outcome of a *selection* process.

Furthermore, let's look, for example, at the collaboration between "LOUIS VUITTON" and "SUPREME" (which have a negative correlation and are part of two different communities C3 and C2, respectively). The reason for the negative correlation is probably related to the different consumers' target (luxury and street, respectively), but at the same time can be brought back to the mechanism of *social influence*. Indeed, the reasons underlying the partnership in the network of co-branding campaigns have a specific meaning from companies' perspective, i.e., to associate the brand with the other market target (social influence).

In contrast, we can highlight a real collaboration actually recalled in consumer mind with positive correlation, i.e., the link between "H&M" and "KENZO". In this case, both single brands are targeted to different kinds of consumers as well, but in our analysis, both brands stand in the same community (C3). Thus, the collaboration is probably related

**Table 3.8:** Kenzo partnerships in 3-shell of the network of co-branding campaigns

| BRAND 1 | BRAND 2 |
|---|---|
| KENZO | DISNEY |
| KENZO | EVIAN |
| KENZO | VANS |
| KENZO | WOLFORD |
| KENZO | H&M |

to obtaining a wider consumer target (as a kind of brand extension, launching a product for a lower market target but exploiting the brand image). Again, a selection mechanism seems to occur and, in this case, the aim is to reach a wider market target by exploiting the characteristics of each other.
The difference between the last two examples may come from the "initiator", i.e., the brand that first proposes the collaboration. In the case of "H&M" and "KENZO", since "H&M" recursively adopt co-branding, the initiator may be "KENZO" that through this collaboration may reach a wider market target, avoiding the negative effect of a brand extension (dilution effect). On the other hand, "H&M" exploits the "KENZO" image to obtain some exclusivity. Opposite, in the case of "LOUIS VUITTON" and "SUPREME", the initiator may be "SUPREME" since it wants to associate its image with a different target (the phenomena of luxury streetwear). These two examples seem to describe perfectly the difference between *selection* (H&M with KENZO) and *social influence* ("LOUIS VUITTON" and "SUPREME").

We can better explain our assumption on the dynamics underlying the partnerships between brands with different market targets through the example of "KENZO", which is a luxury brand. As Table 3.8 shows, in 3-shell, "KENZO" presents different co-branding relationships. Indeed, in addition to "H&M", "KENZO" collaborates with "DISNEY", "EVIAN", "VANS" and "WOLFORD". Within these collaborations, "DISNEY" and "EVIAN" are from two completely different markets, while "VANS" and "WOLFORD" are from two different product categories (sport and luxury underwear, respectively). The links recalled in consumers' mind, on the one hand may connect two different targets (mass and luxury, as in the collaboration with "H&M") and tend to reach a wider market target; on the other hand the links may tend to maintain the "luxury" image of the brand (luxury, as in the collaboration with "WOLFORD"). Consumer recall suggests that partners' choices made by "KENZO" are all directed to avoid the dilution effect.

A particular type of collaboration seems to be less recalled in consumers' mind, i.e. the geographic logic. In this case, obtaining some proximity advantages is the reason to implement the collaboration, as the planar graph in community 6 (figure 3.9) suggests. Indeed, the planarity of a graph may reflect the geographic proximity. In the network of co-branding campaigns, we can observe different collaborations related to this logic. For example, the collaboration between "CHAMPION" and "TODD SNYDER" (figure 3.9), but consumers' minds do not recall in this direction. Indeed, the geographic advancement may come from a kind of geographic identity, as may be the reason underly the link between "FENDI" and "FILA", both Italian brands. This collaboration is an example of real co-branding collaboration (3-shell of the network of co-branding campaigns) that presents a high and positive correlation in the Google-Trends network. Thus, it seems that consumers' minds activate the recall process through motivations not directly related to the companies' logics (proximity advantages).

Finally, in the intersection analysis, the highest negative correlation links "DR.MARTENS" and "HAVEN" which is a collaboration between brands in two different communities (C3 and C1, respectively). In this case, we can highlight a real collaboration between a fashion brand and retail, thus, a kind of "chain" logic that in consumers' mind probably will be never associate. This is a very interesting point since this link is a real collaboration in 3-shell, but at the same time, the link is strongly negative in the Google-Trends network, highlighting a totally different mechanism in consumers' mind, exactly the opposite of the association recall. Indeed, in our analysis, the negative correlation means that the consumers do not search for the two brands simultaneously, activating a kind of contrary of the recall process, as if they push away from each other. In figure 3.13, we can observe how negative correlation links usually involve at least one retail brand ("HAVEN", "BEAMS" and "CONCEPTS"). The exceptions can trace back, on the one hand, to the Social Influence ("LOUIS VUITTON" and "SUPREME"), and on the other hand, to a geographic triad ("ITALIA INDEPENDENT-PINKO-SUPERGA"). Notice that "ITALIA INDEPENDENT" and "SUPERGA" link exist in Google-Trends network but not in the network of cobranding campaigns. Thus, the triad in the intersection has two negative links but a "missing" positive link, between the two extreme nodes, needed to complete the triangle structure. This situation may suggest the tendency to a balanced structure of the signed networks (point 2 in the list), highlighting a strong competition between brands which tends to generate a "coopetitive" structure (point 2 in the list).

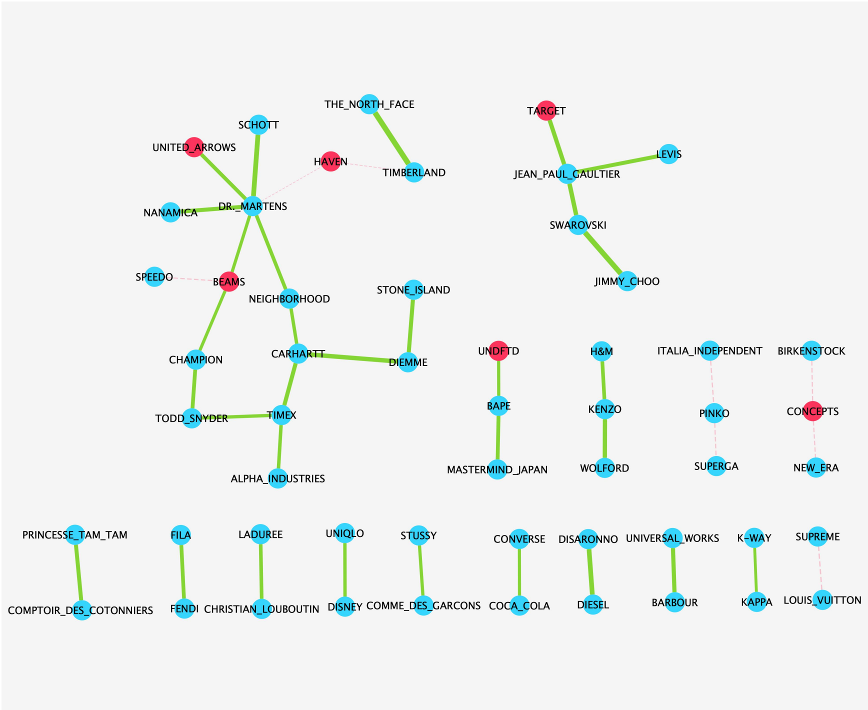



**Figure 3.13:** Network of brand recall in consumers' minds

More generally, looking at figure 3.13, we can observe how the recall process in consumers' mind generate a network (even if it is not well structured, yet). However, some kind of mechanisms appear clearly.

