Universitat Autònoma de Barcelona

Friend or Foe: Exploring the relationship between Organizational Aspira-tions, Ambidexterity and Network paradigms

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DOCTORAL DISSERTATION

Friend or Foe: Exploring the relationship between Organizational Aspirations, Ambidexterity and Network paradigms

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Barcelona, July 2016

Universidad Pública de Navarra
Nafarroako Unibertsitate Publikoa

Universitat de les Illes Balears

Strangers he gulls, but friends make fun of him

Phaedrus

Acknowledgments

This thesis represents not only my efforts; it is a result of almost four years of collaborative work at the Autonomous University of Barcelona. My experience at UAB has been nothing short of inspiring. Since the first day in this university, I felt right at home, especially with regard to the DEMO program where I have been given unique opportunities to engage in fruitful collaborations with other universities, and especially with the Public University of Navarra where my dissertation collaboration truly started.

This thesis represents the lessons learned these years in an effort to understand organizational behavior. It is also the result of the experiences I have encountered at UAB from dozens of remarkable individuals who deserve a special place in this acknowledgment.

First and foremost, I wish to thank my advisors, Martin Larraza Kintana and Ainhoa Urtasun Alonso, both professors at the Public University of Navarra who took me under their wings since the days of my Master's Degree. Their unconditional support, effort and professional dedication have been incredible, and paramount for this thesis completion; in short, the best mentors I have ever had.

Additionally, my sincere thanks go to the thesis committee: Isabel Gutierrez, Esteban Garcia Canal and Jordi Surroca for their availability and great commentary work, as well as to Andrea Fosfuri at Bocconi University for his unconditional support during my research stay in Milan.

My deepest thanks go also to the DEMO program at the UAB, headed by Miguel Angel Cestona, and to all its incredible staff, teachers and support personnel who were always there for me, and helped this thesis reach its annual milestones, as well as providing financial support throughout the dissertation development.

This work wasn't possible without my friends and acquaintances at the UAB whom I thank for their friendship, patience, professional support and laughter throughout this time. They made Barcelona my second home.

Last but not least, I want to thank my family: Mahmut, Elefteria, Enzo and Nathalie for their unconditional love, sacrifice, and dedication to support my work. This dissertation is dedicated to them.

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1. Thesis introduction

1.1 Organizational behavior in dynamic networks

Cyert and March’s (1963) seminal work on the Behavioral Theory of the Firm (henceforth, BTF) has been one of the major scholastic contributions in the quest of understanding the ‘black box’ (i.e. the organization), and its adaptive mechanisms during various stages of firm’s lifecycle. Through its key arguments namely, bounded rationality, imperfect environmental matching and unresolved conflict, this theory set the stage for a sequential setting of organizational goals which takes into account firms’ past performance, while acknowledging the role of the ‘environment’ in such process. This viewpoint changed the way how organizational resources, learning and innovation were categorized, with the introduction of concepts such as ‘organizational slack’ and ‘problemistic search’ (Pitelis, 2007).

According to BTF, managers develop aspirational (i.e. goal-driven) performance levels based on firm’s historic performance, and the observed performance of its industry peers (O’Brien and David, 2014). This definition of organizational aspirations serves as a feedback model that managers use as a reference for performance assessment purposes, thus influencing firm’s motivation to engage in strategic changes. Specifically, performance below aspirations triggers a ‘problemistic search’ due to the firm’s acknowledgment of potential problems related to underperformance in an effort to seek potential solutions. Performance above aspirations, instead, provides a ‘slack search’ response, seeking alternatives and leading firms to work on new ideas.

As more studies began to dwell into BTF assumptions, theoretical gaps began to emerge. One of the recurrent themes requiring additional research has been the ‘environment’ that affects organizational aspirations, with studies pinpointing at interorganizational networks as sources of organizational behavior alteration through value creation (Agarwal et al., 2010), and recognizing the cardinal effect of network embeddedness in the process (Nahapiet and Goshal, 1998). Initially, network embeddedness was defined as the impersonal configuration of ties between actors which include network measures such as structural holes, connectivity, centrality and hierarchy (Moran, 2005). With the advent of social network analysis, embeddedness became a synonym of network centrality, with indicators such as degree, betweenness and closeness becoming the standard measures of network interactions between organizations. The use of complex network analysis via specific software such as UCINET and R, led the research community to gradually move away from static snapshot analysis of networks (Opsahl and Hogan, 2010), and towards more dynamic Markovian and multi-agent simulation models (Lin et al., 2007). This said, the new models suffer from a sudden and too severe departure from the classic snapshot model to the other dynamic end of social network modeling. We believe both models are instead viable, and should be combined to properly capture firm-level dynamics in a given network of choice. This is the rationale behind the concept of 'dynamic embeddedness' that captures actor position throughout network evolution.

While aspiration performance could trigger interorganizational relationships, firm's structural position within its network molds the context in which such intention becomes an actual strategic change decision. This decision is coupled with another view closely related to BTF which refers to the firm's engagement in exploration or exploitation activities via interorganizational collaborations. March's (1991) seminal work on this matter calls for a balance between these strategic activities under the name of organizational ambidexterity. This original term was later adapted to interorgaizational networks with alliances being the majority type studied (Tiwana, 2008), and a preference of establishing a unidirectional relationship from ambidexterity to firm performance disregarding firm's aspiration performance contribution in the matter. The purpose of this dissertation is to fill these research gaps, and extend the state-of-the-art analysis on BTF and Social Network Theory (henceforth, SNT) by shedding light on the interdependence of aspiration performance, alliance ambidexterity and dynamic embeddedness in order to disentangle the firm's behavioral mechanisms under network constraints.

1.2 Purpose and research goals

Understanding these overarching themes in BFT led to the development of this dissertation as an effort to address several issues. First, embeddedness-related studies have largely focused on a static view of the strategic networks. Even 'embeddedness' studies that include dynamic network perspectives (Uddin et al., 2013) lack the empirical testing of their measures in a context of interorganizational networks where firms are often subjected to exogenous shocks that alter their network structure.

Second, from a BTF perspective, even though there are contributions addressing the relationship between firm embeddedness and aspiration performance, these fail to consider how organizational aspirations may also affect other firms' willingness to establish an agreement with the focal firm itself. Thus a 'friend or foe' situation is triggered by the effect that aspiration performance has on the 'inducement-opportunities' perspective where performance above or below aspirations causes a behavioral change in the firm's attitude to deal with other cooperating organizations in its network.

Third, given that aspiration performance has been associated with firm's ability to balance between the strategic activities of exploration and exploitation, we extend this area of research by including the dynamic network perspective via a triangulated theoretical framework that combines aspirations, ambidexterity and embeddedness. We believe that the integration of theoretical concepts from separate disciplines such as social networks and organizational behavior into a multidimensional theoretical setting, coupled with a unique empirical analysis that encompasses global pharmaceutical industry evolution, provides an interesting area of interdisciplinary framework analysis.

1.3 The setting

In order to study the feasibility of dynamic embeddedness in an interorganizational context, and analyze its effect on organizational aspirations and alliance ambidexterity, we need to focus on several theoretical issues. First, as interorganizational collaborations are very different in nature, it is important to focus on those networks that show a consistent intensity whereby a certain number of firms (i.e. actors) are usually present and serve as egocentric hubs to connections with other organizations. Second, in order to gauge on the evolutive features of the chosen social networks, we need to be able to capture the level of collaborative interaction between firms which means that a time series database is needed to properly analyze actor-oriented actions. Third, we feel that BFT fits better to single industry settings as opposed to multiple ones, as they would add complexity to the variable interactions and eventual interpretation. Fourth, the nature of the collaborations has to be similar to the ones used in BTF which is why we focus mainly on alliance transactions. Last but not least, data has to be easily accessible to count for possible budget constraints.

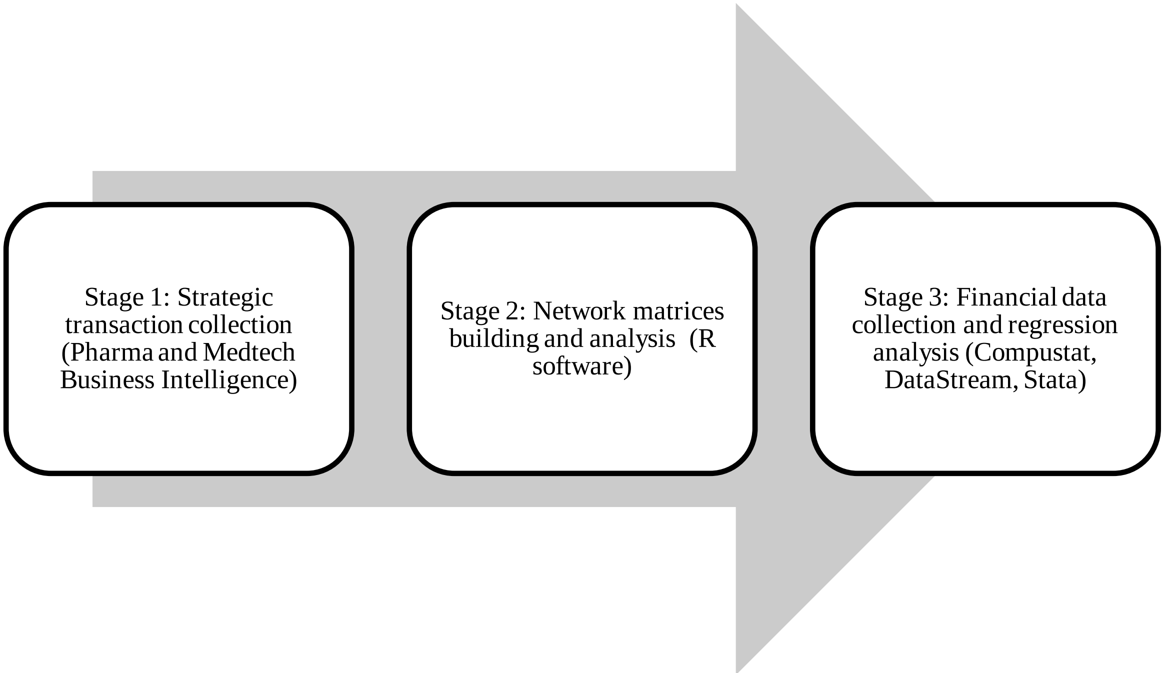
Given the aforementioned constraints, we focus on the top 90 firms of Global Pharmaceutical Industry for the period 1991 – 2012 which satisfies all our preliminary conditions (i.e. intensive collaborations, egocentric firms, time-series data, single industry, strategic transactions, free of charge). The top 90 pharmaceutical firms are selected on the basis of their single appearance in the top 50 list of the Pharma Exec magazine, (a renowned and highly respected source in the sector) from 2001 to 2013 according to sale revenues.

Figure 1.1 shows the key stages of data collection and processing. In stage 1, strategic transactions are directly and singlehandedly collected from the source (Pharma and MedTech Business Intelligence website). The original data is divided into several categories including: deal date (yearly), deal type (alliance, acquisition or financings and subtypes), headline (a short description of each transaction), deal ID (specific number attached to each transaction), industry (subtypes related to Pharmaceuticals such as, Medical Devices, In Vitro Diagnostics, Biotechnology and Services), and name(s) of all companies involved in each strategic transaction. The total number of strategic transactions amounts to 12,055 new yearly collaborations.

In stage 2, we build the matrices according to three main criteria found in the data. First, the data includes weighted values that signify firm's engagement with the same actor(s) for more than one strategic transaction within the same year of analysis. Second, the connections between the actors are undirected meaning that we do not know which participant starts the actual alliance, acquisition or financing transaction. This makes sense since we have many transactions which include more than two actors at a given time. Third, during matrix building, we do not discriminate between firms and their attributes which means that we focus on one-mode networks. Based on the aforementioned criteria, we discriminate between two separate networks: (i) the core-core network which includes the strategic transactions between the top 90 pharmaceutical firms, and (ii) the full network which includes the strategic transactions between all 4,735 firms present in the data population. Last, we use R software that enables us to handle very large vectors to build 46 matrices, 22 for each network, and 2 aggregate networks that combine data from all yearly collaborations.

Finally, for regression purposes, we collect financial data for the initially chosen top 90 pharmaceutical firms. Due to the lack of firm-specific data (for a given year) because of the presence or not of the firm in the industry, we combine information from COMPUSTAT and DATASTREAM, and supply missing information whenever necessary using annual reports of the firms in question. Regression analysis is made using Stata software. Regardless of all used information, the panel data used in the regression models is unbalanced for reasons cited above.

Figure 1.1 Stages of the data collection process



1.4 Thesis structure

The dissertation's contributions are structured in three papers described in sections 2-4 (see Table 1.1 for a summary). Section 2 explores insights on dynamic embeddedness analysis under network perturbations by analyzing core and full networks' behavior during the global financial crisis of 2007-2008, and the subsequent global and Eurozone recessions of 2009-2012. We introduce and test literature grounded hypotheses as well as report network visualizations, and nonparametric tests that reveal important discrepancies in both network types before and after the financial crisis offset. We observe that firms in core and full networks behave differently, with smaller top pharmaceutical firms of core networks particularly being affected by the crises, potentially due to a collaboration reduction with bigger top pharmaceuticals. On the other hand, big pharmaceuticals in full networks maintain their centrality position as a possible consequence of their strategic collaborations not only with other similarly sized firms but also due to their connections with subsidiaries, and other private entities present in the total sample. Our results confirm the significant dynamic embeddedness reduction during financial crisis and recession periods for core and full networks, and highlight the importance that exogenous factors as well as network types play in centrality-based dynamic longitudinal network analysis.

Section 3 integrates BTF and SNT in order to analyze organizational behavior in relation to dynamic network structures and their closely association with organizational aspiration models. We posit that strategic alliance formation is driven by aspiration performance, and further affected when the firm is dynamically embedded in a given longitudinal network. Our results show that strategic alliance formation decreases the further firm performance departs from organizational aspirations. However, this effect is reduced the higher the firm's dynamic embeddedness. The findings provide important insights on the role of dynamic network measures in the traditional performance-based aspiration models and their continuous development.

Finally, section 4 presents a study on organizational behavior effect in strategic alliance formations that acknowledges the ambidextrous efforts of the firm both in the structural domain via new or recurrent partner selection, and functional domain via upstream or downstream alliance activity. Even though alliance ambidexterity has an established unidirectional relationship with firm's financial performance, little is known on the reverse effect of performance feedback (i.e. organizational aspirations) on firm ambidextrous behavior. We posit that performance based aspiration models in strategic alliance networks have a positive effect on organizational ambidexterity, and probe the impact of dynamic network centrality measures (i.e. dynamic embeddedness) on firm's tendency to balance alliance exploration and exploitation. Through a multidimensional (i.e. structural and functional) approach, we find support for the determinant effect of organizational aspirations on alliance ambidexterity for both structural and functional domains of decision-making as well as observe the significant moderating effect of dynamic network centrality measures in the aspiration – ambidexterity relationship. Our study provides a new theoretical perspective that integrates aspirations, ambidexterity and network embeddedness as well as enhances previous BTF literature on the effect of dynamic centrality measures.

Table 1.1 Conceptual summary of the dissertation

Authors	Motivation	Theoretical framework	Data and Methodology	Contribution	Publication
Section 2 - Organizational Dynamic Embeddedness and External Shocks: the impact of Financial and Recession Crises in Strategic Networks of the Global Pharmaceutical Industry					
Elio Shijaku Martin Larraza-Kintana Ainhoa Urtasun-Alonso	Evolution of firm network embeddedness under exogenous network perturbations	social network analysis, dynamic embeddedness, strategic transaction formation	Network vizualizations; panel OLS, ANOVA; 46 symmetric matrices on core (top 90) and total population (4735 firms)	Dynamic embeddedness evolution and stability, firm rankings within the industry; financial and recession crises effect on longitudinal network	Published in *Complexity* (DOI: 10.1002/cplx.21776)
Section 3 - Beauty or Beast: Organizational Aspirations and Dynamic Embeddedness in Strategic Alliance Formation					
Elio Shijaku Martin Larraza-Kintana Ainhoa Urtasun-Alonso	Linking performance feedback with dynamic networks via strategic alliance formation	Performance feedback theory; relationship choice in strategic alliances	Negative binomial and 2SLS regression models; 9,600 alliance collaborations for all 4,735 firms	Analyzing the factors that influence interorganizational strategic alliance formation via aspiration performance	Best Conference Paper and Best SIG Paper, *EURAM 2016*
Section 4 – Explore or Exploit? Ambidextrous Strategic Alliances and Organizational Aspirations in Dynamic Networks					
Elio Shijaku Martin Larraza-Kintana Ainhoa Urtasun-Alonso	Integrating concepts from SNT and BTF such as organizational aspirations, network embeddedness and ambidexterity into a multidimensional theoretical setting	Performance feedback theory; structural and functional ambidexterity; SNT	Panel OLS models; 9,600 alliance collaborations for all 4,735 firms	Proposing an intricate relationship where the concepts of alliance ambidexterity, aspiration performance and dynamic embeddedness overlap with significant consequences	Unpublished manuscript

2. Organizational Dynamic Embeddedness and External Shocks: The impact of Financial and Recession Crises in Strategic Networks of the Global Pharmaceutical Industry

2.1 Introduction

Organizations often engage in clusters of collaborations forming complex networks of a dynamic nature. This dynamic complexity is crucial as it provides an important area to study the behavior of organizations upon which recent literature has gained new learning insights via complex computational analysis. These insights have involved the capture of organizational dynamics in a longitudinal setting, where collaborative networks are observed by focusing on the contribution that each network member (i.e. actor) provides to the overall network structure and stability (Brandes et al., 2009; Snijders, 2011; Gull et al., 2012). Particularly insightful is the combination of both static and dynamic network topologies resulting in studies that shed light on both endogenous and exogenous network perturbations, with a special interest in capturing actor's contribution to any given network dynamics (Braha and Bar-Yam, 2006; Hossein et al., 2013). This actor-level approach, embodied by the concept of dynamic embeddedness, has enabled researchers to study the effect of specific critical events (i.e. perturbations) that dramatically alter the structure of the longitudinal network (Uddin et al., 2013).

Traditional longitudinal social network analysis has been mainly focused on dyadic (i.e. interactions between only two actors) computational approaches, often neglecting simultaneous interactions that a firm has with multiple partners at any given time (Das and Teng, 2002; Inkpe and Tsang, 2005). Even studies on structural embeddedness that consider constellation analyses (i.e. interactions between more than two actors) have missed out the relevance of specific actors' influence by purposefully focusing on a specific type of collaboration. Often, as it is the case, embeddedness-based studies have relied on strategic collaborations such as alliances (Lin et al., 2009; Yang et al., 2011; Afuah, 2012) neglecting other collaborations of equal importance to network dynamic behavior.

Our study provides additional insights on dynamic network evolution by considering a multitude of strategic transactions between organizations including alliance, acquisition and financing collaborations that provide an enhanced picture of the 'constellation' view in state-of-the-art social network analysis. We do so by analyzing strategic transactions in an industry of strategic importance such as the global pharmaceutical industry, and a longitudinal setting that enhances the chances of understanding dynamic behavior of organizations. Our empirical analysis is based on the novel concept of 'dynamic embeddedness' defined as the individual actor's structural positions' variability in a longitudinal network compared to its structural position in an aggregated network (Uddin et al., 2013). In particular, we claim that macro-level exogenous shocks, such as the financial crisis of 2007-2008 and the subsequent Eurozone recession during 2009-2012, might have a significant impact on firm-level measures of dynamic embeddedness within a specific network. Critical to this proposition is the idea that exogenous event impacts on a specific organization can be transmitted to any other connected member. Supporting this claim, our findings show a significant reduction of firm-level degree of dynamic embeddedness within networks, after crisis and during recession periods, highlighting the importance that exogenous factors as well as network types play in centrality-based dynamic longitudinal network analysis. To our knowledge, this is one the first attempts to analyze the effects of exogenous shocks on interfirm dynamic embeddedness.

The present study develops a theoretical framework that serves as the substrate for testing hypotheses on both strategic collaborations between the top global pharmaceutical firms and their connections with other firms and institutions. It also provides detailed and fine-grained empirical tests that include computational network visualizations, Kernel density estimates, revised longitudinal data estimations to increase statistical robustness, as well as ANOVA tests. These methods coupled, with the inclusion of necessary descriptive data, provide an enhanced view of the critical impact that large exogenous perturbations such as global crises have on dynamic longitudinal networks between top-level actors and their partnering members in the global pharmaceutical industry.