First, the main component (up-left) presents, a star-shaped structure centered on "DR.MARTENS". The surrounded links connect the brand with retail ("UNITED ARROWS", "BEAMS" and "HAVEN") or brands specialised in the production of jackets ("SCHOTT" and "NANAMICA"), the only exception is "NEIGHBORHOOD" (clothing). The co-branded products of these collaborations are always the traditional "DR.MARTENS" shoes. Thus, in this context, the image shared between brands may play a central role. Moreover, all the brands surrounding "DR.MARTENS" are from Japan (exceptions are "SCHOTT" from the USA and "HAVEN", which is a Canadian brand, but linked through a negative correlation). Besides these considerations, we can observe that a concentration of brands from the same geographic area (USA) characterise the bottom side of the main component. They are: "CHAMPION", "TODD SNYDER", "TIMEX", "CARHARTT" and "ALPHA INDUSTRIES". This cluster reaches the upper part of the component through two Japanese brands ("BEAMS" and "NEIGHBORHOOD"), and it ends with two Italian brands ("DIEMME" and "STONE ISLAND"). Thus, we may hypothesis a kind of collaboration based on identity and heritage sharing within this main component. Notice that the link with the highest positive correlation is a geographic collaboration as well ("TIMBERLAND" with "THE NORTH FACE"). The geographic collaboration also characterises some of the dyads present in the figure. The exceptions are:

- "DISNEY" with "UNIQLO" which present a positive correlation and the relationship is probably related to sharing the expertise among each other since "DISNEY" provide the image and "UNIQLO" implement it in its products.
- "SUPREME" with "LOUIS VUITTON" which present a negative correlation, and can be related to the *social influence* mechanism underlying the *homophily.*
- "STUSSY" with "COMME DES GARCONS" which present a positive correlation and, since the two brands are involved in similar market target but come from two different countries, this collaboration may be related to the *selection* mechanism underlying the *homophily.*
- "K-WAY" with "KAPPA" which present a positive correlation, and can be related to the coopetition alliance, associate to the stable configuration "- - +" of a signed network.

Also, the triad "ITALIA INDEPENDENT", "PINKO" and "SUPERGA" is a geographic cluster but characterised by negative correlation, meaning that there may be strong competition effects among the three brands that prevent the recall process in consumers' minds. This case may be associated with a triplet characterized by three "-" edge in the signed triadic closure mechanism (point 4).

Second, another cluster (up-right in the figure), shows a brand extension dynamic. Indeed, we can observe links between brands from different targets, and the link between the only two luxury brands, "JEAN PAUL GAULTIER" and "JIMMY CHOO", does not exist neither in the Google-Trends correlation network nor in 3-shell. In this cluster, we can observe how brand extension may produce a kind of indirect advantage for those brands (e.g. SWAROVSKY) that exploit this strategy for step-up extension purpose by exploiting association with luxury brands in consumers' minds. In the same directions, as previously mentioned, the brand extension mechanism can be associated with the triad "KENZO", "H&M", and "WOLFORD" too, which highlights that brands may implement the partner selection process with the aim to avoid dilution risks. Indeed, consumers recall the association with the luxury brand (WOLFORD) or the mass brand that adopt co-branding strategy recursively (H&M).

Finally, it seems that the structure is broken by retail brands (red node in the figure), such as "HAVEN", "BEAMS" (in the direction of "SPEEDO") and "CONCEPTS", through the negative correlations. Indeed, they act as a bridge to divide the structure. Thus, it may be interesting to better understand the role of the retail brands within the recall process. Indeed, the reason that justifies the positive correlations between retail and fashion brands may be related to the consumers' need to know where they can buy the product. In this case, since we know the mechanism underlying the consumers brand recall process, we test if, by removing these types of links from both the co-branding network and the Google-Trends correlation based network, the intersection become more or less significant. Results show that the intersection becomes smaller by removing these links, with 29 links in the intersection. By removing the retails, the number of links in the co-branding network becomes 392, in the Google-Trends network becomes 1181, and also the total number of nodes becomes 150. The $p - value$ associated with the intersection is 0.019. Thus, it slightly decreases.
Another interesting element is to note how, in the intersection between the two networks, it seems that consumers tend not to recall the nodes that act recursively in the network of co-branding campaigns. For example, two of the strongest brands in 3-shell ("NIKE" and "ADIDAS") do not appear at all in the intersection. Other brands that adopt co-branding recursively are just marginally recalled, see for instance, "H&M", "CONVERSE" or "COMME DES GARCONS" that, in the intersection, appear to be linked in dyads or less more.

To summarise, the intersection between the two analysed networks shows the consumers brand recall mechanism in relationship with actual co-brands. Indeed, we observe that some links are present in both the co-branding network (real co-brand) and the Google-Trends network (consumer brand recall). In particular, in the intersection network, we notice a significant presence of brands from community C3 of the Google-Trends network (35 brands out of 54 in the intersection network). On the contrary, the same brands are scattered among the several communities of the co-branding network.
The reason underlying the presence of links in both networks appears to be different but,

in some way, compatible. Specifically, on the one hand, the network of co-branding campaigns reflects company logics (first of all related to the brand extension). On the other hand, in consumer's mind, it seems to reflect the psychological cue that generates the purchase intention (a consumer search for a luxury product but probably she can't afford it; thus she look for the same product but branded by a mass brand). In this context, co-brand seems to solve the conflict, making a co-branded product better than the two single branded product.

## 3.6 Partner and Product prediction

As previously shown in section "Methods", we propose an automatic recommendation system that companies can use for partner selection purpose.
Specifically, recommendation methods alone can produce a ranked list of suggested co-branded products each brand can do. We have taken a step forward into the implementation of this method to suggest potential partners by using the similarity between brands, i.e., the overlapping of the list of recommended products.
As a next step, we propose a method that suggests partners and types of co-branding products jointly.
Specifically, for each brand, we aim to provide a list of suggested partners and, for each one of them, produce a list of suggested co-branded products.
The effectiveness of the proposed procedure has been evaluated, also in this case, through the *leave-one-out* procedure.
Specifically, as described in section "Methods", to implement the leave-one-out procedure, we apply the recommendation system to the bipartite network in which we remove two links brand-product at each step (single leave-one-out), which correspond to a specific collaboration removed from the data. Let's indicate the brands in the removed collaboration as $B_i$ and $B_j$ and the related product with $p$. The recommendation system provides for each brand in the system, including $B_i$, and $B_j$, a ranked list of recommended products, say, $L_h$ for brand $B_h$ ($h = 1, \cdots T$). According to the analysis of performance presented in the previous section, we set a threshold to select the top $L = 35$ products in each list. Now, we separately calculate the overlapping of the lists $L_i$ and $L_j$ with the lists of recommended products of all the other brands in the system. We calculate the correlation associated with each overlapping through the binary Pearson's correlation coefficient (equation 5) and its statistical significance through equation 6. Then, for each statistically

significant correlation (1% after Bonferroni correction), we determine the list of products recommended to the corresponding brand pair as the intersection between the top $L = 35$ products in the lists of the two brands. Each product in the intersection has two scores associated, one for each brand in the pair. We propose defining the score of the product associated with the brand alliance, i.e., with the brand pair, as the geometric mean of the two scores. Finally, we use such an integrated score to sort the recommended list of alliances and products obtained for each brand of the removed link, i.e., $B_i$ and $B_j$.
At the end of this procedure, our results are two sorted lists of triplets, one including all of the suggested alliances and co-branded products of brand $B_i$, and the other all of the suggested alliances and co-branded products of brand $B_j$. In principle, the two lists have different length, depending on the (different) number of significant correlations and products in the corresponding intersections that the two brands present with the others, and depending on the number of co-brands $K_i - 1$ and $K_j - 1$ of brands $B_i$ and $B_j$, respectively[7]. We indicate the maximum allowed length of the list of recommended alliances and products obtained for $B_i$ ($B_j$) with $N_i = L \cdot (N - K_i)$ ($N_j = L \cdot (N - K_j)$), and proceed with calculating the *R-score* of the removed triplet $B_i$, $B_j$, and $p$, in each one of the two lists. Specifically, *R-score* for $B_i$ ($B_j$) is calculated as the position in the ranked list of $B_j$ ($B_i$) divided by $N_i$ ($N_j$). It is possible that such a link does not belong to either or both lists of triplets of brands $B_i$ and $B_j$. That outcome occurs if the correlation associated with the two brands is not statistically significant or if the co-branded product $p$ does not belong to the intersection list of the two brands. If the list of brand $B_i$ ($B_j$) does not include the link, then the position of the removed link in the ranked list is set equal to the average between the actual length of the list of $B_i$ ($B_j$) and $N_i$ ($N_j$). Given the two *R-scores*, that is, the *R-score* of the removed link in the lists of $B_i$ and $B_j$, then the link *R-score* is taken as the mean value of these two quantities.

After performing the analysis for each (removed) link in the network–leave-one-out cross-validation method–the average *R-score* is taken as an overall measure of performance of the recommendation system. In the present application, we obtain an average *R-score* equal to 0.259. This result indicates that the performance of the system involving the recommendation of co-branded products is higher than the one obtained by disregarding the product recommendation and just focusing on suggesting the alliance.

[7] $K_i - 1$ ($K_j - 1$) corresponds to the degree of brand $B_i$ ($B_j$) after the removal of the alliance between $B_i$ and $B_j$ for the network.

We observe that the *R-score* obtained in the leave-one-out procedure varies a lot across links, showing extremely low values for some links (excellent performance) and high values for others (poor performance). Thus, we look for an explanation of such heterogeneity of performance in terms of the brands' features involved in the link prediction process.

In this context, it is worth notice that each one of the 172 brands in 3-shell was classified according to its features, highlighting three different levels of classification. Specifically, we categorise each brand with[8]:

- TYPE: dividing fashion brands (157) from other sectors (15).
- MAIN PRODUCTION: dividing brands according with their key production (Accessories(3), Bags(4), Beauty(2), Car(1), Clothing(94), Drink(4), Entertainment(1), Food(1), Hat(1), Hi-Tech(1), Jackets(7), Jewellery(1), Retail(22), Shoes(27), Watch(2) and Other(1)).
- PLUS: dividing brands according with their specialisation(s) (Accessories(1), Bags(3), Beauty(2), Car(1), Clothing(25), Clothing Denim(5), Clothing Hip-Hop(1), Clothing Luxury(34), Clothing Retail(4), Clothing Skateboard(3), Clothing Street(8), Clothing Street Alternative(1), Clothing Underwear(2), Clothing Underwear Sport(1), Clothing Urban(1), Clothing Work(1), Drink(4), Entertainment(1), Food(1), Hat(1), Hi-Tech(1), Jackets Clothing(8), Jewellery(1), Retail(10), Retail Other(1), Retail Sport(4), Retail Street(4), Shoes(3), Shoes Boots(2), Shoes FlipFlop(2), Shoes Luxury(4), Shoes Sport(5), Sport(16), Sport Equipment(3), Sport Jackets(1), Sport Swimwear(1), Sport T-shirt(2), Sunglasses Glasses(1), Watch(2) and Other(1)).

Thus, after classifying the *R-score* into two categories: *Low* for values lower than 0.4 and *High* for the others, we performed a logistic regression analysis to understand the features of brands that mostly influenced the performance of the recommendation system.

We firstly applied a *Logistic Regression* analysis with the aim of selecting the most relevant features (*Feature Selection*). This regression involves the categorised *R-score* as response variable and eight different explanatory variables (features), namely:

- Product degree;

[8] The numbers in brackets refer to the frequency of occurrence of each category. The analysis of this chapter considers only 3-shell and the brands that compose it. It means that the total number of occurrence may be different for the complete brands' list of the whole network of cobranding campaigns.

- Average and Minimum degree of $B_i$ and $B_j$ in the bipartite network of co-branding campaigns;
- Average and Minimum mean degree main production of $B_i$ and $B_j$;
- Average and Minimum mean degree main production and plus of $B_i$ and $B_j$;
- Constant[9].

The reasons underlying the choice of these explanatory variables are the following. Firstly, in our analysis, the only variable related to a link measure is the product degree. Thus, we try to transform the other variables from node variables to link variables by considering the relation between the two partner brands (the means). Secondly, we exclude the maximum values; indeed, we use only the minimum and the average of variables. The choice bases on avoiding the linear correlation between the variables involved in the regression. Finally, by using these listed variables, we investigate three different levels of aggregation. Indeed, we include the micro-level (brand degree), the Meso-level (main-plus degree), and the macro-level (main degree).

Thus, the results of this regression for *Feature Selection* purpose show that the only three variables which are significant at 5% level of statistical significance are:

- Degree of Product. It is the variable with the strongest significant influence on the recommendation methods' performance. The higher is the Degree of Product, the higher is Recommendation Methods Performance (low value of *R-score*).
- Minimum mean degree main production $B_i$ $B_j$. It negatively influences the Recommendation Methods Performance. To higher values of minimum correspond higher scattered main production within the network, even if highly connected. This result highlights the loosing of localisation information (communities). Thus, with Recommendation Methods, the connections among the main production tend to be less predictable.
- Constant. It considers the disproportion between the two levels of *R-score*value (low and high) used as the response variable.

More generally, with these results, we can observe how at the increasing of the details characterising the partnership (characteristics of both brands and products), the perfor-

[9] We reproduce the regression two times, the first time with a constant value and the second time without the constant value.

**Table 3.9:** Level of R-scores by co-branded products degree

| Co-branded Product degree | R-score Level | Level n.occurrence | % |
|---|---|---|---|
| From 1 to 2 (131 total occurrences) | High | 85 | 64.88% |
| | Intermediate | 46 | 35.11% |
| | Low | 0 | 0% |
| From 3 to 5 (109 total occurrences) | High | 49 | 44.95% |
| | Intermediate | 59 | 54.13% |
| | Low | 1 | 0.92% |
| From 6 to 17 (132 total occurrences) | High | 18 | 13.64% |
| | Intermediate | 78 | 59.09% |
| | Low | 36 | 27.27% |
| From 18 to 75 (168 total occurrences) | High | 9 | 5.36% |
| | Intermediate | 28 | 16.67% |
| | Low | 131 | 77.98% |

**Table 3.10:** Recommendation Methods Performance by main and plus production

| Main B1 | Plus B1 | Main B2 | Plus B2 | Dummy r-score | Occurrence |
|---|---|---|---|---|---|
| RETAIL | RETAIL STREET | SHOES | SPORT | Low | 16 |
| RETAIL | RETAIL SPORT | SHOES | SPORT | Low | 15 |
| CLOTHING | CLOTHINGS LUXURY | DRINK | DRINK | Low | 12 |
| CLOTHING | CLOTHINGS LUXURY | SHOES | SPORT | Low | 11 |
| RETAIL | RETAIL | SHOES | SPORT | Low | 11 |
| CLOTHING | CLOTHINGS | SHOES | SPORT | Low | 9 |
| CLOTHING | CLOTHINGS LUXURY | JACKETS | JACKETS CLOTHINGS | Low | 9 |
| RETAIL | RETAIL | SHOES | SPORT | Low | 7 |

mance is higher (i.e., low *R-score* values). We notice that the information of only main production is not able to produce a valuable performance, and by adding some additional elements, the high values of *R-score* tend to be scattered in the results. Indeed, it seems that the performance of recommendation methods increases together with the details of partner brands and especially with product elements. The performance of recommendation methods may be intrinsically related to information about the product. Indeed, we observe that the performance of recommendation methods tends to be strongly related to the frequency of co-branded products. Indeed, at the increasing of the degree of co-branded products, the average *R-score* are lower and, to low value of co-branded products degree correspond higher *R-score* values. In table 3.9, we provide a summary of this conclusion. As the table shows, to high co-branded products degree correspond higher occurrence of lower *R-score* levels and *vice-versa*.