2.2 Theoretical framework

In order to understand the timing of strategic transactions' influence on firm's dynamic embeddedness in a specific network, we build on three complementary theoretical lenses: longitudinal social network analysis, embeddedness and strategic transactions. Social networks have been defined as relational structures formed by interactions between social actors where each individual is represented by a node, and a tie between two nodes represents whether an interaction has occurred or a relationship exists between the individuals during the observation time (Snijders, 2011; Takaffoli et al., 2011).

2.2.1 Evolutionary social network dynamics

Most social networks can be considered dynamic as their structure tends to evolve gradually, due to frequent changes in activity and interaction between individuals (Newman and Park 2003), and relations between actors may rise or decay over time thereby altering the network structure they continuously form (Kossinets and Watts, 2006; Lazega et al., 2009; Hill and Braha, 2010; Lubbers et al., 2010; Takaffoli et al., 2011; Kim and Leskovec, 2013). Thus, actors inside a dynamic network are highly mobile as their relationships and positional structure continuously change hence, network dynamics is intrinsically connected to the longitudinal context in which it is observed. Recent literature on the subject has seen an increase of studies concerned with the analysis of these longitudinal networks in which the time of relationship creation is registered, and network evolution is analyzed (Butts 2008; Brandes et al., 2009; Gull et al., 2012). Longitudinal or dynamic networks are similar to cross-sectional or static networks in that they can be one-mode (i.e. each link represents a social actor´s relationship to another) or two-mode (i.e. each link represents a social actor’s affiliation to a group (Latapy et al., 2008), and data involved may be either binary (i.e. the relationship between any two actors is either present or not) or weighted (i.e. the relationship between any two actors presents differing weights) (Newman, 2004).

Generally, two main approaches have been considered to capture longitudinal network dynamics: (i) network-level and (ii) actor-level (Uddin et al., 2012). Network-level dynamics have traditionally relied on dependence of likelihood tie formation for which complex simulation methods of structural configurations such as exponential random graph models (Robins et al., 2007) and stochastic actor-oriented models (henceforth, SAOMs) (Snijders, 1996; Snijders, 2001) have been developed. These Markovian models define network’s future structural behavior as depending from both current and previous state, and explore the evolution of a network based on primary (direct) and secondary (indirect) relationships between actors, as well as on internal or external factors that might affect network change (Brunt and Broenewegen, 2007; Uddin et al., 2012; Buchmann and Pyka, 2012). Additionally, evolutionary models based on ‘multi-agent’ simulation methods have been developed simulating dynamic network changes over time by modeling the behavior of its actors as computer agents (Uddin et al., 2012). However, both evolutionary and multi-agent models suffer from few considerable limitations. Specifically, SAOMs infer continuous time processes even though they only observe discrete network snapshots (Opsahl and Hogan, 2010). Additionally, Markovian models present convergence issues when facing complex endogenous (i.e. structural-based) and exogenous (i.e. attribute-based) social changes (Uddin et al., 2012). On the other hand, multi-agent models oversimplify complex decision-making of specific actors such as individuals or organizations which can in turn distort real-life network evolution. Most importantly, both Markovian and multi-agent models offer a generalist view of network dynamics, often failing to capture individual actor-level involvement in the longitudinal context.

2.2.2 A dynamic embeddedness approach to longitudinal network analysis

In the myriad of network evolution studies, little attention has been paid to dynamics of individual importance based on actor-level analysis (Braha and Bar-Yam, 2006; Uddin et al., 2012, Uddin et al., 2013). Such 'actor-level dynamics' approach captures actor's positional evolution in longitudinal networks by centering itself around two key topologies: (i) static topology which applies traditional social network analysis methods over an *aggregated* network encompassing all observational time periods, and (ii) dynamic topology which applies longitudinal analysis techniques over each observational time period referred to as *short-interval* network. Thus, actor`s activity, its structural embeddedness, proximity to other important actors, and brokerage position can be captured and analyzed over time. Moreover, this approach can capture the positional change of each actor in longitudinal networks and is useful to determine actor's effect in specific networks such as 'disease spread networks' (Uddin et al., 2012) but also in strategic transaction networks where alliances, financing transactions, and merger and acquisition operations (henceforth, M&A) significantly alter network compositional structure.

Expanding the actor-level approach presented by Uddin et al., (2012), we introduce the concept of dynamic embeddedness observed by an individual actor as the variability of structural positions of that actor in all short-interval networks compared to its structural position in the aggregated network. This measure is used to quantify actor involvement and contribution in longitudinal communication networks and its behavior against specific perturbations such as organizational crisis. By doing so, the measure takes into account missing data in form of actors' presence and absence which if not counted can severely distort network indicator estimates (Kossinets, 2006). We also avoid certain shortcomings inherited in similar measures used by the academia. Specifically, by choosing yearly short-interval networks, as well as global firms as actors for the longitudinal setting, we avoid potential ambiguous behavior observed in Uddin et al., (2012) and Hossein et al., (2013) with regard to individual's communication network structure. Additionally, by tracing actor's contribution in the network, we shed light on the dynamic behavior of organizations such as pharmaceutical firms.

2.2.3 The structure of actor's network embeddedness

The actor-level approach has its own followers in SNT literature, with most studies researching the structural position of actors and particularly their embeddedness. In general, firm's embeddedness in a network of interorganizational ties has been viewed as a strategic resource, and its important impact on both firms' economic and innovative performance in terms of future capability and expected performance has been rigorously researched (Burt, 1992; Granovetter, 1992; Uzzi, 1997; Andersson et al., 2002; Borgatti and Foster, 2003; Gilsing et al., 2008; Giuliani, 2010). However, the extensive use of the term for various conceptualization purposes has somewhat faded its polish in network literature, in part due to scholars' disagreeing conceptual views on embeddedness but also due to the nature of actors involved. Initially, Nahapiet and Goshal (1998) dichotomized embeddedness in two conceptual types: (i) structural embeddedness defined as the impersonal configuration of ties between actors which include network measures such as structural holes, connectivity, centrality and hierarchy (Moran, 2005), and (ii) relational embeddedness defined as the personal relationships actors have developed due to historical interactions, including measures such as interpersonal trust, trustworthiness and solidarity.

For the purpose of this paper, we focus exclusively on structural embeddedness and specifically on the evolution of key network centrality indicators such as degree, betweenness and closeness, which are widely accepted by SNT scholars (Moran, 2005; Gilsing et al., 2008; Yang et al., 2011). While SNT literature has showed that centrality measures are only a part of actor's structural embeddedness, researchers believe these indicators are enough to provide a dynamic view of social networks' evolution (Lin et al., 2009; Yang et al., 2011; Afuah, 2012). Centrality, which refers to the network position of an individual actor, denotes the extent to which the focal actor occupies a strategic network position by its involvement in strategically significant ties (Wasserman and Faust, 1994; Gnyawali and Madhavan, 2001; Whittington et al., 2009). According to Faust (1997) there are several motivators for the existence of network centrality measures. Degree centrality measure is motivated by the fact that actors are central if they are active in the network. Betweenness centrality refers to centrality role of actors if they have the potential to mediate flows of resources or information between other actors, essentially playing a brokerage role (Täube, 2003). Finally, closeness centrality arises if central actors can contact others through efficient (i.e. short) paths.

2.2.4 Strategic transactions as a combined form of interorganizational ties

Structural embeddedness analysis is a result of actors' tie dynamics which depending on the type of actor (i.e. individual or organizational) can take several forms such as friendship (van de Bunt et al., 1999; Burk et al., 2008), communication (Uddin et al., 2012), strategic alliances (Gulati, 1999; Ahuja et al., 2009), innovation networks (Dittrich and Duysters, 2007), knowledge networks (Clarke and Roome, 1999; Carlsson, 2003), and research and development partnerships (henceforth, R&D) (Hagedoorn et al., 2006) among others. The emergence and formation of ties among organizational actors attributable to both organizational and individual characteristics is at the core of interorganizational networks' formation whose ties are usually created by 'boundary spanners' (Brass et al., 2004). The rationale behind tie and subsequent network formation can be traced from organizational objectives, management vision for organizational development, and specific strategies necessary to improve firm competitiveness in rapidly changing environments (Cravens et al., 1996). Given the nature of our data, we focus on networks generated by several interorganizational ties referred to as *strategic transactions*. We use this term to denominate close interfirm ties that are enduring and of strategic significance for the firms entering them, and include interfirm deals such as strategic alliances, acquisitions and financing collaborations (Gulati et al., 2000). By analyzing several types of collaborations at once, we contribute to network literature on embedded alliance activity and its impact on structural patterns (Arya and Lin, 2007; Ahuja et al., 2009), and also enrich literature area devoted to M&A and financing collaborations (Berger and Hinz, 2008; Fabac et al., 2011).

Research on strategic transactions varies according to whether the analysis concerns alliance networks or M&A collaborations. In general, strategic alliance studies have enjoyed continuous popularity in SNT literature (Madhavan et al., 1998; Gulati, 1999; Baum et al., 2000; Koka and Prescott, 2002; Bignoux, 2006). Viewed as access relationships, alliances act as conduits for the flow of hitherto unavailable resources and capabilities (Koka and Prescott, 2008). Leading firms, particularly in dynamic industries such as biotechnology, computers and telecommunications, have used strategic alliances (e.g. contractual alliances, consortia, joint ventures) to improve their resource endowment and strategic technological uncertainty towards competitors (Hoffmann, 2007; Karamanos, 2012). The key advantages attributable to the establishment of these transaction types include entry in new markets, increased market power, acquisition and exchange of skills, risk and investment sharing, increased institutional legitimacy, accruing network capital and securing firm-level advantages (Dacin et al., 2007). While these studies have gone to great lengths to describe the nature of strategic alliances, their focus has primarily been on bilateral relationships (i.e. dyadic) often and due to complexity analysis issues, neglecting the role that multilateral alliances play in overall single or multi-industry networks. In fact, firms do engage themselves in alliance groups forming *alliance constellations* such as code-sharing alliances among airlines (Das and Teng, 2002; Inkpe and Tsang, 2005), and especially in our case of the global pharmaceutical industry where a wide portfolio of strategic transactions is available, as seen in Table 2.1.

Table 2.1 Strategic transactions by type

Alliance	Financing	Acquisition
• Co-marketing	• Convertible Debt	• Acquisition of Private Biotech
• Co-promotion	• FOPO	• Buy-out
• Disease Management	• Includes Contract	• Full Acquisition
• Includes Contract	• IPO	• Includes Contract
• Includes Equity	• Nonconvertible Debt	• Includes Earnout
• Includes Royalty or Profit Split Information	• Private Investment in Private Biotech	• Intra-Biotech Deal
• Intra-Biotech Deal	• Private Placement	• Partial Acquisition
• Joint Venture	• Special-Purpose Financing Vehicle	• Payment Includes Cash
• Manufacturing or Supply	• Spin-Off	• Payment Includes Stock
• Marketing-Licensing		• Reverse acquisition
• Product or Technology Swap		
• Product Purchase		
• R+D and Marketing-Licensing		
• Reverse Licensing		

Source. Pharma & MedTech Business Intelligence

On the other hand, strategic transaction studies based on acquisition or financing networks are considerably fewer (Havila and Salmi, 2002; Lin et al., 2009; Fabac et al., 2011). For example, Lin et al., (2009) show that networks, learning and institutions represent three building blocks that can enhance our understanding of drivers behind M&A events. Researchers have supported a view of M&A network formation based on prior alliances (Lin et al., 2009; Zaheer et al., 2010) which is not our case since we do not necessarily assume acquisitions as a direct result of prior alliance networks. Fabac et al., (2011) hypothesize that organizational networks with compatible mixing patterns based on assortativity (i.e. similar actors connected to each-other) will be integrated more successfully while newer network actors will be less attracting components. On the other hand, Havila and Salmi (2002) consider M&A as critical events leading to disruption or establishment of actor ties and thus to a radical change in network structure. There has been very little in-depth research on how financing-based transactions contribute to network evolution with Borges and Filion (2013) analyzing the spin-off processes that contribute to the development of academic entrepreneurs' social capital. We contribute to this literature by including in our analysis of firm's dynamic embeddedness not only alliances but also financing and acquisition transactions, a reasonable choice from an organizational behavior perspective where strategic transactions are not restricted to specific types.

2.2.5 Large perturbations' effect on strategic transaction networks

Inherently embedded in a dynamical setting, strategic transaction networks are continuously affected by perturbations or shocks (i.e. critical events) of both endogenous nature such as organizational crisis (Uddin et al., 2012; Hossain et al., 2013) and exogenous nature such as global financial crises (Fenn et al., 2009; Minoiu and Reyes 2013; Nobi et al., 2014). While few studies on endogenous perturbations have analyzed dynamic actor-level patterns (Uddin et al., 2011; Uddin et al., 2013; 2015; Hossein et al., 2013), exogenous perturbations' research has focused on understanding complex interactions between engaging actors in a quest to uncover structural pattern formation and evolution (Minoiu and Reyes, 2013; Kuzubas et al., 2014). Critical events such as organizational crisis are found to have a profound effect on centrality measures such as degree, betweenness and closeness (Hossain et al., 2013; Uddin et al., 2013; 2015). Specifically, Uddin et al., (2013) propose the measure of dynamicity based on centrality indicators to explore underlying endogenous perturbations (i.e. organizational crisis of Enron) to different phases of longitudinal social networks, observing an increase in dynamicity for the crisis period.

On the other hand, Minoiu and Reyes (2013) find a negative relationship between traditional static degree centrality indicators and network perturbations caused by the financial crisis of

2007-2008, uncovering that structural properties and dynamics of cross-country financial linkages are crucial to understand how the global financial system reacts to shocks, and how systemic risk emerges. On the same lines, Kuzubas et al., (2014) show that static centrality measures perform well in identifying and monitoring systemically important financial institutions, providing useful insights for financial regulations by showing that after critical events (i.e. Turkish financial crisis), network evolution is considerably less centralized than before. Having said this, evidence on the effects of exogenous shocks on actor-level dynamics as a result of actor's strategic transaction evolution is practically inexistent. Even studies concerning such perturbations (Hale, 2012; Minoiu and Reyes, 2013; Kuzubas et al., 2014) exclude recession effects succeeding these critical scenarios. Our study addresses these shortcomings by not only analyzing the combined effect of the financial crisis of 2007-2008 and the global recession of 2008-2009, but also by including the impact that perturbations such as the Eurozone recession of 2011-2012 have on dynamics of the global pharmaceutical actors and their networking partners. Based on the aforementioned theoretical review which highlights the reduction of centrality measures in the presence of exogenous shocks, we posit our hypotheses for testing as follows:

Hypothesis 1 (H1): The levels of an actor's dynamic embeddedness will be negatively associated to global effects such as the financial crisis of 2007-2008 and the global recession of 2008-2009.

Hypothesis 2 (H2): The levels of an actor's dynamic embeddedness will be negatively associated to effects such as the Eurozone recession of 2011-2012.

2.3 Empirical analysis

2.3.1 Research context

We choose to conduct our research in the global pharmaceutical industry for several reasons. First, this industry is renowned for its contribution to the global economy. Second, strategic transactions such as alliances, financings and acquisitions are the norm in the global pharmaceutical industry. Third, strategic transactions are a meaningful measure of firm´s structural embeddedness as confirmed by the literature review in the theoretical framework section. Specifically, strategic alliances which make up 74.5 percent of all strategic transactions in our data have long been considered an optimal source for centrality measures' analysis (Stuart, 1998). Fourth, there is a lack of studies on dynamic embeddedness applied to the global pharmaceutical industry.

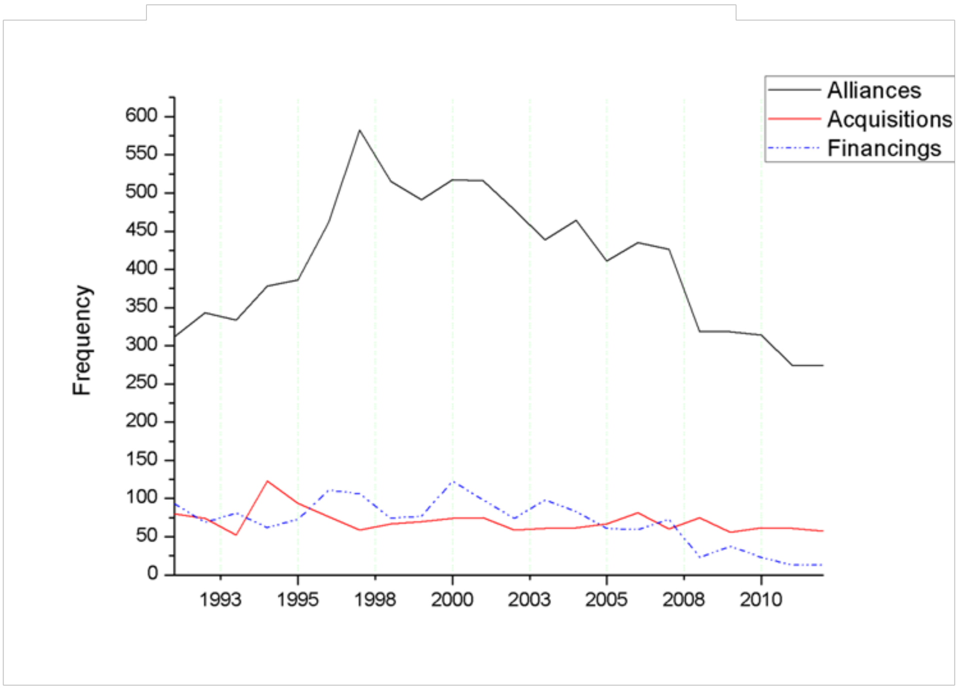
2.3.2 Data

We conduct our analysis on a longitudinal dataset (T = 22 years, 1991-2012) comprising the strategic transactions of 90 leading firms from the pharmaceutical industry in Western Europe, United States, Asia, Africa and Australia. The sample is selected by identifying those firms that have appeared at least once in the top 50 of the Pharmaceutical Executive Magazine (www.pharmexec.com) yearly editions from the period 2002-2013. Once the sample is defined, we use the Pharma & Medtech Business Intelligence database (www.pharmamedtechbi.com) to collect all the strategic transactions that involve the firms in question for the available period 1991-2012. We consider transactions starting from 1991 because of the potential contribution of this analysis in determining the global pharmaceutical network structure for an unprecedented period of 22 years, shedding light on the interactions of an industry whose information is difficult to obtain due to the pharmaceutical firm's inherent dynamic embeddedness in complex networks of collaborations and market's share concentration in few competitors.

The 90 firms of the sample have engaged in alliance, financing and acquisition collaborations with 4,645 firms creating a total of 12,055 strategic transactions. It should be noted that due to their nature, the top 90 firms do not engage transactions only in the pharmaceutical industry but have differentiating portfolios which include biotechnology and chemical industries as well. In fact, the total population of firms includes biotech and chemical firms as well as public and private institutions such as research centers and universities. To minimize bias, we decide to include all transactions that firms made with each-other throughout the study period. Additionally, due to data retrieval limitations, we apply the fixed choice effect (Holland and Leinhard, 1973) meaning that strategic transaction constellations are deliberately reduced to 4 participants. Due to our selection process, we consider two types of firms, the *core* comprised of the top 90 pharmaceuticals and the *periphery* including the rest of the population, with a total population of 4,735 firms whose full list is available from the authors. The obtained longitudinal data for both core and periphery firms, is unbalanced since some firms are acquired by others, or simply are not active for any particular year. This is taken into account when operationalizing the dynamic embeddedness variable for each actor, using a constant term whose purpose will be explained in the following paragraphs.

For regression purposes, we obtain financial data using COMPUSTAT (www.compustat.com) and DATASTREAM (www.financial.thomsonreuters.com) databases, supplying missing data using company annual reports. Since financial data concern firms from different countries, we convert all currencies to USD with an exchange rate based on the particular year the data is retrieved. The amount of strategic transactions evolution differs depending on whether the transaction is an alliance, financing or acquisition as seen in Figure 2.1.

Figure 2.1 Strategic transactions' evolution 1991-2012



Once our sample is defined, we proceed to build the social networks for both core and periphery firms. We model each year over the sample period as a separate network and analyze the following networks based on a similar approach by Minoiu and Reyes (2013): (i) the core network, referring to the ties between the top 90 actors; and (ii) the full network comprising all available data from a total of 4,735 actors. To formally characterize such networks, we use the adjacent matrix mathematical concept, meaning a symmetric (i.e. square matrix that is equal to its transpose) N x N binary adjacent matrix (i.e. sociomatrix) whose generic entry $a_{ij} = a_{ji} = 1$ if and only if a link between actor i and j exists and zero otherwise (Fagiolo et al., 2010). This means that networks are constructed with binary data, i.e. any two actors can either be connected by a tie or not, and the ties between actors are undirected (i.e. reciprocal ties). In accordance with existing literature, we assume the actors shall not have self-referenced ties, meaning the main diagonal of the sociomatrix will always contain zeroes (Ouzienko and Obradovic, 2014).

However many researchers have pointed out that the majority of socio-economic relationships are characterized by a non-reducible heterogeneity. Therefore involving an assessment of how intense (if any) an interaction between two actors is (Fagiolo et al., 2010; Opsahl et al., 2010), binary tie networks run the risk of considering both ties that carry weak and strong flows in a similar manner. Additionally, ties with large weights can potentially have a much larger impact than ties with smaller weights (Opsahl et al., 2010). Therefore, in our analysis, we consider a weighted approach, defined as an *N* x *N* 'weight' matrix, whose generic entry $w_{ij} = w_{ji} > 0$ measures the interaction intensity between any two actors (zero if no link exists between actor *i* and *j*). This means that ties between actors are valued according to the actual number of strategic transactions, a procedure already seen in the network literature (De Montis et al., 2008). Additionally, due to data availability issues, the ties considered are of undirected nature. Following this framework and using the software R that enables us to handle very large vectors, we build 22 symmetric 90 x 90 matrices to track the evolution of the core network and 22 symmetric 4,735 x 4,735 matrices to track the evolution of the full network for the period 1991-2012. For dynamic embeddedness calculation purposes, we build two aggregate matrices which include the strategic transactions for the entire 22 years period for both core and full networks.

2.3.3 Measures

Prior to the network analysis, we define the indicators used to both track the global pharmaceuticals' evolution and test our hypotheses.

Degree centrality (annotated as C_D) formally represents the simplest centrality measure and determines the number of ties for each actor, i.e. the number of actors that the focal actor is connected to. However, when analyzing weighted networks, the original measure (Wasserman and Faust, 1994) has been modified to take into account the sum of weights in each tie (Barrat et al., 2004; Opsahl et al., 2008) formalized by the following mathematical expression: $C_D^w(i) = \sum_j^N w_{ij}$ where *i* is the focal actor, *j* represents all other actors, *N* is the total number of actors, *w* is the weighted adjacency matrix, in which w_{ij} is greater than 0 if the actor *i* is connected to actor *j*, and the value represents the weight of the tie. This expression is equal to the definition of degree if the network is binary (i.e. each tie has a weight of 1) (Opsahl et al., 2010). As a consequence, degree centrality scores for any actor will be higher, the more transactions the actor actually has (Landherr et al., 2010).

Betweenness centrality (annotated as C_B) formally represents the number of shortest paths between any two actors passing through a specific actor (Freeman, 1980). Therefore, an actor is considered to be well connected if he is located on as many of the shortest paths between pairs of other actors (Landherr et al., 2010). However, in weighted networks, the actors with the highest actor strength are more likely to be connected in networks from a range of different domains (Opsahl et al., 2008). This means that the shortest (i.e. geodesic) path to reach an actor would be the path that has more weight, i.e. the likelihood of an actor acting as a broker in a network would increase if it has stronger ties with other actors. The mathematical expression for this measure is: $C_B^w(i) = \frac{g_{ij}^w(i)}{g_{ij}^w}$ where g_{ij}^w is the number of the weighted shortest paths between actors i and j ($i \neq j$) and $g_{ij}^w(i)$ is the number of those paths that go through actor *i*.

Closeness centrality (annotated as C_C) formally represents the inverse total length of the paths from an actor to all other actors in the network. This measure is based on the idea that actors with a short distance (i.e. path) to others can spread information very productively through the network (Landherr et al., 2010). Therefore, closeness centrality values increase when the geodesic distance between any two actors decreases. The mathematical expression for this measure is: $C_C^w = \left[\sum_{j=1}^{N} d^w(i, j)\right]^{-1}$ where $d^w(i, j) = \min\left(\frac{1}{w_{ih}} + ... + \frac{1}{w_{hj}}\right)$; $d^w(i, j)$ is the shortest path between actors *i* and *j*, and *h* are intermediary actors on paths between *i* and *j* as observed by Opsahl et al., (2010). All weighted centrality measures in our analysis have been normalized and are calculated using 'tnet' package available in R software.

Dynamic embeddedness represents the variability of structural positions of an actor in all short-interval networks compared to its structural position in the aggregated network. The mathematical expression for this measure originally proposed by Uddin et al., (2013) is given in the following equation 1:

$$DDA^i = \frac{\sum_{t}^{m} \alpha_{t,t-1} \times |OV_{AN} - OV_t|}{m} \tag{1}$$

where DDA^i is the degree of dynamicity (i.e dynamic embeddedness) shown by i^{th} actor, OV_{AN} is the observed value (i.e. degree centrality) for the aggregated network, OV_t is the observed value (i.e. degree) fort t^{th} yearly network for the i^{th} actor, m is the number of yearly networks considered in the analysis, and $\alpha_{t,t-1}$ is a constant valued according to whether the actor is present or missing in the current and previous short-interval network. The presence of this constant is of crucial importance to properly count for actors that disappear from the network due to simple inactivity or possible lack of presence due to acquisition effects. The possible combination of values that $\alpha_{t,t-1}$ takes are the following: (i) 1 if the actor is present in both current and previous period (t), (ii) 0.5 if the actor is present in current period but absent in the previous one and (iii) 0 if the actor is absent from the current period irrespective of his presence in the previous period.

For the first short-interval (yearly) network (i.e. $\alpha_{i,0}$ for t = 0), the value of the constant will depend on the presence or absence of each actor (i.e. either 1 or 0) at that particular period which further differentiates our model from the original one. It should be noted that degree, betweenness and closeness measures are introduced in their absolute form to both equations 1 and 2. The dynamic embeddedness model differentiates between two types of measures, the dynamicity of an actor represented by equation 1 and the average dynamicity shown by an actor of the t^{th} short-interval network represented by equation 2:

$$DDN^t = \frac{\sum_{t}^{w_t} \alpha_{t,t-1} \times \left| OV_{AN}^{j} - OV_t \right|}{w_t} \qquad (2)$$

where DDN^t is the average dynamicity shown by an actor embedded in the t^{th} short-interval network, and w_t is the total number of actors in the t^{th} yearly network. Therefore, our analytical approach is based on three dynamic variables: degree, betweenness and closeness centrality constructed by substituting each centrality measure to equations 1 and 2.

In order to analyze the effect of exogenous critical events such as financial crises and recessions on the global pharmaceutical industry, we construct two main effect variables: *financial crisis* represents the combined effect of the global financial crisis of 2007-2008 and the great recession of 2008-2009 that followed as a direct consequence. To avoid potentially high correlations between the crisis and the recession, as well as knowing that the great recession was originally a direct consequence of the financial crisis, we decide to combine both these critical events into one dummy variable that takes the value of 1 for the years 2007-2009 and zero for the rest. *European recession* represents the exogenous effect of the Eurozone recession during 2011-2012. Even though the recession continued well into 2013, due to lack of data, we consider only the effect for the period 2011-2012. Specifically, we create a dummy variable that takes the value of 1 for the years 2011-2012 and zero for the rest. Additionally, we do not include 2010 in our analysis as it has been deemed a 'recovery' period.

In multivariate analyses, we use various actor-specific measures including several financial controls, a well-known procedure accounting for the possibility that differentiates between firms in terms of how financial performance affects their propensity to engage in strategic transactions (Ahuja et al., 2009). The control indicators include strategic transaction frequency, R&D intensity, profitability, headquarters (HQ) location and financial leverage. *Strategic transaction frequency* represents the relative frequency in percentage with which firms engage in strategic transactions. Knowing that about 75 percent of strategic transactions present in the data are alliances, with the rest split evenly close (about 12.5 percent) between financing and acquisition collaborations, it is deemed important to control for the effect of each transaction type on actor's dynamic embeddedness. *R&D intensity* represents the firm's R&D expenditure scaled by total sales, as seen in network literature (Ahuja, 2000; Demirkan and Demirkan, 2012). We measure *profitability* for each firm by computing the ratio of net income to total assets (ROA), an indicator that has been well-accepted as a proxy of firm's performance (Demirkan and Demirkan, 2012). Another important financial measure is *financial leverage* (i.e. debt-to-total assets including both short- and long-term debt) (King and Santor, 2008). While the use of this measure as such is subject to scrutiny (Welch, 2011), we believe its use as a control variable for this type of network-based study is feasible. Additionally, based on the existing network literature (Loderer and Waechli, 2010; Demirkan and Demirkan, 2012), we control for the *age* of the firms, operationalized as the foundation year minus the year considered in the 2002-2012 longitudinal analysis and *size*, operationalized as the natural logarithm of company's employees. Since our data consists of global firms and knowing that the majority of top pharmaceutical firms are either US- or EU-based, we control for *headquarters (HQ) location* based on two separate dummy variables representing whether firms are U.S. or EU firms.

We use the dynamic embeddedness-based centrality measures for two purposes: (i) to analyze network evolution from the perspective of actors' dynamic embeddedness for the period 1991-2012 applied to both network types, and (ii) to test our hypotheses using a specific panel (i.e. longitudinal) regression model for the period 2002-2012 (i.e. +/- 5 years from the offset of the global financial crisis) for the core network and a mean comparison ANOVA test for the full network. An important question regarding actors' dynamic embeddedness is how to determine the stability of dynamic embeddedness distribution throughout the study period. To achieve this, we use a two-step analysis process similar to Minoiu and Reyes (2013); first we compare Kernel Density Estimates (henceforth, KDE) for core network dynamic embeddedness in the beginning and the end of our sample period, second we assess these distributions using Kolmogorov-Smirnov (henceforth, KS) tests for both core and full network. By controlling for firm-specific effects, we investigate the effect that global crisis (including the global financial crisis of 2007-2008 and the great recession of 2008 - 2009), and the local crisis referring to the Eurozone recession observed for 2011 and 2012, have on degree, betweenness and closeness dynamic embeddedness.

In order to test our hypotheses, we choose an econometric model conditioned by several factors. First, as the panel exhibits first-order serial correlation, we use GLS estimators for random effects with the disturbance term modeled as an AR (1) process. Second, since we consider a short panel of ten years, fixed-effects models are biased over short periods, thus RE models are preferred (Gulati and Gargiulo, 1999). Third, the RE model is preferred after a Hausman test indicates consistency and efficiency for our choice. Fourth, we run a Breusch-Pagan Lagrange multiplier test to determine whether a pooled OLS regression would have been more appropriate which gives a significant result rejecting the null hypothesis, therefore preferring the RE model (Breusch and Pagan, 1980). Additionally, we control for multicollinearity by computing Variance Inflation Factors (henceforth, VIF) on all explanatory variables. VIF are well below the 2.5 threshold considered for weaker models. Since the financial information considered for regression analysis presents missing data throughout the years, our regression models use unbalanced data. In order to explore the effects of the global and local crises on the full network, we conduct several one way Analysis of Variance (ANOVA) tests, similarly to the methodology shown by Fogel and Nehmad (2009) in order to compare the dynamic embeddedness for the years prior and post to the financial crisis offset. Specifically, we compare the mean between the periods before the financial crisis (2004-2006), the global crisis period (2007-2009) and the local Eurozone crisis included in the period (2010-2012). Table 2.2 shows a detailed description of the above-mentioned variables.

Table 2.2 Descriptive statistics of variables used in regression models

Variables		N	Mean	SD	Min	Max
A. Dependent variables						
	Degree dynamicity	753	0.13	0.17	0.00	1.02
	Betweenness dynamicity	753	0.07	0.12	0.00	0.81
	Closeness dynamicity	753	0.02	0.02	0.00	0.08
B. Network characteristics						
Strategic transaction frequency						
	Alliance	752	0.71	0.31	0.00	1.00
	Financing	752	0.06	0.13	0.00	1.00
	Acquisition	752	0.12	0.18	0.00	1.00
C. Industry characteristics						
Financial crisis		753	0.27	0.44	0.00	1.00
Eurozone recession		753	0.15	0.36	0.00	1.00
D. Firm characteristics						
Age		753	74.98	66.13	0.00	344.00
Size		752	9.30	1.76	0.00	12.04
HQ Location						
	U.S. firms	753	0.38	0.49	0.00	1.00
	EU firms	753	0.39	0.49	0.00	1.00
R&D intensity		753	1.42	34.90	0.00	957.72
Profitability		753	0.07	0.09	-0.84	0.61
Financial leverage		753	0.20	0.18	0.00	1.20

2.4 Results

We describe the dynamics of the global pharmaceutical industry using four key estimates: (i) tracking dynamic embeddedness evolution based on average dynamic embeddedness estimate plots, (ii) monitoring the stability variation of actors' dynamic embeddedness based on KDE and KS-tests, (iii) constructing the top ten firm rankings based on yearly network average dynamic embeddedness estimates, and (iv) understanding the financial crisis and recession association effect on dynamic embeddedness based on computational visualizations and panel regression estimates. Results (i) – (iii) concern the total panel period 1991-2012 while results (iv) concern the panel period 2002-2012.

2.4.1 Dynamic embeddedness evolution

Table 2.3 provides summary statistics for selected dynamic embeddedness measures including start and end years of our sample. Looking at both networks, we observe dynamic embeddedness means of all centrality indicators increase in 1998 compared to 1991, but decrease in both 2008 and 2012 with the latter showing a marked drop compared to previous years. Additionally, actors' dynamic embeddedness in 2012 reaches values never seen since the beginning of the sampling period. For some measures, this change is most visible for the period 2007-2012, suggesting some critical event impacting the values. This effect is more visible in the full network compared to the core one, suggesting a more stable relationship between actors within the top 90 network. Furthermore, the standard deviation values are comparable to the mean, suggesting a high degree of variation in the dynamic embeddedness across centrality measures. This result, coupled with the observed difference between mean and median, provides further proof to the variability and skewness of actors' dynamic embeddedness.

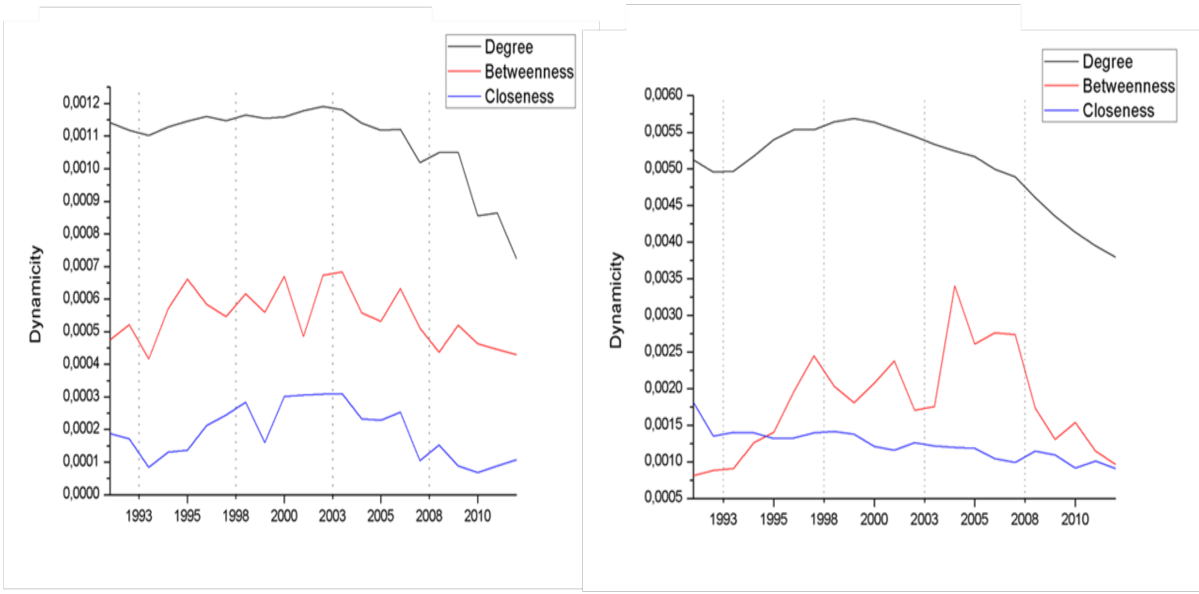
Table 2.3 Summary statistics for selected years

	Panel A: core network			**Panel B: full network**		
	Degree	*Betweenness*	*Closeness*	*Degree*	*Betweenness*	*Closeness*
1991						
Mean	1.14E-03	4.75E-04	1.88E-07	5.13E-07	8.15E-08	1.81E-12
Median	5.87E-04	0.00	1.23E-07	0.00	0.00	0.00
S.D.	1.60E-03	1.04E-03	2.01E-07	4.08E-06	9.22E-07	5.13E-12
Min.	0.00	0.00	0.00	0.00	0.00	0.00
Max.	9.69E-03	5.99E-03	1.71E-07	1.08E-04	2.96E-05	2.74E-11
1998						
Mean	1.16E-03	6.17E-04	2.84E-07	5.64E-07	2.03E-07	1.41E-12
Median	6.18E-04	1.03E-04	3.08E-07	0.00	0.00	0.00
S.D.	1.54E-03	1.13E-03	2.02E-07	4.02E-06	2.94E-06	3.67E-12
Min.	0.00	0.00	0.00	0.00	0.00	0.00
Max.	9.55E-03	5.67E-03	6.23E-07	1.06E-04	1.13E-04	2.11E-11
2007						
Mean	1.02E-03	5.11E-04	1.53E-07	4.90E-07	2.73E-07	9.90E-13
Median	2.43E-04	0.00	8.34E-08	0.00	0.00	0.00
S.D.	1.65E-03	1.08E-03	1.85E-07	4.08E-06	3.51E-06	2.72E-12
Min.	0.00	0.00	0.00	0.00	0.00	0.00
Max.	9.91E-03	5.07E-03	7.03E-07	1.10E-04	1.09E-04	1.57E-11
2012						
Mean	7.24E-04	4.30E-04	1.07E-07	3.79E-07	9.66E-08	9.09E-13
Median	0.00	0.00	0.00	0.00	0.00	0.00
S.D.	1.63E-03	1.28E-03	1.71E-07	3.98E-06	1.42E-06	3.46E-12
Min.	0.00	0.00	0.00	0.00	0.00	0.00
Max.	1.02E-02	5.54E-03	7.46E-07	1.13E-04	3.85E-05	2.73E-11

Figure 2.2 plots the cross-sectional averages of dynamic indicators during 1991-2012. For visualization simplicity, all values related to dynamic embeddedness (i.e. degree, betweenness, closeness) have been re-scaled using an appropriate constant for both plotting and regression purposes. Results show that dynamic embeddedness values are stabile for degree centrality, but vary substantially for betweenness and closeness centrality. Particularly of interest is the values' behavior during the offset of the global financial crisis of 2007-2008, with the estimates plummeting for both types of network. Specifically, for the core network, degree and betweenness dynamic embeddedness drop respectively 20 percent and 17 percent while closeness dynamic embeddedness is almost halved by 40 percent during the global cri-

sis. The Eurozone crisis of 2011-2012 shows a similar trend with both networks' dynamic embeddedness severely reduced. An exception is closeness centrality, whose dynamic embeddedness shows an upward trend for the core network, with signs of a more clustering-