**Table 3.11:** Recommendation Methods Performance by main production, plus production and co-branded products

| Main B1 | Plus B1 | Main B2 | Plus B2 | Product B1-B2 | Dummy r-score | Occurrence |
|---|---|---|---|---|---|---|
| CLOTHING | CLOTHINGS LUXURY | DRINK | DRINK | 57 | Low | 11 |
| RETAIL | RETAIL SPORT | SHOES | SPORT | 89 | Low | 10 |
| RETAIL | RETAIL STREET | SHOES | SPORT | 89 | Low | 10 |
| RETAIL | RETAIL | SHOES | SPORT | 89 | Low | 7 |
| CLOTHING | CLOTHINGS RETAIL | CLOTHING | CLOTHINGS LUXURY | 26 | Low | 6 |
| CLOTHING | CLOTHINGS | SHOES | SPORT | 96 | Low | 4 |
| CLOTHING | CLOTHINGS LUXURY | DRINK | DRINK | 57 | Low | 4 |
| CLOTHING | CLOTHINGS LUXURY | JACKETS | JACKETS CLOTHINGS | 68 | Low | 4 |
| RETAIL | RETAIL SPORT | SHOES | SPORT | 101 | Low | 4 |

Tables 3.10 and 3.11 provide examples of results of the procedure.

Finally, the results show that the product carries valuable information on co-branding and explains the reason why the *R-score* values are better for an alliance with co-branding products with a high occurrence. From the managerial point of view, these conclusions may imply that in a co-branding campaign, the product becomes crucial, since the higher is the *standardisation* of the product (in terms of the most recognisable products), the higher is the ability to predict future fruitful partnerships with this method. Moreover, the results seem to identify a tendency in the direction of the market standardisation, probably related to the consumers' needs and requests. The company probably tend to make co-brand alliances characterised by "*standard product*" (again, the most recognisable products, i.e., the iconic products) that consumers may easily understand and use as a kind of "*status*" towards other people.

## 3.7 Conclusions

The aim of this chapter was twofold: on the one hand, to study the relationship between the consumers brand-to-brand recall map and the network of co-branding campaigns, on the other hand, to exploit the information contained in both networks to suggest partner and product for a future co-branding campaign.

A comparative analysis of the network of co-branding campaigns and the consumers brand-to-brand recall map shows that the two networks are significantly different and, thus, carry complementary information. This is due to the evidence that the intersection between the two networks is significantly smaller than what expected under the assumption of network independence. However, our analysis of such an intersection network shows that consumers' mind mildly recalls some co-branding ties, though the recall logics and the logics underlying the company alliance are different. In particular, it turns out that the three types of alliance mostly recalled are:

i) *Chain co-branding*, which identifies a tie between a fashion brand and a retail. This kind of ties have a different meaning for consumers and companies. By implementing a partnership with a retail, brands gain advantages in the distribution channel. Consumers, instead, given the product of a specific fashion brand they want to purchase, associate the brand with the retail where they can buy the product.

ii) *Geographic logic*, in terms of culture and heritage sharing. For companies, implementing a partnership with another brand in the same geographic area may have proximity advantages. Whereas, consumers tend to associate cultural and image elements related to that specific area.

iii) *Step-up logic*. Consumers' minds seem to mildly recall a brand extension strategy in which one "mass" brand allies with two "luxury" brands. The presence of such triplets in the intersection network suggests an indirect advantage for the "mass" brand that, through the (multiple) extension with two luxury brands, which are significantly correlated in consumers' mind, better reaches the goal of being perceived as closer to the category of "luxury".

Given the significantly small overlapping, the two networks contain different information. Indeed, an in depth analysis of the network of co-branding campaigns points out company logics that stimulate co-branding [see also Chapter 2], and do not reflect consumers recall mechanisms. Examples of these phenomena are, for instance, ingredient branding-which is totally absent in the intersection network-and brand extension, which consumers recall only marginally. Complementary, a careful analysis of the consumers' brand-to-brand recall map points out how brand association in consumers' mind does not reflect co-branding strategies, since the recall process is mostly related to brands in direct competition. Thus, the network of co-branding campaigns carries information about the companies' logics, whereas the consumers brand-to-brand recall map carries mostly information about specific types of consumers. However, the present analysis shows that combining these two different points of view produces added information that can be used to improve the performance of a fruitful co-branding campaign.

Second, our analysis shows that the performance of the recommendation methods improves by exploiting both networks to evaluate pair similarity among brands, since the networks carry complementary information. Indeed, we identify a value of the shrinkage parameter between the two networks that optimises the performance of the recommendation system (that is, minimises the *R-score*). More in detail, the 0.3 shrinkage parameter highlights how, in the prediction of co-branding, a smaller weight should be given to the information related to consumers' logics. Indeed, as Chapter 2 shows, co-branding mostly depends on company goals and expected strategy outcomes, which involve-but are not limited to-a careful consideration consumers needs and perception.

Moreover, our analysis shows that the performance of the recommendation system significantly improves by taking into consideration the co-branded product. Specifically, more common co-branded products, such as shoes and bags, make it easier to predict the brands that would ally to launch those products. This conclusion leads to a further development of the theoretical implication proposed in ref. Pinello *et al.* (2020) and reported in Chapter 2. Indeed, according to the results reported in the present chapter, the proposed theoretical model of partnership formation should consider the inclusion of the co-branded products in the signal shared between the brands. In particular, the signal the initiator sends to the other brands should be composed of the portfolio of previous partnerships together with the cobranded products. Moreover, the product category itself carries information about the target consumer to reach and, in the partner selection process, it may be a further element to exploit in order to identify the best (new) partner in a campaign. Indeed, the main characteristic of recommendation systems is that the products (particularly their categories) carry information about the market target. Thus, the proposed recommendation system, which strongly involves products for the purpose of partner selection, works as an implicit tie between the consumers brand-to-brand recall map and the co-branding network. Along this line of thinking, the product category represents an implicit boost to recommendation systems, which plays a role similar to the shrinkage parameter used to explicitly mix co-brand network and brand-to-brand map in the evaluation of brand similarity.

Finally, the results of the present analysis also confirm the presence of the feedback loop of the conceptual framework Pinello *et al.* (2020b) emerged in Chapter one: the company motivations to implement a co-branding campaign strongly depend on the expected consequences (i.e., expected positive outcomes) of the campaign. Indeed, the present analysis suggests that the product to launch in co-branding is strongly involved in the partner selection process, and it implicitly carries information about the target consumer. This implies that the product category also carries information about the expected outcomes for the brand.

## 3.8 Limitations and Future Research

This analysis also presents some limitations and directions for future research.

First of all, this study is limited to the fashion industry. Replicating or extending the analysis on other sectors may provide a clue on the general value of the present results. Similarly, it would be interesting to extend the analysis by including other types of alliances and complementing the dataset with data related to the performance of both single brands and campaigns. Such an additional information could be exploited in the prediction model and increase the performance of the recommendation system.

As a future research, an interesting development of this study may be to analyse the impact of the launch of a given co-branding campaign on Google-Trends data-how this event affects single brand searches, and how that effect endures over time. In this way, it may be possible to understand the reasons why some brands recursively adopt co-branding strategies.

Another research that may provide relevant insights on the topic would be to implement an experiment on consumers to precisely draw the brand-to-brand recall process in consumers' minds. Such an experiment, for instance, may help identify original ways to implement brand alliances, according to the goals each company has.

Finally, a comparison between empirical outcomes and synthetic data obtained through an agent based model implementation of the theory proposed in ref. Pinello *et al.* (2020) and reported in Chapter 2 may help to assess the scope and eventually improve the proposed theoretical model.

# Conclusions

In the last decade, the market has witnessed a burst of brand alliances.

Indeed, during the last years, such partnerships have spread over several industries, from the fashion to the music industry, involving different market targets. Brand alliances have also evolved in various forms, spanning from ingredient branding to celebrity endorsement. Thus, it is interesting and scientifically relevant to investigate co-branding by taking a holistic perspective, to understand how such a phenomenon influenced market evolution, and eventually shaped company strategies in specific industries.