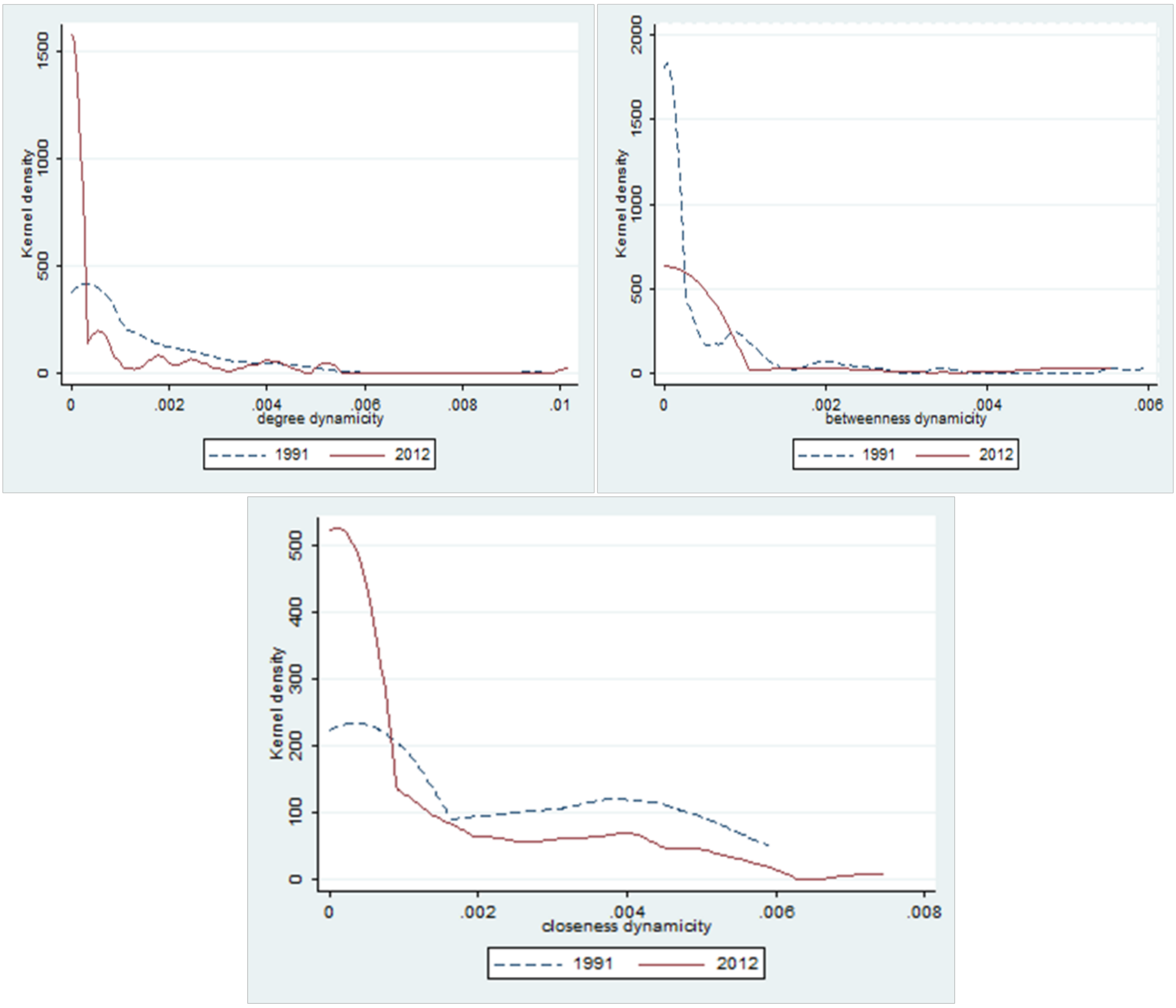
Figure 2.2 Dynamic embeddedness evolution 1991-2012 for both core and full networks



2.4.2 Dynamic embeddedness stability

We assess actors' dynamic embeddedness stability by analyzing dynamic embeddedness distribution via KDE comparisons. Specifically, we plot the nonparametric density estimates for centrality-based dynamic embeddedness including the sample's start and end year for the core network. As seen from Figure 2.3, dynamic embeddedness has a similar shape for all three centrality measures; however degree and closeness dynamic embeddedness have shifted downwards showing a clear tendency for the firms to reduce connections and proximity to each-other while betweenness dynamic embeddedness plotting the brokerage tendency of the firms shows signs of alternation with both left and rightward movements.

Figure 2.3 Dynamic embeddedness distribution for core networks



To understand whether this tendency is a mere isolated event or a result of dynamic network evolution, we test the stability of core network dynamic embeddedness distributions and compare it with the full network. For this, we compare each dynamic embeddedness distribution in the first year of each decade as well as last year's available (1991, 2001 and 2012) with subsequent years in the same decade, a procedure seen in Minoiu and Reyes (2013) and which results are given in Table 2.4.

Table 2.4 Empirical distribution stability for dynamic embeddedness

Panel A: Core network	1991	2001	2012	**Panel B: Full network**	1991	2001	2012
Degree				Degree			
1991-2001			1.00	1991-2001	0.54	0.27	1.00
2002-2012	0.36	0.27	0.72	2002-2012	0.54	0.45	0.63
Betweenness				Betweenness			
1991-2001			1.00	1991-2001			0.18
2002-2012	0.27	0.36	0.54	2002-2012		0.18	
Closeness				Closeness			
1991-2001	0.54	0.72	0.90	1991-2001	1.00	0.81	1.00
2002-2012	0.63	0.63	0.45	2002-2012	1.00	0.72	0.63

Note. Only significant coefficients reported for * $p < .05$

We show the proportion of years when dynamic embeddedness distribution is statistically different (at 5 percent level of significance) in each decade compared to 1991, 2001 and 2012. Not reported values mean that the distribution of a particular year compared to a particular decade is statistically close, such as the case for degree and betweenness dynamic embeddedness for years 1991 and 2001 compared with the period 1991-2001. This means that in both core and full networks firms have kept a similar centrality structure. On the other hand, the distribution for the decade 2002-2012 is statistically different for almost all dynamic embeddedness variables in both core and full networks, meaning that actors' dynamic embeddedness has been highly unstable for the second decade. An exception concerns betweenness dynamic embeddedness for the full network, whose results show a relatively unaffected actors' brokerage tendency, with only 18 percent of significant distribution change. Interestingly, closeness dynamic embeddedness exhibits the most significant change in both networks with overall distributions' difference higher in the full network.

2.4.3 Firm rankings in the global pharmaceutical industry

One of the key contributions of the dynamic embeddedness measure is its ability to provide a ranking based on actor's network measures' evolution. This is crucial in understanding the contribution of each actor to network dynamics. Knowing the high market share that few pharmaceutical firms have in the global industry, we focus on the top ten dynamic embeddedness ranking, and report the first ten pharmaceutical firms that have the highest score for centrality measures of both network types as seen in Table 2.5.

Table 2.5 Top-10 firms ranking (1991-2012) in core and full networks according to dynamic embeddedness

Core network								
Degree			*Betweenness*			*Closeness*		
Rank	*Name*	*Value*	*Rank*	*Name*	*Value*	*Rank*	*Name*	*Value*
1	**Pfizer**	0.879	1	**Novartis**	0.407	1	**GlaxoSmithKline**	4.68E-05
2	**Roche**	0.460	2	Daiichi Sankyo	0.381	2	Baxter International	4.66E-05
3	**Sanofi**	0.455	3	**Sanofi**	0.369	3	**AstraZeneca**	4.42E-05
4	**Novartis**	0.385	4	**GlaxoSmithKline**	0.344	4	MedImmune	4.31E-05
5	**Merck**	0.366	5	**Pfizer**	0.232	5	Tanabe Seiyaku	4.15E-05
6	Teva	0.358	6	**Roche**	0.202	6	Ratiopharm	4.14E-05
7	**AstraZeneca**	0.356	7	Teva	0.189	7	**Johnson and Johnson**	4.08E-05
8	**GlaxoSmithKline**	0.334	8	**Abbott Laboratories**	0.165	8	Allergan	4.02E-05
9	Genzyme	0.306	9	**AstraZeneca**	0.160	9	Genzyme	3.89E-05
10	Genentech	0.257	10	**Merck**	0.153	10	Daiichi	3.78E-05
Full network								
Degree			*Betweenness*			*Closeness*		
Rank	*Name*	*Value*	*Rank*	*Name*	*Value*	*Rank*	*Name*	*Value*
1	**Pfizer**	0.516	1	**GlaxoSmithKline**	0.269	1	**Pfizer**	9.40E-08
2	**GlaxoSmithKline**	0.384	2	**Pfizer**	0.231	2	**GlaxoSmithKline**	9.04E-08
3	**Johnson and Johnson**	0.360	3	**Johnson and Johnson**	0.182	3	**Roche**	8.54E-08
4	**Sanofi**	0.326	4	**Novartis**	0.181	4	**Sanofi**	8.52E-08
5	**Roche**	0.311	5	**Roche**	0.180	5	**Novartis**	8.20E-08
6	**Novartis**	0.298	6	**Bristol-Myers Squibb**	0.178	6	**Bristol-Myers Squibb**	8.11E-08
7	**Bayer AG**	0.277	7	**Merck**	0.166	7	Genzyme	8.10E-08
8	**Bristol-Myers Squibb**	0.254	8	**Sanofi**	0.161	8	Genentech	8.08E-08
9	**Merck**	0.250	9	**Abbott Laboratories**	0.154	9	**Johnson and Johnson**	7.87E-08
10	Bayer Corp.	0.246	10	Aventis	0.118	10	**AstraZeneca**	7.85E-08

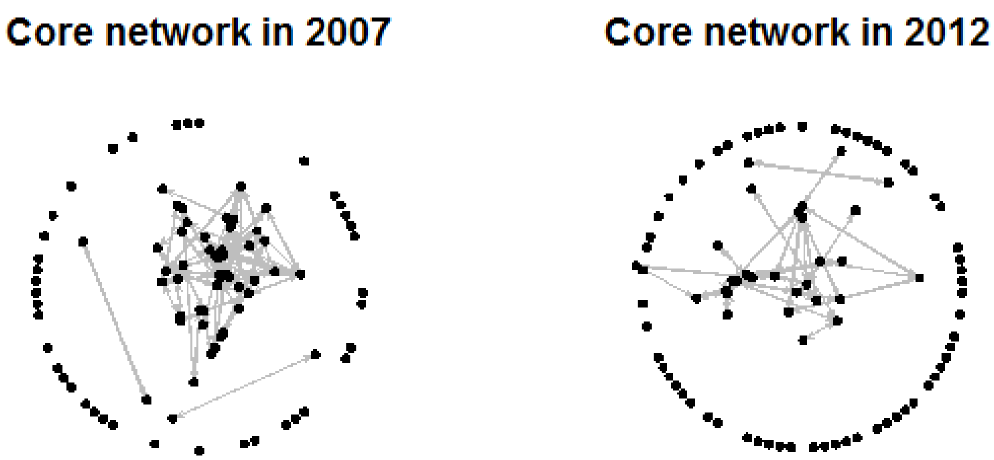
Note. Firms in bold are present in the top ranking according to sales

We observe that the top ten ranking for both degree and betweenness dynamic embeddedness includes seven of the biggest pharmaceutical firms (based on their average total sales) which are highlighted in bold, meaning these firms score high in their centrality position during core network evolution. Interestingly, closeness dynamic embeddedness shows only three big pharmaceuticals in the top ten, with a clear tendency of smaller firms reducing their mutual proximities. However, big pharmaceutical firms' hegemony is reinstated in the full network where we observe nine big pharmaceuticals scoring high in their degree and betweenness dynamic embeddedness measures and eight big pharmaceuticals scoring high in closeness centrality.

2.4.4 The financial crisis and recession effects on dynamic embeddedness

The dynamic embeddedness distribution results shown in the KS test give us a statistically important clue that during the 2002-2012 decade some major perturbation event occurred. In order to understand the network instability of the second decade, we focus our attention on the global crisis with its offset in December 2007 and the Eurozone recession starting in 2011. Following this line of thought, we proceed by visualizing the strategic transactions between actors for core networks during the global financial crisis offset in 2007 and the Eurozone recession in 2012, as seen in Figure 2.4 using R software.

Figure 2.4 Core network activities during global financial crisis offset and ongoing Eurozone recession



As observed, the overall strategic transactions between core network members have seen a marked reduction when comparing the global financial crisis offset in 2007 with 2012, the last year in our analysis. In addition to the reduced transactions, the number of isolates (i.e. firms without ties) represented as dots encircling the connections, has increased though this is often the case due to firms not making it to the top 50 list or being acquired by others. Prior to showing the regression analysis estimates, we provide the correlation matrix of all variables used in regression models as seen in Table 2.6.

Table 2.6 Correlation matrix of variables used in regression models

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Age	1														
2 .Size	0.2515*	1													
3. US firms	-0.1496*	0,4930556	1												
4. EU firms	0,1305556	-0.0010	-0.6228*	1											
5 .R&D intensity	-0.0182	-0.1945*	-0.0281	0,3173611	1										
6. Profitability	0.0813*	0.2938*	0,3993056	-0.0169	-0.0755*	1									
7. Financial leverage	-0.0260	-0.2517*	0.0017	0.2182*	0.0748*	-0.3161*	1								
8. Alliance frequency	0.0889*	0.1249*	0.0016	-0.0912*	-0.0830*	-0.0127	-0.0541	1							
9. Financing frequency	-0.1181*	-0.0911*	0.1583*	-0.0543	0.2672*	0,1319444	0.0099	-0.2112*	1						
10. Acquisition frequency	-0.0372	0.0025	0,4902778	0.0076	-0.0252	0,1784722	0.0803*	-0.3352*	-0.0667	1					
11. Financial crisis	0.0087	0,275	-0.0038	0.0082	-0.0219	0,2270833	0,3090278	-0.0061	-0.0140	0,2208333	1				
12. Eurozone recession	0,3048611	0.0849*	-0.0416	0,1027778	0.0861*	-0.0249	0.1000*	-0.0432	-0.1155*	-0.0033	-0.2549*	1			
13. Degree dynamicity	0,3916667	0.4081*	0.1451*	-0.0106	-0.0262	0,4694444	-0.1081*	0.2221*	0,2034722	-0.0080	0,0951389	-0.0615	1		
14. Betweenness dynamicity	-0.0487	0.3076*	-0.0482	0,475	-0.0204	0,3736111	-0.0615	0.1562*	0,1694444	0,1368056	-0.0203	-0.0195	0.6204*	1	
15. Closeness dynamicity	-0.0853*	0,3604167	0.1291*	-0.0353	0,1041667	-0.0181	-0.0944*	0.1500*	0.0767*	-0.0331	-0.1939*	-0.1948*	0.2538*	0.1492*	1

*. Correlation is significant at 0.05 level

The correlation coefficients show high and significant values for certain variables such as degree dynamic embeddedness, betweenness dynamic embeddedness and firm size. Overall, the dependent dynamic embeddedness variables are positively and significantly correlated to each-other, with the explanatory variables having relatively low correlation coefficients. This tendency points to no multicollinearity problems as acknowledged by the VIF analysis mentioned in the previous section. The analyses performed so far seem to support our hypotheses of a negative effect of financial crisis and recession on actor's dynamic embeddedness. To further explore their accuracy, we perform a multivariate analysis, meaning a panel regression analysis with random-effects using the core network of 90 firms as our sample. Table 2.7 summarizes the results.

Table 2.7 Dynamic embeddedness during crises: RE GLS regression with AR (1) disturbance estimates

	Dynamic embeddedness		
	Model 1	**Model 2**	**Model 3**
Variables	**Degree**	**Betweenness**	**Closeness**
Controls			
Age	-0.000129	-0.000321*	-0.0000312
Size	0.00817*	0.0184***	- 0.000196
HQ location			
US firms	0.0820*	-0.0227	0.00978*
EU firms	0.0429	0.00302	0.00648
R&D intensity	-0.0000596	0.0000133	0.00000101
Profitability	-0.0048	0.0371	-0.0180*
Financial leverage	-0.0062	0.0321	-0.0181***
Strategic transaction frequency			
Alliance	0.0194***	0.0151	0.00634**
Financing	0.0116	0.00373	0.00398
Acquisition	0.0220**	0.0154	0.00392
Main effects			
Financial crisis	0.00273	-0.0143†	-0.00512***
Eurozone recession	-0.0184***	-0.0210*	-0.00731***
Model statistics			
Constant	-0.00242	-0.0916†	0.0189*
R^2 overall	0.1088	0.1272	0.1071
N	751	751	751

Note. Coefficients are reported † *p*<.1 * *p* < .05 ** *p* < .01 *** *p* < .001

Looking at the main effects, our hypotheses are confirmed by the regression results. Specifically, we find strong support for hypothesis 1 regarding the negative effect of the global crisis on dynamic embeddedness indicators except degree dynamic embeddedness (model 1), meaning that the combined effect of the global financial crisis 2007-2008 and the subsequent great recession of 2008-2009 have significantly affected betweenness and closeness dynamic embeddedness of the core network members. Moreover, we find strong statistical significance in all three models for the negative effect that Eurozone crisis has had on firms' dynamic embeddedness in support of hypothesis 2. Interestingly enough, each model presents its own significant peculiarities for example, firms' size impacts degree and betweenness but not closeness dynamic embeddedness, meaning that larger firms have an increased probability of engaging in strategic transactions as well as functioning as intermediaries between each two other firms.

From financial measures' viewpoint, we observe that closeness dynamic embeddedness is significantly reduced by profitability and financial leverage. Additionally, strategic transaction types have an influence on dynamic embeddedness. While this result in the case of alliance transactions can be attributed to the relatively high distribution of this transaction type in the sample (about 75 percent), the positive and significant effect of acquisition transactions on degree dynamic embeddedness is rather interesting considering that both acquisition and financing transactions show similar distributions in the sample (about 12.5 percent each). Table 2.8 shows the one way ANOVA test results, in an attempt to understand the mean distribution of dynamic embeddedness in the full network population for the years prior and after the financial crisis triggering both the global and Eurozone recessions.

Table 2.8 One way ANOVA tests for degree, betweenness and closeness dynamicity

	Factor	Mean	S.D	Freq.	Source	SS	Df	MS	F	Prob > F	Bartlett's test for equal variances: chi2(2) = 5.3540 Prob>chi2 = 0.069
Degree	1	5.14E-04	4.08E-03	14205	Between groups	9.86E-07	2	4.93E-07	3.02	0.0488	W0 = 7.7056585 df(2, 42612) Pr > F = 0.0004509
	2	4.62E-04	4.05E-03	14205	Within groups	6.96E-03	42612	1.63E-07			W50 = 3.0201364 df(2, 42612) Pr > F = 0.04880501
	3	3.96E-04	4.00E-03	14205	Total	6.96E-03	42614	1.63E-07			W10 = 3.1135924 df(2, 42612) Pr > F = 0.04445113
	Total	4.57E-04	4.04E-03	42615	Source	SS	Df	MS	F	Prob > F	Bartlett's test for equal variances: chi2(2) = 9.3e+03 Prob>chi2 = 0.000
Betweenness	1	2.92E-04	3.89E-03	14205	Between groups	2.09E-06	2	1.05E-06	12.44	0.0000	W0 = 47.160614 df(2, 42612) Pr > F = 0.00000000
	2	1.93E-04	2.70E-03	14205	Within groups	3.58E-03	42612	8.41E-08			W50 = 12.435369 df(2, 42612) Pr > F = 0.00000399
	3	1.22E-04	1.67E-03	14205	Total	3.58E-03	42614	8.41E-08			W10 = 12.435369 df(2, 42612) Pr > F = 0.00000399
	Total	2.02E-04	2.90E-03	42615	Source	SS	Df	MS	F	Prob > F	Bartlett's test for equal variances: chi2(2) = 152.4477 Prob>chi2 = 0.000
Closeness	1	1.14E-09	3.07E-09	14205	Between groups	2.84E-18	2	1.42E-18	13.30	0.0000	W0 = 27.956622 df(2, 42612) Pr > F = 0.00000000
	2	1.08E-09	3.35E-09	14205	Within groups	4.55E-15	42612	1.07E-19			W50 = 13.300444 df(2, 42612) Pr > F = 0.00000168
	3	9.46E-10	3.37E-09	14205	Total	4.55E-15	42614	1.07E-19			W10 = 44.041424 df(2, 42612) Pr > F = 0.00000000
	Total	1,05E-09	3,27E-09	42615							

According to the ANOVA tests, the distribution mean for factor 1 representing period 2004-2006, factor 2 representing period 2007-2009 and factor 3 representing period 2010-2012 significantly differ from each-other (i.e. $p < .05$) for the three dynamic embeddedness indicators. Therefore, also for full networks, degree, betweenness and closeness dynamicity indicators show a decreasing tendency across the ANOVA factors supporting the negative and significant effect of the crisis and subsequent recessions on firm-level degree of dynamic embeddedness. However, the low p-value based on Bartlett's test cannot confirm that the assumption of variances being same across time periods is not violated. In order to further explore the existence of significant differences between the three dynamic embeddedness indicators, we use the *simnova* function in Stata as well as conduct Bonferroni, Scheffe and Sidak multiple comparison mean tests. These tests' results, which are available from the authors upon request, confirm the mean difference between dynamic embeddedness distributions for the selected years.

2.5 Discussion and concluding remarks

According to extant research, dynamic embeddedness can track the evolution of a network by assessing the contribution of each network member in the overall structural dynamics. Furthermore, this measure can capture firm's behavior in critical events such as organizational crisis that disrupt the structure of the network where the firm is embedded. In this context, the focus is given towards an endogenous shock causing an effect on actor's dynamic embeddedness in a given network inside the organization. While this approach is sound, we think it could be enhanced by including the impact that critical exogenous events originating outside the organization have not only on the organization itself, but on every member to which this organization is connected to. Specifically, there seems to be little research on the effect that the global financial crisis of 2007-2008 and its subsequent recessions have on any given industry.

This paper aims to fill this gap by analyzing the effect of both crisis and recessions on organizational dynamic embeddedness evolution, focusing on strategic transactions of the global pharmaceutical industry from an actor-level approach. We do this by plotting average firm's dynamic embeddedness evolution, analyzing dynamic embeddedness stability over the study period, listing the most important firms in the global pharmaceutical industry according to their dynamic embeddedness ranking, and testing the financial crisis and recession effects on firm's dynamic embeddedness. Results on firm´s dynamic embeddedness suggest that prior to the global crisis the global pharmaceutical industry has been relatively stable, with firms' centrality reflecting their market position. Specifically, top pharmaceutical firms that rank high in terms of sales have a noticeable central position in both the core and full networks. This is observable in the plotting of average degree dynamic embeddedness but less so for betweenness and closeness measures, suggesting that brokerage and proximity are more volatile indicators of dynamic embeddedness. Looking at top firm rankings, we observe that even though firms from different industrial backgrounds (i.e. biotechnology, pharmaceutical, and chemical) enter the global pharmaceutical industry, key players remain the same throughout the whole study period. This behavior indicates little dynamics as far as new players is concerned probably due to big pharmaceuticals' powerful hub effect on sub-networks made of subsidiary firms, private and public institutions with whom they presumably have a long tradition of strategic collaboration.

The type of network greatly affects the centrality rankings of dynamic embeddedness, with smaller firms reducing their proximity to each-other while increasing their intermediary (i.e. brokerage) role in the core network, and bigger firms maintaining their hegemony over the whole full network as a possible result of their collaborations with subsidiaries and other private entities. More importantly, the overall general trend for all dynamic embeddedness indicators shows that the global pharmaceutical industry has reduced its activity to even lower levels than the beginning of our sampling data, year 1991. While the reduction effect varies for specific centrality measures, its effect is more prominent after 2007, which coincides with the offset of the global financial crisis of 2007-2008. From there, dynamic embeddedness deteriorates further, potentially aided by the great recession of 2008-2009 and the Eurozone recession of 2011-2012. Regression results confirm this by showing significant dynamic embeddedness reduction during both crises. This significance is stronger for closeness dynamic embeddedness but consistent for all dynamic embeddedness measures. Furthermore, regression results indicate that Eurozone recession has had a far deeper negative effect on global pharmaceutical industry than the great recession. One possible explanation could be that being so close to each-other, the negative effect of the Eurozone recession might have been augmented by the previous great recession. In fact, during our robustness analysis check not shown in this paper but available upon request, we observe that 2010, considered a recovery year, has no negative effect on dynamic embeddedness. This confirms a double-dip pattern behavior for both recessions. Moreover, the crises effect is noticeable in full networks as well, as significant mean differences among pre- and post-financial crisis period are observed. Regression results also confirm the impact that financial measures such as profitability and financial leverage have on dynamic embeddedness. In particular, the more profitable and leveraged a pharmaceutical firm is, the higher the tendency to grow its proximity from other firms, a conclusion which is in line with the top firms' ranking analysis.

Our study highlights the importance of acquisition transactions in the expansion of the firms' importance as central hubs. Specifically, the significant effect of acquisitions on degree dynamic embeddedness demonstrates the different impact that strategic transactions have on centrality indicators and further reinforces the reasoning behind our choice to study centrality measures evolution through dynamic embeddedness conceptualization. However, this also raises questions as to why comparable effects of strategic transaction types (i.e. acquisitions and financings) respond differently to centrality-based dynamic embeddedness. One explanation could be the nature of acquisition transactions allowing a particular actor to enlarge its existing ties by including those of the newly acquired actor which does not exist anymore as an independent entity. Simply put, the firm will have more transactions when it acquires another firm since the latter's transactions will be incorporated to the former. This may not be necessarily true for brokerage or proximity reasons; throughout the study, we observe that bigger firms tend to be selective in their brokerage role and more interestingly distance themselves from smaller firms.

We enhance existing knowledge on dynamic social networks by presenting theory-based hypotheses for testing, and validating the concept of dynamic embeddedness. We emphasize our study's precision in describing critical events which include not only endogenous perturbations such as organizational crisis (Uddin et al., 2013; 2015) but also exogenous critical events such as the global financial crisis of 2007-2008 and the subsequent recessions affecting global industries. Specifically, we show how each firm's dynamic embeddedness tracks the evolution of actor´s structural embeddedness as well as ranking the contribution of each actor's centrality footprint. In this context, we observe that dynamic embeddedness can successfully be combined with the network concept of structural embeddedness by analyzing the evolution of actor-level centrality measures, thus unifying these concepts under the singular theoretical framework of dynamic embeddedness. By considering both top firms and especially their ego-network (i.e. networks in which they participate) partners, our study gives an enhanced view of the global pharmaceutical industry dynamics. Additionally, it contributes to the research on strategic collaborations, by considering the multiple impacts of alliances, acquisitions and financing transactions on the global pharmaceutical network. From the practical point of view, this study is a novel approach to the analysis of a highly convoluted industry such as the pharmaceuticals. By tracing its evolution on global perspectives, we shed light on industry´s key players as well as highlight the movement of smaller firms on the overall network structure. Moreover, our results show the true impact of both global and more regional recession effects on the pharmaceutical network, suggesting the importance and at the same time fragility of strategic transactions toward exogenous perturbations of critical nature.

Our study’s limitations could potentially provide interesting areas of future research. First, we should be careful when generalizing our results about the global pharmaceutical industry, knowing that not all firms in both core and periphery networks are dedicated to pharmaceuticals but come from other adjacent industries such as biotechnology and chemicals. In this light, a study across industries using bimodal network analysis could be beneficial to uncover the crisis effect on dynamic embeddedness. Second, dynamic embeddedness measure calculation is based on a novel design which takes into account missing actors during network evolution using a specific constant. However, the use of this constant is subject to further research to properly assign to it more robust values. Third, it could be interesting to test our results using traditional network measures and see whether the dynamic effect captured by dynamic embeddedness is present or not. Fourth, due to the availability of the data, we could not test for causality inferences as this would have involved the inclusion of robust instrumental variables that we did not have at our disposal. Finally, the dynamic embeddedness measure could be expanded to consider other centrality measures (i.e. Eigenvector, Bonacich Power) or be included in the analysis of network measures such as actor’s structural similarity, structural holes and brokerage elasticity.

3. Beauty or Beast: Organizational Aspirations and Dynamic Embeddedness in Strategic Alliance Formation

3.1 Introduction

Back in 2006, Pfizer, one of the world's biggest pharmaceutical firms, acknowledged that its successful strategy of forging winning alliances needed a retouch due to the changing of competitive landscape, and the reduction of opportunities for large and late-stage agreements of expensive and rare nature. This was a year when Pfizer did not meet its target aspiration performance, which is why the management decided to take a new approach into business development, looking at the science done outside the firm labs, and working to find the right opportunities at the right prices. A new strategy was concocted that included more downstream alliances focused on marketed drugs and investigational compounds, a focused research on acquiring products and services that add value to the firm's business streamline, and investing in adjacent healthcare businesses such as biologics and vaccines to increase opportunity commercialization.

Organizational behavior is often conditioned by strategic changes that involve interorganizational alliances, increasing firm's adaptability to various opportunities, and threats when embedded in a networked context of relationships (Cyert and March, 1963; Greve, 1998; Greve, 2010; Shipilov et al., 2011; O'Brien and David, 2014; Lungeanu et al., 2015; Tyler and Caner, 2015). In this regard, extant research has largely focused on two perspectives: Performance Feedback Theory and SNT. Performance feedback theory draws on BTF to argue that performance above and below aspirations' level influences motivation to change and risk preferences (Cyert and March, 1963; Greve, 1998; 2011; Baum et al., 2005). In particular, while performance falling short of aspirations may trigger a 'problemistic search', for potential solutions (Cyert and March, 1963; Greve, 1998; 2011), performance above aspirations is seen as a good enough reason to avoid the risks inherent to organizational change therefore reducing new strategic alliances (Baum et al., 2005; O'Brien and David, 2014). However, empirical evidence is not fully consistent with this view and proposals exist on the possibility of a 'slack' motivated search of new alternatives for firms performing above their aspiration level, and rigidity behavior motivated by threats to firm survival for firms performing below their aspiration level (Staw et al., 1981; Greve, 1998; Di Lorenzo et al., 2011). More importantly, researchers have observed how performance feedback theory fails to consider firm embeddedness in interorganizational networks, and particularly that 'it takes two to tango' when it comes to explain interorganizational strategic alliance formation (Baum et al., 2005; Kim and Rhee, 2014).

While aspirations may trigger the firm's intention to establish new interorganizational alliances, firm's structural position within its network molds the context in which such intention becomes an actual strategic change decision. Supporting this idea, Kim and Rhee (2014) show the importance of considering both aspirations and structural antecedents to understand strategic decision making. On the other hand, SNT has analyzed external relationships that create strategic interorganizational ties, a byproduct of complex dynamic firm behavior, ultimately embodied in organizational strategic actions and choices (Uzzi, 1997; Gulati et al., 2000; Zaheer and Bell, 2005). Their important impact in taping knowledge and cooperation opportunities enhances the role of both network members' identity and the structural pattern of the network itself (Gulati, 1999). SNT specifically acknowledges that the formation of interorganizational collaborations such as strategic alliances requires an 'inducement-opportunity' perspective referring to the focal firm's desire and its potential partners' interest in forming partnerships (Ahuja, 2000a).

With few exceptions (e.g. Baum et al., 2005; Kim and Rhee, 2014), performance feedback and social network theoretical approaches to interfirm strategic alliances have remained largely unconnected. Those studies trying to integrate both perspectives have not considered the effect that organizational aspirations have on the 'inducement-opportunities' perspective. That is, they have not explicitly acknowledged that in addition to its effect on the firm's inducement for new strategic alliances, performance relative to aspirations may also affect other firms' willingness to establish an agreement with the focal firm itself. This study sheds further light into these theoretical issues by integrating performance feedback and social network theories in order to analyze firm's dynamic network structures, and their closely association with organizational aspiration models explored in a unique dataset that takes into account strategic alliances of the top 90 global pharmaceutical firms for the period 1991-2012.

Since conflicting predictions emerge both in theoretical reasoning and empirical findings about the effects of relative performance on actors' risk preferences and motivations to change, recent studies have begun to focus their attention on identifying and examining moderating variables that take into account firm's network embeddedness (Shipilov et al., 2011; Kim and Rhee, 2014). However, extant definitions of network embeddedness do not consider the dynamic positioning of the actors throughout the network evolution, which is why we introduce the concept of ‘dynamic embeddedness’ defined as the individual actor’s structural positions’ variability in a longitudinal network compared to its structural position in an aggregated network (Uddin et al., 2013, Shijaku et al., 2016). In this regard, we consider the moderating role of firm’s dynamic embeddedness of network structures in the aspiration – alliance formation relationship. In particular, we argue that firm’s dynamic embeddedness influences its performance feedback effect on potential partners’ desire to collaborate as well as its attractiveness to other firms, altering interorganizational strategic alliance formation behavior.

In sum, this study aims at two primary contributions. First, it links performance feedback and social network theories, with performance being the nexus bridging these theoretical perspectives. By positing a direct relationship between strategic alliance formation and organizational aspirations, we find that new alliances decrease the further firm’s performance departs from aspirations’ level, as a result of both actors’ desires and opportunities. Second, by incorporatiing the concept of dynamic embeddedness that takes into account the dynamic nature of interfirm collaborations, we propose the moderating role of dynamic embeddedness in the aspiration-alliance relationship. In this vein, our observed effects are especially prominent if the firm is dynamically embedded in a given longitudinal network. Finally, from a practical viewpoint, our study provides a framework for managers to consider new alliance formations as a key determinant for successful strategic practice formulation.

3.2 Theory and hypotheses

3.2.1 The structural nature of strategic collaborations

Interorganizational ties have been viewed as a relatively inimitable and non-substitutable resource in itself that firms draw on to acquire competitive capabilities (Andersson et al., 2002; McEvily and Marcus, 2005; Huggins, 2010). In this sense, strategic collaborations have observable benefits in reducing organizational risk by enabling firms to form strategic collaborations in order to spread the financial risk and share costs of research and development associated with new products or production methods (Elmuti and Kathawala, 2001). A critical advantage of strategic collaborations over single-firm strategies is their ability to draw upon resources and opportunities of more than one firm which in turn ensures better success odds for the collaboration and its participating members (Das and Teng, 2000). Despite such advantages, Das and Teng (1996; 2002) and Mani and Luo (2015) argue that strategic networks often carry some elements of organizational risk and uncertainty as a result of organizations facing both relational risk (i.e. probability and consequences of not having satisfactory cooperation), and performance risk (i.e. probability that an alliance fails due to intensified rivalry, new entrants, demand fluctuations, etc.). Therefore, strategic collaborations have both inhibiting and stimulating effects on organizational risk.

3.2.2 Performance feedback and strategic relationship choice

Several studies have attempted to link strategic relationship choice to organizational aspirations using performance feedback theory (Baum et al., 2005; Greve, 2010; Shipilov et al., 2011; Kim and Rhee, 2014). This theory draws on the concept of organizational aspirations originally coined in BTF formulated by Cyert and March (1963) who consider performance feedback as a combination of firm's own performance history (i.e. historical aspiration) with the performance of other firms in the same industry (i.e. social aspiration). Performance below aspirations indicates potential problems in attaining long-term goals and hence triggers a 'problemistic search' for solutions to close the gap, and stimulates the exploration of new practices, strategies and courses of action. Thus, the low performing firm will engage in new strategic practices (e.g. alliances) in an attempt to turn things around. On the other hand, for performance exceeding both historical and social aspirations, performance feedback model predicts that the high performing firm will be more reluctant to change its already familiar and successful strategy and refrain from taking unnecessary risks associated with new strategic choices (Simon, 1947; March and Shapira, 1992; Baum et al., 2005). Thus, the high performer will exhibit a rigid behavior that stems from its reluctance to abandon successful strategic routines.

Empirical evidence has proved to be fairly consistent with the patterns proposed by performance feedback theory. In this vein, current research on the subject also seems to be consistent with the idea that performance-based aspirations specifically affect interorganizational strategic relationships. For example, Di Lorenzo et al., (2011) show that firm financial performance either above or below aspirations has a significant influence on changes in partnering behavior. On the other hand, Tyler and Caner (2015) show that in firm's new product introduction context, performance below aspirations increases the number of R&D alliances entered by the firm.

Nonetheless, it has also been proposed that this general pattern (i.e. search of new strategic options for firms performing below aspirations also referred to as exploration and a tendency to avoid change for those performing above aspirations referred to as exploitation) can change under certain circumstances. For example, performance below aspirations may trigger a conservative behavior if threats to firm survival are perceived (Staw et al., 1981; Greve, 2010). In an underperforming event defined by performance below aspirations, the probability of the firm behaving rigidly and resisting organizational change is increased since low performing firms have an increased chance to reach a critical survival point where any further failure could threaten organization's existence (March and Shapira, 1987; Di Lorenzo et al., 2011). Furthermore, a firm performing below aspirations is seen as incapable of achieving acceptable performance through local search and incremental adjustment to its status quo (Baum et al., 2005), therefore maintaining existing routines could be a cost effective option instead of establishing new ones (Di Lorenzo et al., 2011).

On the other hand, when performance surpasses organizational aspirations, the existence of slack resources may motivate an experimentation behavior that leads firms to work on new ideas, predicting a 'slack search' effect (Cyert and March, 1963; Greve, 1998; 2011; Baum et al., 2005; O'Brien and David, 2014). There seems to be a lack of consistent empirical evidence on the generalized occurrence of threat rigidity or slack search (Iyer and Miller, 2008). For example, threat rigidity seems to be more likely for small firms than for big ones (Greve, 2010). O'Brien and David (2014) observe that slack search is contingent upon the national culture of the country, observing that such behavior occurs to a great extent in communitarian contexts, like Japan. Thus, it seems both threat rigidity and slack search are contingent on firm-specific factors such as size and organizational culture that may differ within a given industry.

3.2.3 It takes two to tango

A model that explains strategic transaction formation is incomplete if one only considers, as performance feedback models do, the disposition of the focal firm to develop such transaction. Problemistic (or slack) search may result in intentions to form new strategic collaborations but do not directly cause strategic alliances to take place (Baum et al., 2005). Hence, the performance feedback model provides a 'unilateral' view of the strategic alliance formation process in that it helps us understand why a company may be willing (or not) to enter strategic alliances with other firms. However, it says nothing about the other side of the agreement. As noted by Ahuja (2000a), firm's linkages with other partners reflect the firm's incentives to collaborate and increase its attractiveness to potential partners. That is, a model of strategic alliance formation should consider the firm’s desire to seek strategic partners (i.e. actors that may be willing to form a strategic alliance with the focal firm) but also acknowledge the inclination of other firms to transact with the focal firm itself (i.e. the existence of an opportunity to form an alliance). We note here that this willingness is also, in part, a function of the focal firm’s performance relative to its aspirations.

Seeking strategic partners becomes a staggering job as firm performance decreases and therefore moves away from its aspirations’ level. Firms whose performance does not reach its aspirations may be seen as a burden and an additional risk by potential partners. Even if the low performing firm is, due to its relative performance, eager to form strategic alliances, it will be the ‘beast’ nobody wants to get involved with.

On the contrary, high performers will have more opportunities to form linkages with other firms, and will be more likely to receive propositions to enter new strategic alliances. However, firms performing well above their aspirations (i.e. very high performers) may not be willing to form alliances with other firms, and will behave ‘selectively’ potentially refusing collaborative propositions. In fact, from a performance feedback perspective, performing above aspirations’ level tends to reduce firm’s incentives to find new alternatives and courses of action, which may include new partners (Baum et al., 2005). As firm performance improves so does firm’s image and confidence of its managers, making strategic alliances with other (less attractive) firms less interesting since the focal firm may sense it may learn much less from their partners than vice-versa (Ahuja, 2000a), a situation that could be seen potentially as a threat to the firm’s competitive advantage in the industry. On the other hand, performance above aspirations induces an exploitative behavior of the firm’s current strategies potentially leading to a success trap (Rhee and Kim, 2015) which in turn enhances the chances for rigidity behavior.

Therefore, we suggest that firms’ preferences to develop strategic alliances converge when the focal firm’s performance matches its aspiration level. Conversely, those preferences will not match for firms in the upper and lower ends of the relative performance spectrum: high performers, while attractive to others, will not be particularly interested in forming new strategic alliances; low performers on the contrary, while interested in establishing strategic alliances, will be less likely to find new partners. In view of these arguments, we posit the following hypotheses:

Hypothesis 1a (H1a): For firms performing below their aspiration levels, decreases in performance are negatively related to strategic alliance formation.

Hypothesis 1b (H1b): For firms performing above their aspiration levels, increases in performance are negatively related to strategic alliance formation.

3.2.4 Network embeddedness and alliance formation

The rationale behind tie and subsequent network formation that generate firm's network embeddedness can be traced from organizational objectives, management vision for organizational development, and specific strategies necessary to improve firm competitiveness in rapidly changing environments (Cravens et al., 1996). Network embeddedness gives the firm the opportunity to multiply alliance benefits through both alliance-to-network and network-to-alliance transfers (Swaminathan and Moorman, 2009). Firms use position in the network as a competitive tool, and something that can be manipulated to increase performance, profits, or control (Cowan et al., 2007). Even though resource sharing is an important factor in alliance formation, highly embedded firms are provided with preferential treatments due to their central status, and have higher probability to form new collaborations. In this sense, highly embedded firms use their prior connections to build new ties and remain deeply embedded in the network (Ahuja et al., 2009). In fact, network embeddedness is relevant to alliance success because it promotes cohesion between partners during the collaboration process, and provides clues as to which partner selection will be more successful (Polidoro et al., 2011).