The present thesis assumes a systemic vision of the brand alliances in the fashion industry during the period 1990-2019, by using a network approach. This approach allows to shed light on different aspects yet relatively unexplored by scholars. Starting from the systematic literature review reported in chapter one, the proposed network perspective allows us to analyze the interplay among the theories scholars have used to investigate co-branding, and to draw a conceptual map of the variables that come into play in the analysis of the phenomenon. The review has proved precious to identify the main gaps in the literature on the topic and pave the way to further develop branding research. Among the main gaps, the brands' dyadic interactions analysed by researchers so far are not able to capture the indirect effects generated by co-branding campaigns. Thus, this thesis interprets co-branding alliances as the interconnections among the heterogeneous elements (the brands) of a complex system (the fashion industry). Such a holistic perspective allows one to use the data to analyse and infer intriguing logics and processes of alliance formation that would be rather difficult to investigate otherwise. Specifically, it allows to study the indirect effect that previous company alliances have on partnership formation (chapter two). Furthermore, as a methodological improvement, such an approach allows to adapt tools from network theory to model the partner selection process in a way that takes indirect effects into account. The last chapter includes a comparative analysis of the network of co-branding and the network of association among brands in consumers' minds.

Such a comparison demonstrates that the two networks carry complementary information. In other words, the logics that bring companies to form an alliance do not typically reflect the logics that determine brand pair association in consumers' mind.

The analysis carried out in this study highlights that the choices a brand does to engage in a specific partnership with a specific brand do not necessarily depend on the *expected* consumers' perception and reaction. Indeed, we demonstrate that brands make decisions on partner selection by considering company-oriented logics, rather than just considering consumer-oriented variables.

This result and the demonstrated predictive power of past collaborations on future alliances suggest that company logics drive brand-alliances, which are mostly unrelated to the expected output, that is, the expected impact on consumers' behavior. Such a conclusion represents an innovation in the co-branding literature. Indeed, according to the concept map drawn in chapter one, previous research on the topic hypothesise that the logics driving co-branding campaigns are typically consumer oriented.

Even looking at the few connections that appear in both networks, the different logics of companies and consumers behind such connections are apparent. Specifically, the analysis of the intersection network shows that some brand pair associations in consumers' minds correspond to specific co-branding logics, such as identity and chain logics. However, the actual association in consumers' minds is likely due to different logics, which are functional to consumer types. Finally, the implementation of recommendation systems for partner selection purposes allows identifying key aspects that should be taken into consideration in a theory of partnership formation, such as the portfolio of previous partnerships and co-branded product categories, and the brand (sub)sector of activity.

Besides the file-rouge of the thesis described so far, it is worth summarizing separately the conclusions of each one of the presented studies.

## Mapping the knowledge on co-branding

In **chapter one**, the systematic literature review allows to map the current state of the art in co-branding studies and finding a number of interesting research gaps in the literature. An in-depth analysis of the papers in the dataset allows to draw the following conclusions.

The ties between the theories used to analyse co-branding[10] reveals the presence of a significant interrelation between theories from different fields to analyze this phenomenon, which is a clear mark of complexity and interdisciplinarity. The map allows to perceive an apparent process connection between theories. The way they are linked reflects a flow of information from signal perception, through signal processing, to signal evaluation, underlying the traditional process that generates the "buyer value" in consumers' mind. This process leads to the conclusion that two brands together have the potential to increase the buyer value that consumers associate with a specific product.

The analysis of the selected papers also allows to develop a conceptual framework that summarises all the variables used in the process of formation of a brand alliance, including all the inputs, outputs, moderators, and mediators. Intriguingly enough, some of the output variables (the possible consequences of a cobranding campaign) are also represented in extant studies as motivations to establish the co-branding partnerships (companies' expected outcomes), generating a feedback loop in the framework.

These findings lead to construct a detailed research agenda, useful to foster the main lines of future research.

## Co-branding network: direct and indirect influences on partnership formation

The analysis reported in **chapter two** allows us to identify the logics underlying company selection of co-branding partners, and to understand how the partner portfolios of co-branding alliances created in time (direct influence), and the previous interactions between the brands in such portfolios (indirect influences) affect the partner selection process. The empirical study is based on the construction of a comprehensive and original database of co-branding campaigns in the fashion industry and the corresponding network of brands. The study tests the hypothesis that the network structure is predictive of future co-branding campaigns, and shows that the portfolio of previous partnerships and the position of brands in the network play a key role in determining the probability of partnership formation. This result is used to draw a theoretical model of partner selection for a campaign through the adoption of the lens of Signaling Theory. According to

[10] Two theories are connected in the map if they were used together in at least one paper.

this model, a company sends a signal to the consumers to reduce information asymmetry. The demonstrated predictive power of the brands' portfolios on the formation of future partnerships indicates that the same signaling mechanism can occur between two brands. Indeed, a brand (the initiator) sends a signal that includes brand's previous co-branding campaigns to the market. Another brand (the aggressor) receives the signal sent by the initiator, together with the signals of all the other (initiator) brands in the system. Then, the aggressor may decide to send back its own signal to the initiator. If both signals are interpreted positively by the parties, then the negotiation process begins, possibly ending with the partnership establishment.

Moreover, since the results confirm the predictive power of the network of co-branding campaigns, an in-depth investigation of the network structure provides further insights on the company logics behind co-branding partner selection. Indeed, the clusters that emerge in the network identify specific logics (geographic, coopetitive, identity, and chain) that may guide companies in the process of forming an alliance. Interestingly, such logics reflect companies' goals (management domain) rather than consumers' logics (marketing domain). The identified logics likely represent the basis on which brands build and interpret the signal they share with other brands in the system, aiming to establish an alliance.

## Brand-to-brand recall map and co-branding network: an integrated recommendation system of partners and products

**Chapter three** investigates the extent to which the association between brands in consumers' minds reflects: i) the partnerships that compose the network of co-branding campaigns; and ii) the revealed (company) logics of partnership formation. Additionally, this study takes one step forward in modeling the partner selection decision-making process, by including the product in the selection mechanism.

The study aims to contribute towards: i) the comprehension of the way brand-pair association in consumers' minds reflect both direct and indirect co-branding partnerships; and ii) the way a brand may use this information to establish a fruitful partnership. As a starting point, the study proposes to operationalize the association between brands in consumers' minds through the linear correlation between time series of brand searches on Google, as downloaded from Google-Trends. Specifically, the method of Statistically Validated Networks, as applied to the correlations between brand-search time series, allows to construct a proxy of the brand-to-brand recall network in consumers' minds. Then, a comparison between the recall network and the network of co-branding campaigns shows that the two networks mostly carry complementary information: the overlap between the two networks is significantly smaller than expected under an assumption of random overlapping. Therefore, the small intersection (few links in common) between the two networks under investigation leads to conclude that consumers' minds tend to not recall the network of co-branding campaigns, and the two networks reflect different logics of link formation. This result is confirmed by an in-depth analysis of the communities of brands identified in the two networks, which shows that the network of co-branding campaigns mostly reflects company logics, whereas the community structure of the brand-to-brand recall network mainly identifies different types of consumers. However, an analysis of the small intersection between the two networks suggests that consumers' minds associate some brands that actually collaborated as guided by specific logics—mostly heritage and chain logics. This result suggests that some brands may ally to leverage the already existing association in consumers' minds, likely for the sake of customer loyalty.

Given the complementarity of the information carried by the two networks, they are jointly used to evaluate brand pair similarity as an input to recommendation systems for partner and product selection. The performed out-of-sample tests indicate that the performance of the recommendations is maximized by weighting 30% the brand-to-brand recall association and 70% the brand portfolios of previous collaborations. Such an optimal weighing indicates that consumers' preferences weigh less than companies logics in the partner selection process for a co-branding campaign. The proposed recommendation method adapts the collaborative filtering procedure to produce a ranked list of partner-product pairs for each brand, that represents a methodological advancement in recommendation-system research.