As firms tend to find partners close to them in the network space, this affects the probability that they will form partnerships in the future (Cowan et al., 2007). For example, Gulati (1995b; 1999) finds a positive effect of firm's embeddedness in prior ties affecting subsequent alliance collaborations. However, a positive relationship between network embeddedness and alliance formation is not always warranted. In fact, Chung et al., (2000) show that direct ties and indirect ties have an inverted U-shaped relationship with the probability of alliance formation. This said, the curvilinear effect is sometimes not assumed directly but arises from the way the processes of alliance formation are modeled.

Traditional network embeddedness models are mostly related to the structural dimension of embeddedness, and make use of network indicators that measure firm centrality such as degree, betweenness and closeness. One of the major issues with the current representation of such measures is the staticity of structural embeddedness that does not consider the interchengability of the partners throughout the network evolution. This warrants the use of dynamic embeddedness (Shijaku et al., 2016) that corrects such structural myopia, and injects a dynamic value into the concept of network embeddedness, if we are to analyze longitudinal collaboration evolution over time. In comparison terms, both static and dynamic embeddedness are believed to behave similarly, with highly embedded firms tending to engage more in strategic alliances (Ahuja 2000a; 2000b) which is why we believe dynamic embeddedness positively affects strategic alliance formation. More formally, we posit the following hypothesis.

Hypothesis 2 (H2): Highly dynamically embedded firms are more likely to initiate alliance collaborations.

3.2.5 Network dynamism and strategic behavior: the role of dynamic embeddedness

Many scholars have provided a socialized account of firm behavior by establishing a direct connection between networks of external relationships and firm strategic actions, observing the advantages that network structures have on firm's strategic management especially with regards to firm performance (Granovetter, 1985; Uzzi, 1997; Gulati et al., 2000; Kogut, 2000; Zaheer and Bell, 2005). This impact is a direct result of the network's ability to offer access to knowledge and cooperation opportunities that an isolated firm may not possess (Burt, 1992; Uzzi, 1997). In fact, networks of contacts between actors can be vital sources of information for the participants, a process that enhances both the identity of network members and the structural pattern of the network itself (Gulati, 1999). In this sense, a network of interorganizational ties has been viewed as a strategic resource, and its important impact on both firm's economic and innovative performance has been extensively researched (Burt, 1992; Granovetter, 1992; Uzzi, 1997; Andersson et al., 2002; Borgatti and Foster, 2003; Gilsing et al., 2008; Giuliani, 2010).

Given that the theoretical arguments concerning performance feedback show some level of contradiction, both in theoretical reasoning and empirical findings regarding the effects of relative performance on the actors' risk preferences and motivations to change, recent studies have begun to focus their attention on identifying and examining moderating variables that take into account firm's embeddedness in network structures (Shipilov et al., 2011; Kim and Rhee, 2014). For example, Baum et al., (2005) show that partner selection tendencies in alliance networks are influenced by performance feedback on firm's market share and network status. On the same lines, Shipilov et al., (2011) successfully combine Structural Hole theory with performance feedback by identifying determinants of alliance partner selection, and showing that organizations in brokerage positions set social and historical aspiration levels differently from the rest; that in turn affects decisions about partner selection and subsequent tie formation. Additionally, Kim and Rhee (2014) argue that the actor's structural position in a network, moderates divergent behavioral mechanisms, in terms of risk preference and motivation to change, by inducing decisions that change courses of action based on performance relative to aspirations.

We acknowledge that firms form networks and that network position is important in this interaction. Specifically, we posit that network embeddedness influences firm's desire to form linkages, and modifies its attractiveness to other potential partners by moderating the relationship between performance relative to aspirations, and strategic transaction activity of the firm posited in Hypotheses 1a and 1b. Given that extant embeddedness models linked to alliance ambidexterity disregard the dynamic positioning of the firms throughout the network evolution, we have introduced the concept of 'dynamic embeddedness' defined as the individual actor's structural positions' variability in a longitudinal network compared to its structural position in an aggregated network (Uddin et al., 2013, Shijaku et al., 2016). This concept is used to track the evolution of firms' network centrality measures such as degree, betweenness and closeness throughout a longitudinal setting.

As argued in Hypothesis 1a, a firm is less likely to engage in strategic alliances, the further its performance falls below aspirations. We argue that this behavior will be reversed when the firm is dynamically embedded in a network of collaborations since a highly dynamically embedded firm (i.e. central throughout network evolution) will have a stronger network position which will translate itself into higher attractiveness (Li et al., 2008). Despite few exceptions (e.g. Lin et al., 2007), the majority of the studies involving embeddedness view this concept from a static perspective which is neglects the evolution (i.e dynamicity) of the firm's centrality through time (Uddin et al., 2013). Even simulation models (e.g. Lin et al., 2007), that are able to dwell on the contents of a dynamic network do so holisitically, without being able to gauge on the effect of each network member's position on the network and firm themselves. Using the concept of dynamic embeddedness, we are able to capture the evolution of firm's centrality through time in each of its ego-networks.

Being already central gives the firms access to more potential partners (hypothesis 2). Hence, it is easier to find a potential partner for an underperforming firm that is central, that for an underperforming firm that is not central. The highly and dynamically embedded 'beast' will herein give a better image to its potential collaborators who will in turn increase repeated ties and engage in new alliances despite its view as underperformer. In other words, low performers will establish new collaborations simply because they are attractive due to their central status. Even though new alliances can signify higher uncertainty and risk (Das and Teng, 2002; Mani and Luo, 2015), the underperforimg firm is willing to take them in its problemisitc search, while the other firms will be eager to tap-in to the level of expertise and knowledge that the highly embedded firm possesses. Therefore, an increased dynamic embeddedness of the firm weakens the negative effect that the increased performance-aspiration distance has on strategic alliance formation.

Similarly, but for different reasons, a firm performing increasingly above its aspirations' level will have a lower propensity to engage in strategic alliances. This tendecny will be reversed, the more centrally, highly statutory a firm is considered in a network evolution which is why we refer to this as the dynamic embeddedness effect. As noted by Ahuja (2000a), incentives to form linkages for those firms that have the opportunity to do so (i.e. high performing firms) vary with firm's structural position in the network, such that they vanish beyond a point of embeddedness. However, successful firms performing above their aspirations might be inclined explore new partnerships due to the slack-driven search (Baum and Dahlin, 2007; Rhee and Kim, 2015). For highly embedded overperforming firms, entering new alliances may be a way to maintain their centrality in the network. Also central firms are also the ones with the largest experience in alliances. This knowledge may help those firms to take advantage of the marginal benefits of alliances while reducing the marginal costs. Therefore, overperforming central firms will be more willing to enter alliances thatn overperforming non-central firms. For highly embedded firms, "the marginal benefits of forming new linkages will be low and the marginal costs of additional links will be high" (Ahuja, 2000a: 322) but high embeddedness would be also be used by the 'beauty' to explicitly manifest its willingness to enter into new relationships with its more 'mediocre' peers due to the firm's resource driven search. More formally, we posit the following hypotheses.

Hypothesis 3a (H3a): The negative relationship between performance below aspirations and strategic alliance formation will be weaker for firms that experience high dynamic embeddedness.

Hypothesis 3b (H3b): The negative relationship between performance above aspirations and strategic alliance formation will be weaker for firms that experience high dynamic embeddedness.

3.3 Data and Methods

3.3.1 Data sources and sample

We test our hypotheses by examining the global pharmaceutical industry chosen due to its traditionally high economic impact, the extensive collaborations between pharmaceutical firms, and the fact that strategic alliances are considered a norm for this type of medium. To study how firm´s dynamic embeddedness and aspirations' level affect strategic alliance formation, we select a sample of 90 firms by identifying those actors that have appeared at least once in the top 50 of the Pharmaceutical Executive Magazine yearly editions from the period 2002-2013 and whose ranking selection criteria is based on the firm's total sales. Subsequently, we use the Pharma and Medtech Business Intelligence database to collect all strategic transactions that involve the top 90 firms in question between January 1, 1991 and December 31, 2012. These transactions used to proxy our network variables amount to over 9,600 collaborations of which about 8,000 (84 percent) involve alliances between the top 90 pharmaceutical firms, and the rest involve alliances between these leading firms and the remaining population totaling 4,645 firms. In order to measure organizational aspiration and control variables, we use COMPUSTAT and DATASTREAM databases supplied by annual report information whenever data is deemed incomplete. Since financial data concern the top 90 firms from Western Europe, United States, Asia, Africa and Australia, we convert all local currencies to USD with an exchange rate based on the particular year the data is retrieved.

3.3.2 Measures and variables

Dependent variable - Our dependent variable, *alliances* is calculated as the number of total strategic alliances that each of the top 90 firms has initiated with other firms of the total sample population in any given year from 1991 to 2012. Our choice on this matter is motivated by the fact that strategic alliances (joint venture, marketing and licensing, intra-biotech deals, reverse licensing and similar) are the most common type of strategic relationships analyzed by empirical studies involving social network concepts as seen in Table 2.1.

While several studies using this type of variable, choose a dummy unit of analysis (Garcia-Pont and Nohria, 2002; Hagedoorn et al., 2006; Ahuja et al., 2009), due to the nature of our weighted sociomatrix networks, we opt for a counted analysis previously used in social network analysis of strategic transactions (Demirkan and Demirkan, 2012). From a post-hoc analysis perspective, we also consider multiple transactions (i.e. *alliances, acquisitions, financings*) as separate dependent variables to see whether effects on particular transaction types can be observed. In this matter, it should be noted that the strategic transactions of the sample are unevenly distributed with alliances comprising the majority bulk (74.5 percent), and the rest (i.e. acquisitions and financings) split evenly close (about 12.5 percent). Each dependent variable takes a nonnegative integer value of 1 or higher for occurrence and repetition of the strategic transaction, and 0 for a nonoccurrence of the transaction collaboration for any given firm in any given year.

Independent variables - The primary independent variables of interest relate to performance relative to aspirations and dynamic embeddedness. To measure performance relative to aspirations, we first construct measures of both firm performance and aspiration levels as seen in the current behavioral theory literature (Greve, 2003; Iyer and Miller, 2008; O'Brien and David, 2014). Aspirations are usually defined with respect to a particular dimension of firm performance which in the current research has generally been associated with return on assets (henceforth, ROA) (Greve, 2010). However, as Bromiley and Harris (2014) duly note, these studies have not addressed whether other performance measures might be superior, nor have they considered the inherent issues associated with single accounting measures such as recognition of discretionary items and depreciation. Therefore, we follow Bromiley and Harris (2014) guidelines and construct a composite measure that includes ROA, return on stockholder equity (ROE) and return on sales (ROS). This measure is constructed using Stata alpha procedure while factor analysis is used as a confirmatory method to validate its outcome. Additionally, AIC and BIC summary statistics used to compare regression results between ROA-based aspiration levels and the ROA, ROE, ROS-based aspiration levels yield a better fit for the latter, legitimating the composite measure's use in our analysis. In order to check for correlation bias between ROA and ROE, we run Pearson correlations that confirm a positive value of 0.42 which we think does not distort factor analysis results used in the performance composite measure.

Researchers often combine self- and social-referent aspirations into a single measure of aspirations which aligns well with corporate practice of the firm usually retaining only one set of stated goals for a given activity at a given time (Bromiley and Harris, 2014). Similar to Greve (2003) and based on Bromiley and Harris (2014), we use a weighted proxy for organizational aspirations that combines both historical and social aspirations. Specifically, we measure historical aspiration as a weighted average of firm's past composite performance calculated as: $HA_t = 0.7(P_{t-1}) + 0.2(P_{t-2}) + 0.1(P_{t-3})$ where P is the composite performance measure that includes ROA, ROE and ROS. Social aspiration is operationalized as $SA_t = \frac{\sum P_t}{N-1}$ where P_t is the composite performance measure for any given year (t), N is the number of all firms (i.e. 90), and the final aspirations' level measure constructed as $AL = 0.8 \times SA + 0.2 \times HA$. The chosen performance and aspiration weights were the ones that gave the highest model likelihood. Similar to Greve (2003) and Kim and Rhee (2014), in order to analyse the relationship between strategic transaction formation and performance relative to aspirations, we subtract aspirations from performance and split the results into positive and negative values meaning *Performance below Aspirations* (henceforth, PbAL) when performance < aspirations and *Performance above Aspirations* (henceforth, PaAL) when performance > aspirations. Both are continuous variables, but while PbAL takes negative values, PaAL takes positive ones.

As per the concept of embeddedness, it should be noted that despite the effort, current research fails to count for the continuous evolution of longitudinal networks' structure of which this term is a clear reflection, by using snapshot views of each network or by aggregating network data into moving windows. Moreover, since longitudinal networks have a dynamic component (i.e. change overtime), translated into the effect of missing actors (i.e. firms), care should be taken in capturing such network dynamism. Bearing in mind various methods of longitudinal social network analysis that take into account missing actors such as stochastic actor-oriented or 'multi-agent' simulation methods (Snijders, 2001; Uddin et al., 2012), centrality measures could be updated to include a specific constant that takes into account their dynamic evolution. This is the rationale behind 'dynamic embeddedness', a concept that has been applied to track evolutionary social network analysis in the global pharmaceutical industry (Shijaku et al., 2016). This actor-level dynamics' approach captures actor's positional evolution in the longitudinal network by centering itself around two key topologies: (i) the static topology which applies traditional SNT analysis' methods over an *aggregated* network encompassing all observational time periods, and (ii) the dynamic topology which applies longitudinal analysis techniques over each observational time period referred to as *short-interval* network (Braha and Bar-Yam, 2006; Uddin et al., 2013; Shijaku et al., 2014). Although there are several indicators used to measure actor's centrality in a network, in this study, we focus exclusively on degree, betweenness and closeness measures whose analysis has been crucial in modeling actors' social influence and interaction (Freeman, 1979; Friedkin, 1991; Newman, 2005). While Bonachich centrality used in the current aspiration-network literature is very effective, we consider the more traditional degree centrality measure since all our network variables are derived from interrelated graph theory concepts therefore making result interpretations easier. Additionally, since our study is based on centrality measures that study firm embeddedness in a given network, we refer to actor's dynamicity as 'dynamic embeddedness'.

In order to operationalize *dynamic embeddedness*, we model each year over the sample period as a separate network, formally characterized as a symmetric (i.e. square matrix that is equal to its transpose so that the main diagonal of the sociomatrix always contains zeroes in order to avoid firm self-reference ties) N x N 'weight' matrix, whose generic entry $wij = wji > 0$ measures the interaction intensity between any two actors (zero if no link exists between actor i and j). This means that ties between actors are valued according to the actual number of strategic transaction formations, a procedure seen in the network literature (De Montis et al., 2008). Following this framework and using software R that enables us to handle very large vectors, we build 22 symmetric 4,735 x 4,735 matrices to capture dynamic embeddedness of the firms for the given period. To minimize bias, we decide to include all alliances that firms make with each-other throughout the study period. The obtained longitudinal sample has a dynamic nature since some firms are active (i.e. forming strategic transactions) in a given network at a given time and others are not. Once our sample is defined, we proceed to build social networks for all participating firms. Dynamic embeddedness represents the variability of the structural positions (i.e. dynamicity) of an actor in all short-interval networks compared to its structural position in the aggregated network. The mathematical expression for this measure originally proposed by Uddin et al., (2013) and later modified and adapted by Shijaku et al., (2016) is given by the following equation 1:

$$DDA^i = \frac{\sum_{t}^{m} \alpha_{t,t-1} \times \left| OV_{AN} - OV_t \right|}{m} \qquad (1)$$

where DDA^i is the degree of dynamicity (i.e. dynamic embeddedness) shown by i^{th} actor, OV_{AN} is the observed variable (i.e. degree, betweenness, closeness centrality) for the aggregated network, OV_t is the observed variable (i.e. degree, betweenness, closeness centrality) for t^{th} yearly network for the i^{th} actor, m is the number of yearly networks considered in the analysis, and $\alpha_{t,t-1}$ is a constant valued according to whether the actor is present or missing in the current and previous short-interval network. The presence of this constant is of crucial importance to properly count for actors that disappear from the network due to simple inactivity or possible lack of presence due to acquisition effects. The possible combination values that $\alpha_{t,t-1}$ can take are given in Table 3.1.

Table 3.1 Possible combination of presence and absence of an actor in two consecutive short-interval networks

Current t	Previous t	Constant α
Present	Present	$\alpha_{p,p}$= 1.0
Present	Absent	$\alpha_{p,a}$= 0.5
Absent	Present	$\alpha_{a,p}$= 0.0
Absent	Absent	$\alpha_{a,a}$= 0.0

Note. Table contents are taken and modified from Shijaku et al. (2016).

For the first short-interval (yearly) network (i.e. $\alpha_{i,0}$ for t = 0), the value of the constant will depend on the presence or absence of each actor (i.e. either 0 or 1) at the particular period, a detail that marks a departure from the original model proposed by Uddin et al., (2013). Separately, we operationalize the observed variables that will be inputted to equation (1) namely degree, betweenness cand closeness centrality. *Degree centrality* formally represents the simplest centrality measure and determines the number of ties for each actor, i.e. the number of actors that the focal actor is connected to, and modified to take into account the sum of weights in each tie (Barrat et al., 2004; Opsahl et al., 2008; Shijaku et al., 2014). *Betweenness centrality* formally represents the number of shortest paths between any two actors which pass through a specific actor (Freeman, 1980), modified to take into account the fact that in weighted networks, the actors with the highest actor strength are more likely to be connected in networks from a range of different domains (Opsahl et al., 2008; Shijaku et al., 2016). *Closeness centrality* formally represents the inverse total length of the paths from an actor to all other actors in the network, and is based on the idea that actors with a short distance (i.e. path) to other actors can spread information very productively through the network (Landherr et al., 2010). This measure is also modified to suit weighted network structure. We note that, all weighted centrality measures in our analysis have been normalized and are calculated using *tnet* package available in R software.

Control variables - In addition to our independent variables, we control for several factors that could potentially impact strategic transaction formation. Specifically, in order to gauge on the mechanism of attractiveness through which the effect of relative performance and network embeddedness influences strategic alliance formation, we control for *Tobin's Q* measured according to Chung and Pruitt (1994) with the following formula: $Q = (MVE + PS + DEBT) / TA$ where MVE is the product of firm's share price and the number of common stock shares outstanding, PS is the firm's outstanding preferred stock, DEBT is the value of both short and long-term debt, and TA is the book value of total assets. Specifically, by analyzing Tobin's Q index, we can determine if the company is undervalued or overvalued at a specific point in time, which affects the perception of firm's attractiveness by other industry players. An undervalued firm would signal potential problems that could affect negatively firm's ability to initiate strategic alliances with its network partners. Instead, an overvalued firm would signal high profitability and lure in firms via alliance formations.

Moreover, we control for several forms of *slack* since according to behavioural theory of the firm, slack (i.e. resources) is highly dependent on whether firm's performance is above or below its aspirations' level. If the firm is performing above aspirations, it will have more slack at disposal while if performance is below aspirations, slack may be lacking as a result of the firm using resources to improve its performance (O'Brien and David, 2014). Specifically, we control for *unabsorbed slack* measured as cash and marketable securities divided by current liabilities, *absorbed slack* measured as the ratio of selling and administrative expenses to sales, and *potential slack* measured as the ratio of total long-term debt to total assets (Bromiley, 1991; Greve, 2003; O'Brien and David, 2014). We also control for the *age* of the firms, operationalized as the foundation year minus the year considered in the 1991-2012 panel analysis, since as firm performance declines with age (Loderer and Waechli, 2009), chances are this will affect the performance-based organizational aspirations. Finally, we control for *size*, operationalized as the natural logarithm of firm's employees as a common proxy used in empirical regression models. This variable has been observed of having an important impact in aspiration models with respect to positional rigidity (Greve, 2001).

3.3.3 Model

As our dependent variable is a nonnegative integer, we apply a negative binomial regression model for our analysis. This choice is motivated by the fact that our data presents overdispersion; therefore an ordinary least regression (OLS) would not be appropriate in this case. However, this form of analysis presents several methodological considerations of a critical nature. First, as the data presents overdispersion either Poission or negative binomial models can be applied. However, since variance and mean of all the dependent variables substantially differ, we choose negative binomial for our regression analysis. This choice is further validated by comparing Poisson and negative binomial models similar to Tylet et al., (2015) implemented via the user written *countfit* function in Stata which plots the residuals from regression models against count outcomes where negative binomial is the model with the smallest residuals. Second, in order to avoid the multicollinearity issue in these regression models and specifically between the two-way interaction items, we mean center all the interaction variables and apply multicollinearity diagnosis based on a calculation of the Variance Inflation Factor (VIF) of each interacted variable which in our case gives a maximum value of 1.57, being well below the critical value of 4.0 observed by Hair et al., (1998). Third, since we do not use OLS which would validate the VIF values, we test again for multicollinearity by implementing *coldiag* Stata test on our dependent variables based on the regression collinearity diagnostic procedures found in Belsley et al., (1980) that gives a value of 9.7 for alliances, well below the 30.00 limit. Fourth, similar to O'Brien and David (2014), we lag all independent variables by one year to correct for serial correlation, and infer causality according Tyler et al., (2015). Fifth, approximately 20 percent of the dependent variable presents zeros; therefore we also examine zero-inflated negative binomial models that count for this problem as well as for overdispersion with similar results to those reported. Sixth, the slack variables contain some outliers, so we follow O'Brien and David (2014) method and winsorize their distributions at the top and bottom of 0.5^{th} percentiles. Additionally, due to the nonlinearity of our model, we include the marginal effects in our results.

3.4 Results

Descriptive statistics and Pearson correlations among the variables used in the negative binomial regression models are provided in Table 3.2 while regression results are given in Table 3.3. The number of observations varies across variables due to missing items in longitudinal data. The correlation table shows that centrality measures are significantly correlated between themselves and the dependent variables which might be a sign of multicollinearity already taken into account in the model part of our study. The significant correlation that PbAL and PaAL have with alliances is an indicator that firms reduce their strategic alliances when performance falls short or exceeds organizational aspirations. Additionally, the high mean of *age* variable is an indicator that the top 90 pharmaceutical firms are quite old. Elsewhere, *size*, *Tobin's Q*[1], and various control slacks introduced into our model are meaningful as significant correlations are observed.

[1] R&D expenditure is the instrumental variable (correlated with Tobin's Q but not with alliances). Given the results, we may cautiosuly say that attractiveness (as approached by Tobin's Q) is not fundamental for allinance formation, and that firm willingness may be a stronger driving force for interorganizational collaborations.

Table 3.2 Means, standard deviations and correlations

Variable	Obs.	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1. Alliances	1604	7.889	10.30	1											
2. PbAL	1512	-0.0717	0.180	0.0752*	1										
3. PaAL	1738	0.0665	0.351	-0.0640*	0.0826*	1									
4. Degree dynamicity	1764	0.0594	0.0711	0.8162*	0.0105	-0.0558*	1								
5. Betweenness dynamicity	1764	0.111	0.290	0.7258*	0.0416	-0.0235	0.8158*	1							
6. Closeness dynamicity	1764	0.0121	0.00932	0.4026*	-0.0203	-0.0896*	0.5335*	0.3625*	1						
7. Age	1364	77.53	66.52	0.1122*	0.1612*	-0.00610	0.1018*	0.1307*	-0.1001*	1					
8. Tobin's Q	852	0.482	0.619	0.1328*	0.0237	0.000200	0.0867*	0.1326*	0.1192*	-0.2993*	1				
9. Size	1313	9.048	1.785	0.4642*	0.2843*	0.0549*	0.5071*	0.3668*	0.2255*	0.3856*	-0.2110*	1			
10. Absorbed slack	1133	0.461	0.869	-0.0230	-0.1597*	-0.0457	-0.00940	-0.000300	-0.0849*	0.0938*	-0.0201	-0.1827*	1		
11. Unabsorbed slack	1103	1.393	2.594	-0.1101*	-0.1710*	0.0678*	-0.0878*	-0.0852*	0.00930	-0.2271*	0.2010*	-0.4428*	0.1686*	1	
12. Potential slack	1132	0.209	0.538	-0.1088*	-0.00450	0.1103*	-0.1046*	-0.0655*	-0.1062*	-0.0375	-0.0416	-0.1226*	0.1684*	-0.0787*	1

Note. Coefficients are reported at + $p < .1$ * $p < .05$ ** $p < .01$ *** $p < .001$

Table 3.3 Determinants and their marginal effects on strategic alliances

	Alliances									
Model	1	ME	2	ME	3	ME	4	ME	5	ME
PbAL	0.372**	5.068**	-0.318*	3.127*	-0.339**	-3.141**	0.310**	3.131**	0.408**	4.181**
PaAL	-0.354**	-4.81**	0.362**	3.559**	0.299**	2.774**	-0.290*	-2.930**	-0.295*	-3.027*
Degree dynamicity	-14.35***	-195.51***	-4.554**	-44.771**	-4.568**	-42.323**	-4.538**	-45.902**	-4.839**	-49.575**
Betweenness dynamicity	6.001***	81.74**	0.856*	8.418*	0.834*	7.722*	0.869*	8.792*	0.895**	9.164**
Closeness dynamicity	6.850*	93.31**	8.878*	87.283*	9.106*	84.365*	8.844*	89.453*	9.258*	94.847*
Age	-0.00498**	-0.068***	-0.00554**	-0.054**	-0.00523**	-0.048*	-0.005***	-0.060**	-0.001	-0.019
Size	-0.0760+	-1.035+	-0.00314	-0.030	0.00550	0.050	-0.008	-0.087	0.095	0.975
Absorbed slack	-0.0789	-1.074	-0.0643	-0.631	-0.0757	-0.701	-0.048	-0.491	-0.0645	-0.661
Unabsorbed slack	-0.0265+	-0.360+	-0.0183	-0.180	-0.0131	-0.121	-0.017	-0.171	-0.0184	-0.188
Potential slack	-0.320**	-4.352**	-0.296**	-2.908**	-0.263**	-2.432	-0.267**	-0.270	-0.441***	-4.522**
Degree dynamicity x PbAL			2.650	26.055			4.346	43.964	3.536	36.223
Betweenness dynamicity x PbAL			0.605	5.944			-5.821*	-58.878*	-5.512+	-56.466+
Closeness dynamicity x PbAL			-47.16***	-463.581***			-0.020	-0.203	-0.307	-3.141
Degree dynamicity x PaAL					-4.888+	-45.283+	1.222	12.356	1.186	12.146
Betweenness dynamicity x PaAL					1.258+	11.654+	-50.76***	-513.456***	-48.01**	-491.875**
Closeness dynamicity x PaAL					19.01+	176.087	26.37*	266.774	20.38+	208.793
Tobin's Q									0.186	1.905
Wald Chi2	129.45		68.67		59.72		82.20		82.20	
N	781		781		781		774		774	

Note. Coefficients are reported at + $p < .1$ * $p < .05$ ** $p < .01$ *** $p < .001$

Model 1 of Table 3.3 contains the base regression model with only the control variables (without Tobin's Q) and the main effects for all three types of strategic transactions. Looking at the main effects, it is observed that alliance transaction formation significantly increases as does PbAL, that is when aspiration levels are approached ($b = 0.37$, $p < 0.01$) while decreases for PaAL ($b = -0.35$, $p < 0.01$) confirming both H1a and H1b. Throughout all the models, we observe a direct effect of dynamic embeddedness measures on alliance formation. However, while the positive main effect suggested by H2 finds support for both betweenness ($b = 6.00$, $p < 0.01$, model 1) and closeness dynamicity ($b = 6.85$, $p < 0.05$, model 1), this is not the case for degree dynamicity, whose effect on alliance formation is negative and strongly significant ($b = -14.35$, $p < 0.001$, model 1).

Model 2 incorporates the two-way interactions between dynamic embeddedness indicators and performance below aspirations. This moderation posited by H3a is statistically significant in the case of closeness dynamicity and PbAL for alliances ($b = -47.16$, $p < 0.001$), and confirmed for the marginal effects as well ($b = -463.59$, $p < 0.001$). Additionally, model 3 incorporating the two-way interactions between centrality-based dynamic embeddedness and performance above aspirations shows significanct results in support of H3b for degree dynamicity ($b = -4.88$, $p < 0.1$), betweenness dynamicity ($b = 1.25$, $p < 0.1$) and closeness dynamicity ($b = 19.01$, $p < 0.1$). Finally, model 4 includes all variables of interest showing strong results in terms of interaction with PbAL and PaAL for the model and the predicted marginal effects.

In model 5, we introduce Tobin's Q as a control variable that measures firm's attractiveness as perceived by the network partners of the industry. By explicitly including the effect of attractiveness (through Tobin's Q) the estimated coefficient of aspiration performance will be focused on firm´s willingness to engage in strategic alliances. Specifically, we model Tobin's Q as an endogenous variable affecting strategic alliance formation. The coefficient of this variable is the residual of a two stage least square regression analysis, and as observed, its inclusion does not affect the overall results presented in the previous models with respect to our hypotheses support.

Figure 3.1 Non-linear effects of betweenness dynamicity on the relationship between aspirations and strategic alliance formation

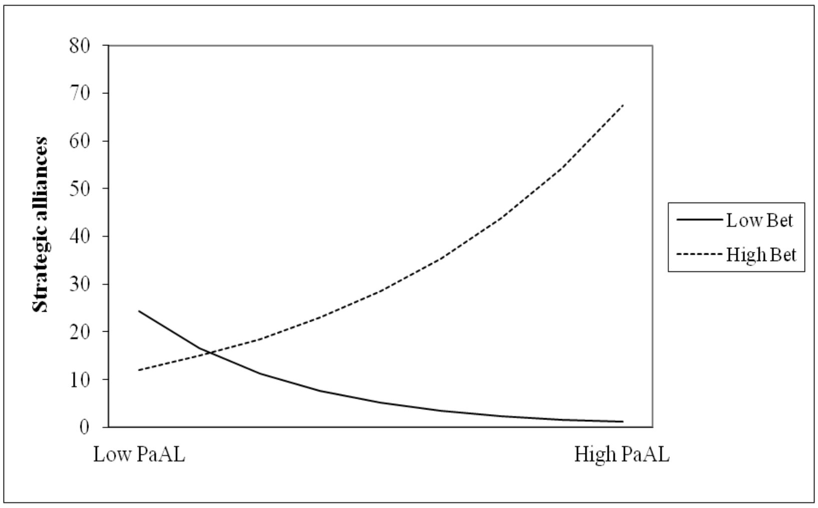


Figure 3.1, shows the two-way interactions, for the negative binomial regression only for betweenness dynamicity which is a log link function plotted from the mean minus one standard deviations to the mean plus one standard deviations. We opt to plot the interactions for this specific variable due to its significant effect in the aspiration – alliance formation relationship across models 3-5. Specifically, Figure 3.1 plot is based on the regression model 3 of Table 4.4 and illustrates the estimated change distances when PaAL and betweenness dynamicity are one standard deviation above or below their means. In particular, it can be observed that for highly dynamically embedded firms via indirect ties as is the case of betweennes indicator, strategic transaction formation increases for positive aspiration performance. The plot seems to suggest that overall alliance activity increases with greater betweenes, but in the extreme, when performance is well below aspirations, alliance activity is stronger for firms with low dynamic embeddedness.

3.5 Robustness tests

In order to validate our results we conducted several robustness tests. Above all, we added a quadratic term to each indicator of dynamic embeddedness in the main effect regression models. Prior studies have suggested a curvilinear relationship between centrality measures and new strategic alliances, pointing out that too many connections information will not necessarily be helpful and might, in fact, be dysfunctional, given that any organization's information and knowledge processing capacity is limited (Ahuja, 2000a; Simsek, 2009; Paruchuri, 2010). The new regression results remain supportive of our hypotheses but do show a weak u-shaped relationship between all dynamic embeddedness measures and new alliance formations. Finally, we ran negative binomial regressions with each dynamic embeddedness indicator separately with similar results to the ones shown in Table 3.4.

3.6 Discussion and conclusions

This study is motivated by a limited research in understanding performance-based aspiration mechanisms of firm strategic behavior in a dynamic network context. We propose an integrated framework bridging such theories as performance feedback, and social networks to test our hypotheses in a database containing information about the biggest firms in the global pharmaceutical industry. Our results show that organizational behavior in the form of strategic transaction formation is more visible the closer the distance between firm performance and its aspirations' level, but less visible the further firm performance departs from its aspirations both above and below, these results being in line with current literature on the topic (Greve, 1998, 2011; Baum et al., 2005; Di Lorenzo et al., 2011; Kim and Rhee, 2014). In this sense, both the 'beauty' and the 'beast' firms seem to encounter a similar pattern of rigidity behavior and reduced network dynamism. However, this similar behavior of firms with radically different performance may be due to different reasons: while the 'beauty' may have access to partners to establish strategic alliances, its preferences avoid new potential linkages, which is consistent with previous research that has found firms are unable to benefit from lower-quality competitors (e.g., Kalnins and Chung, 2004). On the contrary, the 'beast', may have a clear preference towards strategic transaction formation, but will have difficulty finding partners. In other words, behavior based on performance feedback model is countered by both rigidity and firm attractiveness as perceived by its industry peers. For performance below aspirations, the firm reduces its strategic transactions due to a survival threat suppressing exploration possibilities akin to threat rigidity theory (Staw et al., 1981; Rhee and Kim, 2015) but also due to its dynamic network status in form of low attractiveness as perceived by the collaborating partners (Ahuja, 2000a). For performance above aspirations, transactions' reduction is a result of firm's highly praised network status and consequential increased attractiveness as well as a positional rigidity behavior that results from organizational exploitation strategies promoting a 'status quo' (Ahuja, 2000a; Greve, 2002; 2007; 2010).

The positive effect of dynamic embeddedness on alliance formation is confirmed for both betweenness and closeness dynamicity. This result echoes similar findings (Gulati, 1995, 1999) but is more significant in the light of the network evolution captured by the dynamicity measures. However, the consistent negative effect of direct ties (i.e. degree dynamicity) on alliance formation is surprising. We believe, that in a network evolution context, too many direct connections in the long run will be detrimental to the desire of the firm to engage in new partnerships probably due to the inability of the firm to efficiently process simulatenous alliances as observed by the literature (Chung et al., 2000; Simsek, 2009).

Additionally, we confirm that dynamically embedded firms moderate the relationship between strategic transaction formation and performance related aspirations. In fact, we observe that alliance formation increases for highly embedded firms performing below as well as above their aspirations which is in line with previous research on network embeddedness (Baum and Dahlin, 2007; Rhee and Kim, 2015). We also observe that different dynamic centrality measures affect differently new alliance formations. The categorization of dynamic centrality measures into degree, betweenness and closeness indicators, and their separate effect on alliance collaborations reinforces our belief that, while these measures are highly correlated, each one can be treated separately as enhancer of the structural view in the actor-oriented perspective of dynamic networks. Their idiosyncratic role is further reinforced in the models introduced with interaction terms. In this regard, we find that degree dynamic embeddedness has a significant moderating role in the increase of both alliance and financing collaborations when performance falls below aspirations' level. This result makes sense, if we consider that a greatly underperforming firm would make efforts to increase its strategic ties seeking solutions to its performance-related problems, and alter its network structure towards a more central positioning, a logical behavior of sorts in the global pharmaceutical industry where firms are engaged in an ever competitive environment. More importantly, our results confirm similar research into the important effect of structural embeddedness in performance-based aspirations (Baum et al., 2005; Shipilov et al., 2011; Kim and Rhee, 2014).

Our results also seem to suggest that differences may exist between different measures of dynamic embeddedness. In fact, while closeness dynamicity has a significant effect throughout the models, degree and betweenness indicators do not, emphasizing that actor proximity (i.e. closeness) plays a far greater role in the aspiration-transaction relationship than direct or indirect ties (i.e. degree and betweenness). This may well be a consequence of the data itself, where firm's proximity to other partners captured by closeness matters most, and the fact that since closeness dynamicity takes into account the distance of the focal firm from the network members, its effect on aspiration – transaction formation is more prominent.

Having said this, it is important to note that our analyses are not free of limitations. First, the dynamicity measure that captures dynamic embeddness should be further researched with respect to the introduced constant that counts for missing actors in any yearly network. Second, the extrapolation of this study's results to other industries should be carefully motivated as the pharmaceutical industry evolution has historically depended on interorganizational collaborations which might be sparse and of different strategic nature in other industries. Third, other centrality measures such as Eigenvector or Bonachich Power could provide new insights into the firm's dynamic status effect on the aspiration-strategic transaction relationship. Fourth, additional analysis on proxies that identify organizational rigidity is needed to shed light on the risk-taking behavior of firms engaged in strategic transactions, and explain organizational behavior when firm performance is increasingly above or below aspirations. Finally, the inclusion of other complex network analysis could prove useful in further reducing the gap between social network and aspiration-based theories.

Nevertheless, this study hopes to contribute to the literature in several ways. First, from both performance feedback and threat rigidity perspective, we contribute to the strategic decision making behavioral theory (Cyert and March, 1963; Greve, 1998; 2003; O'Brien and David, 2014) by analyzing the factors that influence organizational strategic transaction formation under the lens of performance-based aspiration models. Specifically, we argue that performance below or above aspirations' level significantly affect alliance transactions of the top global pharmaceutical firms. Our results show that performance-based aspirations affect strategic alliance formation. Second, this study contributes to the SNT literature by positing that under the moderation of dynamic embeddedness (i.e. degree, betweenness and closeness dynamicity), the relationship between aspiration performance and strategic alliance formation is significantly altered. In particular, we show that dynamically central firms increase their alliances when their performance falls far below and rises above organizational aspiration levels.

Our study is thus an attempt to integrate elements from both SNT and aspiration performance models by providing a 'dynamic' nexus that we hope bridges these concepts and lays foundations for future research. Specifically, new dynamic measures could be proposed that help the academia understand the nature of organizational behavior in the network level, providing new insights on network consequences and aspiration antecedents as well as the exploitation of other behavioral concepts (e.g. organizational attention) and their potential role in the aspirations of a dynamically embedded firm. Additionally, the deconstruction of the aspiration measure into its original social and historical constituents, and their consideration in the model analysis could be beneficial in understanding the relationship of each factor with dynamic embeddedness and strategic transaction formation.

In addition to our theoretical contributions, our results could potentially provide practical implications as well as answering to the framing of successful strategic processes. In this respect, recognizing the crucial effect of dynamic embeddedness could have important consequences to the aspiration performance. In this vein, managers could focus their attention on tracking the network in which their firm is dynamically embedded by analyzing the aspiration performance consequences of organizational processes and practices that involve strategic alliance formation. Such analysis could potentially yield insights on the crafting of strategic activities that focus on collaborative networks, and avoid threat rigidity behavior that despite its survivalist intentions could isolate the firm in the long run.

4. Explore or Exploit? Ambidextrous Strategic Alliances and Organizational Aspirations in Dynamic Networks

4.1 Introduction

In July 2000, Allergan, one of the world's leading pharmaceutical firms announced the formation of a series of strategic global alliances with Vistakon, Allegiance and Visx to include research, marketing, and co-detailing initiatives. This was a year that marked a jump in Allergan's performance after the relative stagnation of 1999 when the firm barely met its financial objectives, and an indicator of the firm's strategy to engage in ambidextrous value chain alliances that included both technological and marketing actitivites. Allergan maintained its trend of entering ambidextrous alliances with its partners from 2000 to 2003, annually exceeding its performance-based aspirations.

Organizational ambidexterity research has long received important contributions seeking to reconcile the diametrically opposite concepts of exploration and exploitation by highlighting their shifting salience in contexts such as organizational learning, organizational adaptation and technological innovation (March, 1991; Colbert, 2004; Meyer and Stansaker, 2006; Raisch and Birkinshaw, 2008). In this respect, ambidexterity has been defined as the organization's ability to exploit current capabilities while simultaneously exploring new competencies (March, 1991; Raisch et al., 2009). The concept of ambidexterity has been successfully applied to interorganizational collaborations, and specifically to alliance formations which is the focus of our study. In this context, alliance ambidexterity has been defined as a strategy pursuit of both co-exploration and co-exploitation, with extant research on the topic analyzing the specific dimensions such as structural (ie. partner selection) and functional (ie. value chain) activities in alliance networks (Lin et al., 2007; Tiwana, 2008; Nielsen and Gudergan, 2012). The ambidexterity constituents have been thoroughly researched, with exploration referred to as the development of novel capabilities, and exploitation regarded as the efficient employment of current assets and capabilities (Gilsing and Noteboom, 2006).