Finally, the analysis carried out in this study allows to identify the variables that mostly influence the performance of the recommendations. Specifically, it turns out that the Degree of the co-branded product[11] is the variable that most affects the recommendation performance.

Based on this result, the theoretical model of partnership formation proposed in chapter two should be modified to include the portfolio of previous cobranded products, together

[11] The degree of a cobranded product corresponds to the number of campaigns in which the given type of product has been proposed.

with the portfolio of previous partners, in the signal shared between brands.

## Overall Contribution

Overall, this thesis allows to shed light on the necessity to see the co-branding system as composed of a web of connections between brands, where every single brand makes decisions about the strategies to implement, which affect, and are affected by, the other brands' decisions. Therefore, the proposed network perspective may help a company to better reach its goals, by explicitly considering the actions of all the other actors in the system in the decision making process behind the formation of a brand alliance. Furthermore, the holistic perspective proposed in the last two studies underscores the importance of the emergent structures–communities of brands in the networks—to infer the logics that bring to forming an alliance. Indeed, looking at single interactions between brands (dyadic view) will mostly hide some logics that appear crucial to engage in a co-branding campaign with a suitable partner brand.

In conclusion, the thesis contributes to the comprehension of co-branding alliances. Indeed, extant studies indicate expectations on consumers' impact, and, more generally, consumer-oriented logics, as the reasons to establish an alliance. Instead, the analysis reported in this study underscores how company's logics dominate the decision of forming a partnership. In other words, at difference with previous research, our study suggests that company logics are more relevant than the consumer-oriented logics in the process of partner selection.

Finally, this study highlights that the evolution of an industry is strongly influenced by the direct and indirect connections each company forms over time, which should be taken into consideration by managers in implementing new strategic paths. By assuming the proposed systemic vision, single brands may identify opportunities and risks hidden under a simplistic dyadic view of alliances.

## Managerial Implications

The thesis has some direct managerial implications that are also worth summarizing here.

The exponential growing of co-branding campaigns over the last decade probably reflects the general tendency of companies to implement more sophisticated marketing strategies that involve different market targets and companies together. Moreover, this study suggests that the portfolio of a brand's previous partnerships represents a signal that it is worth sharing with other firms, since it may help to gain a reputation among other companies and consumers (indirect effects). The presented study shows that, even if companies would not take advantage of their portfolios of previous alliances to establish a new partnership, this information strongly influences both the decisions of potential partners and, possibly, the implications of the campaign. Indeed, our results indicate that the choice of the partner to ally with carries on a value for the company, which is much stronger than the one assumed in the literature so far.
Indeed, even if sharing such an information is not in the (explicit) intentions of a company, our study demonstrates that it is predictive of future partnerships, and, therefore, it influences the decisions of the potential future partners. The portfolio of previous partnerships represents an incremental information that forms over time, and its impact lasts longer than the duration of a single campaign. Along this line of thinking, each new campaign becomes relevant for the brand also in terms of its coherence with the other campaigns in the portfolio, for instance, in terms of product category or market target.

Given their specific goals, managers can use the conceptual framework proposed in chapter one to identify dimensions and variables involved in the creation and implementation of a brand alliance. In this way, we provide a tool that can be used to develop brand's strengths and reduce brand's weaknesses. The map and the variables therein may also facilitate the partner selection process. The context in which a firm is embedded should be also taken into consideration, since it may guide the identification of factors that may influence the strategies the firm implements to reach its goals. Furthermore, these strategies should be implemented according to the stage of brand life cycle, which may be seen as a cue to identify the right path to follow.

Chapter two underlines that one of the most important implications for managers is to consider the history of previous cobranding partnerships (i.e., the brand portfolio). Indeed, according to the reported analysis, it represents a fundamental element that a manager can leverage upon to establish a new partnership. Depending on the specific company logics followed, managers should preselect the brand target of its signal and share with it its portfolio of previous partnerships as a trust signal. Brand targets may be selected by considering, for instance, the logics emerged in the analysis of the communities in the network of co-branding campaigns: i) Geographic co-branding: exploiting proximity advantages; ii) Chain co-branding: exploiting supply chain advantages; iii) Coopetitive co-branding: two brands join forces to obtain advantages with respect to single direct competitors; iv) Identity co-branding: two allied brands share and stress their own identity and heritage with consumers.

Finally, the results obtained in Chapter three underscore the importance of the co-branded products. Indeed, it appears that one of the elements a company has to take into account in the partner selection process is the type of the potential co-branded product(s)-including market target and duration of the campaign-which should be integrated in the theoretical model proposed in chapter two as a part of the signal a brand (the "initiator") sends to other (specific) brands (the potential "agressors") in the attempt to forming an alliance. Thus, the shared signal should be composed of the portfolio of previous partnerships together with the portfolio of co-branded products.

This results strongly highlight the indirect effects that can influence company decisions, by taking the proposed systemic perspective.

# Limitations and Future Research

This study presents some limitations and offers an opening on some directions for future research.

As concerns the limitations of this study, first of all, it is possible to highlight that the empirical analyses carried out in second and third chapters focus on the fashion industry only. Thus, future investigations should extend the study and tests the extent to which the validity of models and methods developed in this study are applicable to other industries.

A limitation is also related to the evolution of co-branding alliances over time. Indeed, our data do not take into consideration the time in which the alliances were established. At the current state, our analyses demonstrates that partner selection is a phat dependent process (Page, 2006). However, path dependency should also be investigated, which requires knowledge regards the evolution in time of the considered alliances. Such an analysis may lead to a deeper understanding of the whole system's dynamics.

Another limitation concerns the lack of brand and campaign performance indicators. Indeed, our dataset does not include such an information. Compending the presented analysis by including performance indicators may improve our understanding of the logics that guide partnership formation and of the drivers underlying their performance.

As a new path for future research, an in-depth study of the company's decision to implement a co-branding strategy may help to understand the evolution and the outcomes (expected and realized) of this strategy, depending on brand life-stage and business life-cycle. Such a research should also consider the portfolio of previous partnerships, in particular, how the coherence of previous co-branding campaigns (brands' portfolio) affects the attractivity of a potential partner brand, especially according to the companies' logics found in this study.

Furthermore, the theoretical model proposed in Chapter two may be implemented and tested through agent-based models. Comparing the properties of the real network of co-branding campaigns with the properties of the network(s) obtained from synthetic data, that is, realizations of the agent based model, may help to gauge the model's parameters and understand the interplay between the involved variables.

Finally, analysing how consumers' interest in partner brands change after launching an alliance, and exploring the evolution of such interests over time, may lead to a deeper understanding of the logics to implement co-branding, in particular, recursive co-branding.

# Appendixes

# Appendix A - Networks Intersection

**Table A1:** Networks Intersection

| ID | BRAND 1 | MAIN PLUS B1 | BRAND 2 | MAIN PLUS B2 | CORRELATION | PRODUCT |
|---|---|---|---|---|---|---|
| 1 | THE NORTH FACE | CLOTHING SPORT JACKETS | TIMBERLAND | SHOES SHOES BOOTS | 0,97 | SHOES JACKET 200 300 MEDIUMHIGH LIMITED |
| 2 | JIMMY CHOO | SHOES SHOES LUXURY | SWAROVSKI | jewellery JEWELLERY | 0,94 | SHOES 3000 4000 HIGH ONGOING |
| 3 | DR.MARTENS | SHOES SHOES BOOTS | SCHOTT | JACKETS JACKETS CLOTHINGS | 0,85 | SHOES 200 300 MEDIUM HIGH LIMITED |
| 4 | DIESEL | CLOTHING CLOTHINGS DENIM | DISARONNO | DRINK DRINK | 0,83 | DRINK 20 30 ANY LIMITED |
| 5 | JEAN PAUL GAULTIER | CLOTHING CLOTHINGS LUXURY | SWAROVSKI | jewellery JEWELLERY | 0,77 | JEWELLERY 100 200 ANY LIMITED |
| 6 | CARHARTT | CLOTHING CLOTHINGS WORK | DIEMME | SHOES SPORT EQUIPMENT | 0,77 | SHOES 100 200 ANY LIMITED |
| 7 | KENZO | CLOTHING CLOTHINGS LUXURY | WOLFORD | CLOTHING CLOTHINGS UNDERWEAR | 0,74 | CLOTHING 100 200 ANY LIMITED |
| 8 | JEAN PAUL GAULTIER | CLOTHING CLOTHINGS LUXURY | TARGET | RETAIL RETAIL | 0,73 | CLOTHING 100 200 ANY LIMITED |
| 9 | BARBOUR | JACKETS JACKETS CLOTHINGS | UNIVERSAL WORKS | CLOTHING CLOTHINGS | 0,71 | BAGS 200 300 MEDIUM HIGH LIMITED |
| 10 | CARHARTT | CLOTHING CLOTHINGS WORK | TIMEX | WATCH WATCH | 0,70 | WATCH 70 80 ANY LIMITED |
| 11 | DIEMME | SHOES SPORT EQUIPMENT | STONE ISLAND | CLOTHING CLOTHINGS | 0,69 | SHOES 100 200 ANY LIMITED |
| 12 | DR.MARTENS | SHOES SHOES BOOTS | NANAMICA | JACKETS JACKETS CLOTHINGS | 0,69 | SHOES 200 300 MEDIUM HIGH LIMITED |
| 13 | COMPTOIR DES COTONNIERS | CLOTHING CLOTHINGS | PRINCESSE TAM TAM | CLOTHING CLOTHINGS UNDERWEAR SPORT | 0,68 | CLOTHING 20 30 ANY LIMITED |
| 14 | JEAN PAUL GAULTIER | CLOTHING CLOTHINGS LUXURY | LEVIS | CLOTHING CLOTHINGS DENIM | 0,67 | CLOTHING 200 300 MEDIUM HIGH LIMITED |
| 15 | CHAMPION | CLOTHING SPORT | TODD SNYDER | CLOTHING CLOTHINGS | 0,64 | CLOTHING 100 200 ANY LIMITED |
| 16 | BAPE | CLOTHING CLOTHINGS | MASTERMIND JAPAN | CLOTHING CLOTHINGS LUXURY | 0,64 | JACKET 800 900 HIGH LIMITED |
| 17 | DR.MARTENS | SHOES SHOES BOOTS | UNITED ARROWS | RETAIL RETAIL | 0,64 | SHOES 200 300 MEDIUM HIGH LIMITED |

Continued on next page

Table A1 – continued from previous page

| ID | BRAND 1 | MAIN PLUS B1 | BRAND 2 | MAIN PLUS B2 | CORRELATION | PRODUCT |
|---|---|---|---|---|---|---|
| 18 | FENDI | CLOTHING CLOTHINGS LUXURY | FILA | SHOES SPORT | 0,63 | SHOES CLOTHING 700 800 HIGH LIMITED |
| 19 | H&M | CLOTHING CLOTHINGS RETAIL | KENZO | CLOTHING CLOTHINGS LUXURY | 0,62 | CLOTHING 100 200 ANY LIMITED |
| 20 | CHRISTIAN LOUBOUTIN | SHOES SHOES LUXURY | LADUREE | FOOD FOOD | 0,60 | FOOD 10 20 ANY LIMITED |
| 21 | DR.MARTENS | SHOES SHOES BOOTS | NEIGHBORHOOD | CLOTHING CLOTHINGS STREET | 0,60 | SHOES 200 300 MEDIUM HIGH LIMITED |
| 22 | ALPHA INDUSTRIES | CLOTHING JACKETS CLOTHINGS | TIMEX | WATCH WATCH | 0,57 | WATCH 100 200 ANY LIMITED |
| 23 | DISNEY | ENTRATEINMENT ENTRATEINMENT | UNIQLO | CLOTHING CLOTHINGS RETAIL | 0,55 | CLOTHING 30 40 ANY ONGOING |
| 24 | CARHARTT | CLOTHING CLOTHINGS WORK | NEIGHBORHOOD | CLOTHING CLOTHINGS STREET | 0,55 | CLOTHING 100 200 ANY LIMITED |
| 25 | TIMEX | WATCH WATCH | TODD SNYDER | CLOTHING CLOTHINGS | 0,54 | WATCH 100 200 ANY LIMITED |
| 26 | COMME DES GARCONS | CLOTHING CLOTHINGS | STUSSY | CLOTHING CLOTHINGS SKATEBOARD | 0,52 | T SHIRT 300 400 MEDIUM HIGH LIMITED |
| 27 | BEAMS | RETAIL RETAIL | DR.MARTENS | SHOES SHOES BOOTS | 0,51 | SHOES 100 200 ANY LIMITED |
| 28 | BAPE | CLOTHING CLOTHINGS | UNDFTD | RETAIL RETAIL STREET | 0,51 | CLOTHING ACCESSORIES 200 300 MEDIUM HIGH LIMITED |
| 29 | BEAMS | RETAIL RETAIL | CHAMPION | CLOTHING SPORT | 0,50 | CLOTHING 90 100 ANY RECURSIVE |
| 30 | COCA COLA | DRINK DRINK | CONVERSE | SHOES SHOES SPORT | 0,50 | DRINK 20 30 ANY LIMITED |
| 31 | KAPPA | CLOTHING SPORT | K WAY | JACKETS JACKETS CLOTHINGS | 0,45 | CLOTHING 100 200 ANY LIMITED |
| 32 | LOUIS VUITTON | BAGS CLOTHINGS LUXURY | SUPREME | CLOTHING CLOTHINGS SKATEBOARD | 0,40 | BAGS CLOTHING 20000 30000 HIGH LIMITED |
| 33 | ITALIA INDEPENDENT | ACCESSORIES SUNGLASSES GLASSES | PINKO | CLOTHING CLOTHINGS LUXURY | 0,45 | GLASSES 100 200 ANY LIMITED |
| 34 | BIRKENSTOCK | SHOES SHOES FLIPFLOPS | CONCEPTS | RETAIL RETAIL | 0,47 | SHOES 200 300 MEDIUM HIGH LIMITED |
| 35 | PINKO | CLOTHING CLOTHINGS LUXURY | SUPERGA | SHOES SHOES SPORT | 0,49 | SHOES 40 50 ANY LIMITED |

Continued on next page

**Table A1 – continued from previous page**

| ID | BRAND 1 | MAIN PLUS B1 | BRAND 2 | MAIN PLUS B2 | CORRELATION | PRODUCT |
|---|---|---|---|---|---|---|
| 36 | BEAMS | RETAIL RETAIL | SPEEDO | CLOTHING SPORT SWIMWEAR | 0,49 | CLOTHING 70 80 ANY LIMITED |
| 37 | CONCEPTS | RETAIL RETAIL | NEW ERA | HAT HAT | 0,52 | HAT 30 40 ANY LIMITED |
| 38 | HAVEN | RETAIL RETAIL | TIMBERLAND | SHOES SHOES BOOTS | 0,70 | SHOES 100 200 ANY ONGOING |
| 39 | DR.MARTENS | SHOES SHOES BOOTS | HAVEN | RETAIL RETAIL | 0,77 | SHOES 200 300 MEDIUM HIGH LIMITED |

# Appendix B - Planar graph

A planar graph is a graph that can be embedded in a sphere without edge crossing (Tumminello *et al.*, 2005). In our analysis, we built the planar maximally filtered graph (PMFG) associated with the correlation matrix of the Google-Trends time series. We did that to compare the degree distribution of the PMFG with the degree distribution of the Google-Trends network, which is constructed by setting a link between any two nodes that displayed a statistically significant correlation, and, therefore, it is obtained without setting any topological constraint on the resulting network. As previous studies have shown, the degree distribution of a planar graph generally tends to a power law. The genus associated with a planar graph is 0, i.e., the genus of its embedding surface–the sphere. However, as the genus of the network embedding surface increases, the degree distribution tends to become exponential (Aste *et al.*, 2012; (Aste *et al.*, 2012b). Finally, for very dense networks, typically associated with high values of the Graph Genus, the distribution of degree becomes super-exponential. As described in (Tumminello *et al.*, 2005), to build the planar graph, we need a similarity measure between each couple of brands. As a similarity measure, we use the Pearson's correlation coefficient, which has been calculated for each couple of brands, obtaining both positive and negative statistically significant correlations that generate the Google-Trends network. This is an issue since the construction of the PMFG requires one to sort out pair similarities in decreasing order, which may lead to excluding from the graph negative significant correlations. Thus, we applied the procedure both using straight correlations and their absolute value. Given the ordered list of similarities, the network construction proceeds as follows. Starting from an empty network and the first pair of nodes in the ordered list of similarities, a link is added between the two nodes if the resulting network is still planar. The resulting network, the PMFG, includes all of the $n$ nodes in the system, which are connected through $3(n-2)$ weighted links. The method can easily be generalised to surfaces with higher genus than the sphere. It is just sufficient to replace the link inclusion test with the following one. An edge between two elements, say brand $B_i$ and brand $B_j$, is added to the network if the resulting graph can still be embedded in a surface of genus $g$ without edge crossing (Tumminello *et al.*, 2005). In our analysis, we build two planar graphs–the first one by considering the correlation coefficient as a similarity measure (Figure B2) and the second one by using its absolute value (Figure B1). As expected, according to rAste *et al.* (2012 and Aste *et al.* (2012b), the degree distribution of both planar graphs is power-law. On the other hand, the Google-Trends statistically validated network is still a sparse network (1438 links among 131 nodes), though non-planar. It is, therefore, reasonable to expect that its embedding surface is not one with a very high genus, which, in turn, is consistent with the result that the exponential distribution fits well the empirically observed degree distribution of the Google-Trends SVN.

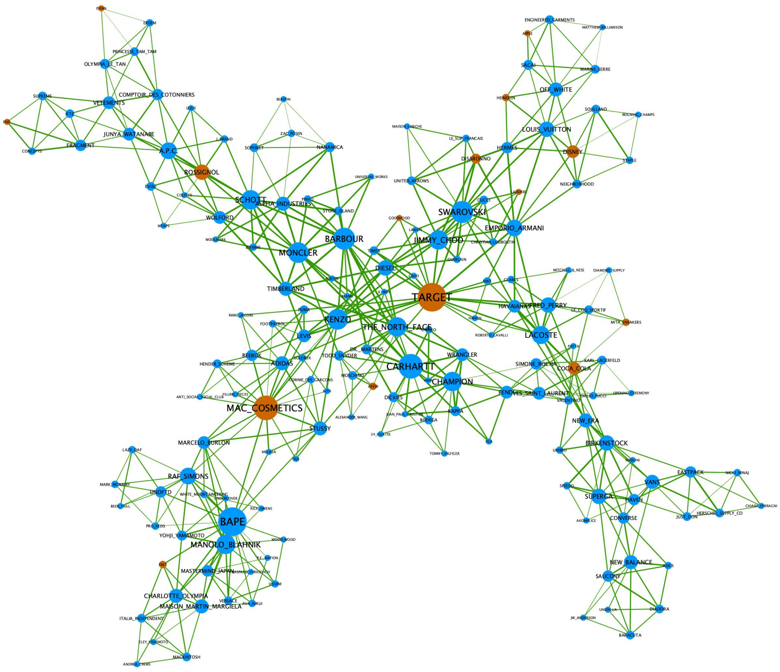


**Figure B1:** Google-Trends planar graph

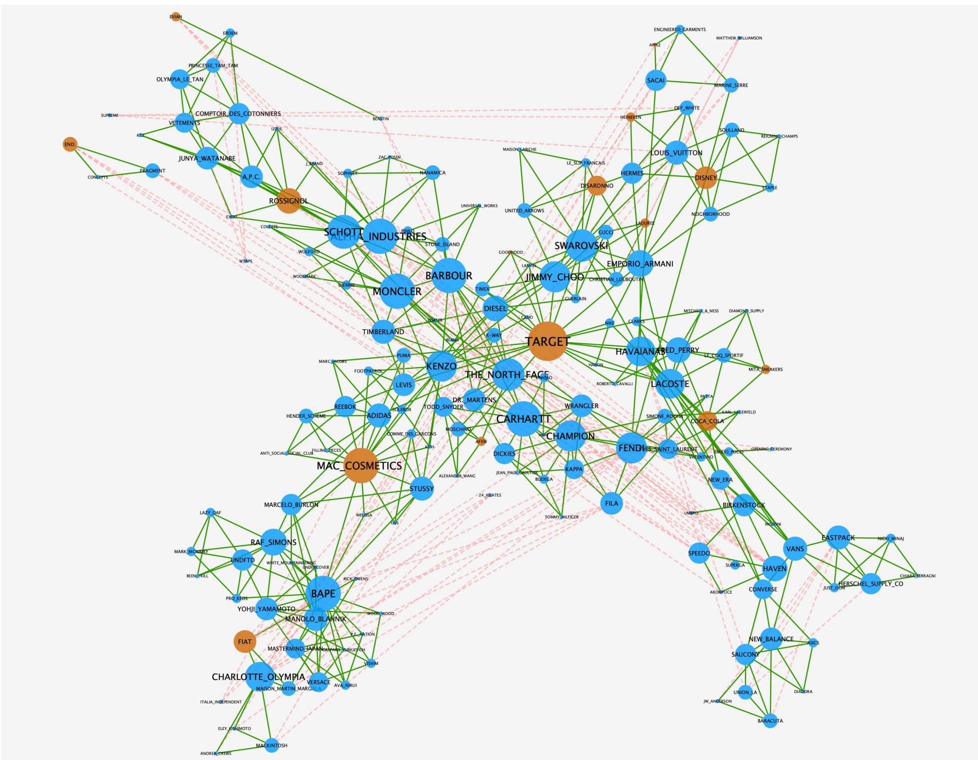


**Figure B2:** Google-Trends signed planar graph

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# Outputs of the PhD research

During the PhD program I produced three papers:

i) C. Pinello, P.M. Picone, A. Mocciaro Li Destri. Birds of a Feather. Co-Branding Research: where we are and where we could go from here. **Paper Under Review**.

ii) C. Pinello, M. Tumminello, A. Mocciaro Li Destri. A Network perspective on co-branding Campaign. Evidences from the fashion industry. **Paper Under Review**.

iii) C. Pinello, M. Tumminello, A. Mocciaro Li Destri, T. Di Matteo. Interplay Between Co-branding Network and Consumers Brand-to-Brand Recall Map: Partner Selection. **Manuscript in preparation**.

Moreover, during the three years of the Ph.D. program, I participated in the following conferences where I presented some of the content of this thesis:

- SIM $5^{th}$ Doctoral & Research Colloquium (May 2019). Luiss University, Rome. Contributed Talk.
- AIDEA 2019 National Conference (September 2019): Identity, Innovation and Impact of Italian Business Studies Inside the Digital Economy. University of Turin. Contributed Talk.
- Publishing in Top Management Journals (September 2019). The Florence Paper Development Workshop. University of Florence. Contributed Talk.
- 2020 Academy of Marketing Science AMS Annual Conference (December 2020): From Micro to Macro: Dealing with Uncertainties in the Global Marketplace. Miami–Florida. Contributed Talk.