The previous Allergan example suggests a relationship between organizational ambidexterity and firm's financial performance in a context of interorganizational collaborations. This fact has been empirically validated with research findings converging to a positive effect of ambidexterity on firm performance (Rothaermel and Alexandre, 2009) and others pointing to negative effects (Lin et al., 2007; Lavie et al., 2011). In a network context, firms are embedded in continuous relationships which SNT has embraced from a theoretical perspective that explores strategy questions (Afuah, 2012). Studying how network affects its embedded firms has been vital in viewing interfirm relationships as resources in themselves. Specifically, through path-dependent processes, firms create their own network embeddedness which in turn influences the firm's aspirations, and affects its ambidextrous behavior (Simsek, 2009; Shipilov et al., 2011; Kim and Rhee, 2014).

Given that aspiration performance, network embeddedness and alliance ambidexterity show some level of theoretical interdependence, it is surprising that attempts to bridge these concepts under an integrated theoretical and empirical framework have been under-explored. From the performance – ambidexterity relationship perspective, little attention has been given to the firm's performance as an antecedent rather than an outcome of organizational ambidexterity. Those that support this under-explored view, use the Behavior Theory of the Firm that serves as the theoretical presentation of organizational aspirations, an argument seeking to explain firm behavior under satisfactory performance levels defined as goals or aspirations (March, 1991; Bromiley and Harris, 2014). More specifically, recent studies have attempted to link organizational ambidextrous behavior and performance-based aspirations, with results showing that an organization is likely to initiate 'problemistic search' via exploration when performing below its aspiration level, and likely to 'slack search' via exploitation when performing above aspirations (Greve, 2007; Rhee and Kim, 2015).

From a network perspective, firm centrality has been successfully linked to aspiration performance by showing that highly embedded (i.e. central) firms set their aspirations differently from the more peripheral actors of a network (Baum et al., 2005). Additionally, firm embeddedness has been linked to structural ambidexterity with both positive (Mura et al., 2014) and negative results (Tiwana, 2008; Lin et al., 2007). Having said this, extant embeddedness models linked to alliance ambidexterity present several problems. First, they do not consider the dynamic positioning of the actors throughout the network evolution, which is why we introduce the concept of 'dynamic embeddedness' defined as the individual actor's structural positions' variability in a longitudinal network compared to its structural position in an aggregated network (Uddin et al., 2013, Shijaku et al., 2016). Second, extant embeddedness models are confined to a structural ambidexterity relationship, disregarding the functional dimension effect that the alliance type brings to firm's strategic behavior in its network.

From an ambidexterity perspective, as extant literature focuses on either structural or functional dimensions (Lin et al., 2007; Hoang and Rothaermel, 2010), the theoretical consideration of aspiration performance and its effect on these domains warrants a multidimensional analysis of alliance ambidexterity (Lavie and Rosenkopf, 2006). Will performance above or below aspirations lead to increased or decreased alliance ambidexterity? What is the effect of organizational aspiration on structural and functional dimensions of alliance ambidexterity? There are several theoretical challenges that provide conflicting reasoning to the answer of these questions. First, resource-specific features constraint firm behavior in pursuing ambidexterity. In this respect, performance below aspirations is a logical trigger for riskier, more explorative interorganizational collaborations that seek to overturn underperforming strategies (Greve, 2007). On the other hand, continuous financial underachievement can also trigger a rigidity behavior of the firm, where explorative endeavors are undermined in favor of less risky exploitative ones (Iyer and Miller, 2008; Greve, 2010). Performance above aspirations is another complicated issue due to the strategic ambiguities faced by the firm including: (i) the exploitation of the successful strategy that resulted in glowing overachievement or (ii) the exploration of new opportunities as a result of extra available resources (i.e. slack) made available from success (Rhee and Kim, 2015). Second, concepts such as partner selection and possibility to engage in interfirm collaborations should be taken into consideration when analyzing the organization’s choice to engage in ambidextrous behavior (Ahuja, 2000a; Baum et al., 2005; Li et al., 2008).

To address these issues, we analyze the relationship between performance-based organizational aspirations and alliance ambidexterity in both structural and functional dimensions of organization activity. Additionally, we propose a moderating effect of dynamic embeddeness on the organizational aspirations’ effect for alliance ambidexterity. Studying the strategic alliance formations of the global pharmaceutical industry during 1991-2012, we observe that as performance departs firm’s aspirations, alliance ambidexterity is enhanced both within and across structural and functional dimensions. Additionally, we show the prominent effect of dynamic embeddedness in the aspiration – ambidexterity relationship.

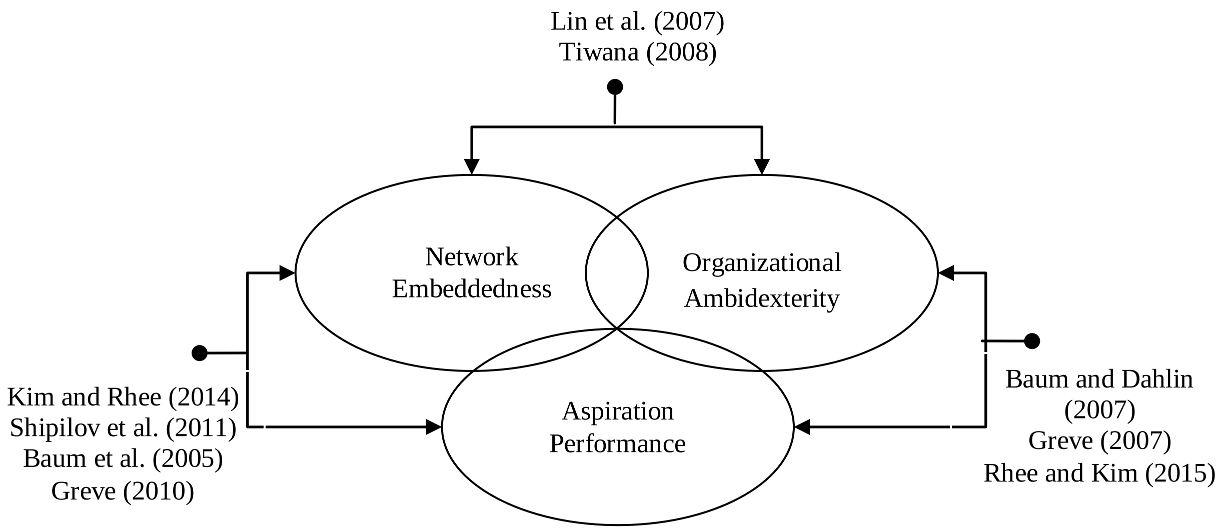
We contribute to the current literature by integrating theoretical concepts from separate disciplines such as SNT and BTF and combining them into a multidimensional theoretical setting coupled with a unique empirical analysis that encompasses the global pharmaceutical industry evolution. We hope this study will serve as an additional layer to the extant theory on organizational behavior by showing the antecedent effect of aspiration performance on organizational ambidexterity in new strategic alliances and emphasizing the prominence of dynamic embeddedness that reflects the firm's evolutionary positioning in a strategic network of choice.

4.2 Theoretical development and hypotheses

4.2.1 Literature perspectives

Management literature commonly applies the concepts of alliance ambidexterity, organizational aspirations and network embeddedness, albeit separately, to denote a relationship between firm's strategic choices and the social context where the firm is embedded. However, few studies have tried to bridge these interdisciplinary dimensions of organizational strategic behavior (see Figure 4.1 for an illustration). A review of the extant research shows an established link between SNT studies and aspiration performance providing strong proof of the relationship between firm's status (i.e. embeddedness) and aspiration performance (Greve, 2010; Shipilov et al., 2011; Kim and Rhee, 2014). Some studies have provided insights into how aspiration performance affects firm's strategic aptitude to explore or exploit effectively balancing these strategic activities in an ambidextrous behavioral perspective (Baum and Dahlin, 2007; Greve, 2007; Rhee and Kim, 2015). However, currently there is little research on the effects of network structure on alliance ambidexterity except for the contribution from Lin et al., (2007) linking network measures such as centrality and structural hole to alliance ambidextrous behavior. More importantly, no research to date attempts to link all three theoretical concepts (i.e. alliance ambidexterity, network embeddedness, organizational aspirations) under a joined theoretical framework whereby we think an overarching gap is visible. In the following paragraphs, we attempt to connect these theoretical constructs and shed light on what we believe are overlapping themes.

Figure 4.1 Theoretical foundations



4.2.2 Balancing alliance exploration and exploitation

A synchronous pursuit of both exploration and exploitation via loosely coupled and differentiated subunits specialized in each of these activities is the classic definition of organizational ambidexterity, widely viewed as a key determinant to firm's survival and sustained competitive advantage (Gibson and Birkinshaw, 2004; Gupta et al., 2006; Sun and Lo, 2014). Exploration is defined as an activity that involves competences in new knowledge development, generalized search and flexible experimentation via the use of unfamiliar technologies and the creation of products whereas exploitation refines existing knowledge, technology and products via localized search and improved efficiency (Greve, 2007; Su and Lo, 2014; Rhee and Kim, 2015).

Having said this, the ambidexterity quest is quite a difficult strategic approach to pursue, due to the fundamental differences that categorize the concepts of exploration and exploitation. Simply put, any organization will struggle to efficiently engage simultaneously in both exploration and exploitation as these strategic and resource-consuming activities are diametrically opposed. In fact, the more immediate economic returns from exploitative activities tend to cause a myopic bias to organizational behavior whereby exploitation is overemphasized at the expense of exploration and firm succumbs to its illustrious success (Fang et al., 2010). Thus, it is important to define the context where exploration and exploitation are most apt to trigger and flourish. Such a mode is undoubtedly the context of interfirm collaborations with alliances spearheading the competition of other lesser researched types.

Interorganizational alliances, viewed as a relatively inimitable and non-substitutable resource, enable the partnering organizations to share knowledge in order to jointly provide technologies, products or services (Gulati, 1998; Andersson et al., 2002; Lavie et al., 2011). In this realm, partner characteristics have a strong impact on whether and how well knowledge absorption and conversion into learning is conveyed from one firm to another (Sampson, 2007). This process is further enhanced as firms rely on past interactions when forming new collaborations, with partner selection seen as one of the most important decisions in alliance formation (Elmuti and Kathawala, 2001; Li et al., 2008; Garcez and Sbragia, 2013). A key theme in partner selection concerns the selection criteria with reciprocity, experience and prior performance being the most suggested factors (Li and Rowley, 2002; Yu and Sharma, 2016). Additionally, intra-industry heterogeneity across partners could pose different levels of selection criterias to the extent that different partners have different incentives as well as abilities to absorb the knowledge gained from a strategic alliance (Diestre and Rajagopalan, 2012).

In doing so, firms engage in a sort of ambidextrous behavior with the continuous juxtaposition of exploration and exploitation (O'Reilly and Tushman, 2004; Greve, 2007). In this regard, extant research has devoted ample space to the concepts of exploration and exploitation with the majority of studies emphasizing the continuous effort of organizations to achieve a satisfactory balance between the two (March, 1991; Benner and Tushman, 2003; Raisch and Birkinshaw, 2008).

In a network context, alliance ambidexterity, defined as the alliance's ability to simultaneously pursue high levels of co-exploration and co-exploitation (Lin et al., 2007), is prominent in both structure dimension (via partner selection) and function dimension (via alliance type selection) (Koza and Lewin, 1998; Lavie and Rosenkopf, 2006; Tiwana, 2008). From a structural perspective, this process entails the firm's strategic focus on discovering knowledge opportunities from new partners via explorative alliances, and a commitment to leverage existing strategic processes already established through repeated collaborations with the same partner via exploitative alliances that improve coordination between the collaborating firms (Lin et al., 2007; Holloway and Parmigiani, 2016). From a functional perspective, the type of alliances affects alliance formations, with explorative technology alliances engaged in upstream activities, and exploitative marketing and production alliances focused on downstream activities (Lavie and Rosenkopf, 2006; Simsek, 2009).

Given that majority of the literature is well acquainted with the structural and functional dimensions of ambidexterity albeit separately, recent studies have attempted to bridge these distinct activities due to their empirical relationship. For example, Lavie and Rosenkopf (2006) find that, as firms shift from hybrid alliances (i.e. a combination of technology and marketing alliances) to production or marketing ones (i.e. downstream alliances), they tend to experiment with new partners potentially widening their resource and knowledge capabilities. Additionally, Lavie et al., (2011) analyze alliance formations in software firms as determinants of firm performance and find a tendency of firms to explore or exploit within structural and functional domains.

Throughout this literature a unidirectional link from alliance ambidexterity to firm's financial performance has been consistent (Cao et al., 2009; Nielsen and Gudergan, 2012). This relationship direction is based on a straightforward understanding that an ambidextrous approach is highly beneficial to firm's performance (Uotila et al., 2009) and more importantly, that firm's performance is an actual effect of the balancing of co-exploration and co-exploitation (Stettner and Lavie, 2014). However, some researchers have found a contingent effect of organizational ambidexterity on firm performance (Lin et al., 2007) while others point to a negative link between the two (Atuahene-Gima, 2005). Given these contradictory findings, we focus on the reverse performance – ambidexterity relationship in an attempt to understand organizational behavior in strategic alliance networks.

4.2.3 Antecedents of alliance ambidexterity

4.2.3.1 The effect of organizational aspirations

Following March's (1991) seminal article, organizational learning rose as an anchor holding together the fragile balance of exploitation and exploitation by attempting to explain these organizational processes as a result of performance improvement (Baum and Dahlin, 2007). Given the learning continuum gained by past performance as suggested by BTF (Cyert and March, 1963), more recently, researchers are turning their attention on the path dependency of organizational evolution which regards firm's past experience as crucial to organizational behavior (Greve, 2007; Rhee and Kim, 2015).

Therefore, a new theoretical approach stemmed from organizational learning has been suggested, seeking to explain firm's past financial performance, through the concept of organizational aspirations, as a determinant of alliance ambidextrous behavior. In this sense, firm's aspirations are defined by a desired performance level triggered via both firm's past performance (i.e. historical aspiration) and its industry's peer current performance (i.e. social aspiration) (Baum et al., 2005; Greve, 2010; Shipilov et al., 2011; Kim and Rhee, 2014).

Supporting the aspiration-ambidexterity relationship, Greve (2007) shows that aspiration performance has different consequences for the ambidexterity constituents of exploration and exploitation. In fact, performance far below aspirations appears to trigger an exploration response of the firm due to the strategic decision to focus on a problem-solving perspective (Baum et al., 2005). However, as firm performance continues to fall past its aspirations, the firm might enter a rigidity behavior which could trigger an exploitation strategy for the firm. In this underperforming scenario, the probability of the firm behaving rigidly and resisting organizational change is increased since low performing firms have an increased chance to reach a critical survival point where any further failure could threaten organization's existence (March and Shapira, 1987; Di Lorenzo et al., 2011). Furthermore, a firm performing below aspirations is seen as incapable of achieving acceptable performance through local search and incremental adjustment to its status quo (Baum et al., 2005), therefore maintaining existing exploitative routines could be a cost effective option instead of establishing new ones (Di Lorenzo et al., 2011).

On the other hand, performance far above aspirations provides a more mixed response with some studies suggesting that performing a slack-driven search triggers exploration (Baum et al., 2005; Baum and Dahlin, 2007; Voss et al., 2008), and other more recent studies pointing at exploitation in successful organizations as a strategic behavioral consequence (Rhee and Kim, 2015). Therefore, as these divergent findings suggest, firms performing above their aspirations could potentially engage in alliance ambidextrous behavior with a balance of exploration and exploitation.

Given that an ambidextrous approach to alliance formation does not always warrant economic benefits for the participating firms (Lin et al., 2007), it seems reasonable to focus on the reversed relationship, which entails the learning benefits embodied by aspirations as a determinant for alliance ambidexterity formation. Knowing that current research shows an ambidextrous tendency for firms performing above or below their aspirations (Greve, 2007; Di Lorenzo et al., 2011; Rhee and Kim, 2015), it seems reasonable to suggest that ambidexterity in new alliance formations is manifested when firm's performance departs its aspiration level. This means that a firm performing above or below its aspirations will balance exploration and exploitations in both structural and functional domains. Therefore, we posit the following hypotheses:

Hypothesis 1a (H1a): As performance relative to aspirations decreases, firm's alliance ambidextrous behahior in both structural and functional domains increases.

Hypothesis 1b (H1b): As performance relative to aspirations increases, firm's alliance ambidextrous behahior in both structural and functional domains increases.

4.2.3.2 The effect of dynamic embeddedness

It is well acknowledged that interorganizational alliance networks can be vital sources of information for the participating firms, a process that enhances both the identity of network members and the structural pattern of the network itself (Uzzi, 1996; Gulati, 1999). Recurrent allying over time enables the investing in interfirm relation-specific assets that reduce transaction costs and thus increase value creation (Hoang and Rothaermel, 2005). Firms seek partners not only on the basis of their own capabilities and resources but also on the indirect access of new partners the network gives access to, which in turn enhances firm performance (Stuart, 2000; Verspagen and Duysters, 2004). Thus, alliances can be used to exploit complementary resources between partners, acquire knowledge, reduce risks and promote stability (Larsson et al., 1998; Tsai, 2001; Russo and Vurro, 2010).

In this regard, the network architecture captured by the concept of structural embeddedness is reserved a critical importance as it restrains firms in their behavior but also creates opportunities for rich resource accessibility (Verspagen and Duysters, 2004). Firm's structural embeddedness pertains to the properties of interorganizational ties (Granoveter, 1985) and is captured by centrality, a measure denoting the extent to which the focal actor occupies a strategic network position by its involvement in strategically significant ties (Wasserman and Faust, 1994). The most prominent centrality constructs used in the SNT are degree, betweenness and closeness (Gnyawali and Madhavan, 2001).

Firms that exhibit high centrality will have increased chances to engage in ambidextrous behavior due to their possibility to explore new resources via the high number of interfirm relationships and exploit existing ones via increased access to information. Mura et al., (2014) show that tie amount and overall network density have a positive effect on knowledge exploration and exploitation. Tiwana (2008) dwell deeper revealing that strong interorganizational ties improve alliance ambidexterity while bridging ties such as structural holes hinder it, providing access to a wide set of skills, expertise and capabilities. Lin et al., (2007) show a significant positive relationship for the interaction between alliance ambidexterity and firm centrality. Therefore, high centrality would theoretically translate into a higher organizational ambidexterity (Tiwana, 2008; Simsek, 2009).

Throughout these contributions, little attention has been paid to the dynamics of individual importance based on actor-level centrality analysis which has proved to be invaluable in capturing the firm's positional evolution in longitudinal networks by centering itself around two key topologies: (i) static topology which applies traditional SNT analysis methods over an *aggregated* network encompassing all observational time periods, and (ii) dynamic topology which applies longitudinal analysis techniques over each observational time period referred to as *short-interval* network (Uddin et al., 2013; Shijaku et al., 2016). This is why, we introduce dynamic embeddedness, a concept that captures firm centrality evolution through time series networks. Additionally, the effect of the functional dimension that considers the upstream and downstream activities should not be disregarded when the firm chooses its network partner which is why we introduce the effect of dynamic embeddedness as simultaneous in both structural and functional dimensions of alliance ambidexterity.

Regardless of the construct, we believe that dynamic measures of degree, betweenness and closeness that capture network evolution will behave similarly to traditional indicators with respect to structural ambidexterity in a context of alliance formations. Given the majority results of extant research that show a positive relationship between firm centrality and alliance ambidexterity, we believe that the relationship between dynamic embeddedness with alliance ambidexterity in both structural and functional domains is better described by a positive relationship. Thus we posit the following hypothesis:

Hypothesis 2 (H2): Dynamic embeddedness has a positive relationship with structural and functional domains of alliance ambidexterity.

4.2.4 A multilevel model of alliance ambidexterity

As argued in Hypothesis 1a and 1b, a firm is more likely to engage in ambidextrous behavior, the further performance exceeds or falls below aspirations. Furthermore, in Hypothesis 2, we posit that dynamic embeddedness affects the firm's tendency to engage in ambidextrous alliance formation through a positive relationship. These arguments set up an interesting scenario concerning the role that dynamic embeddedness plays in alliance ambidexterity for a firm that performs above or below its aspiration level.

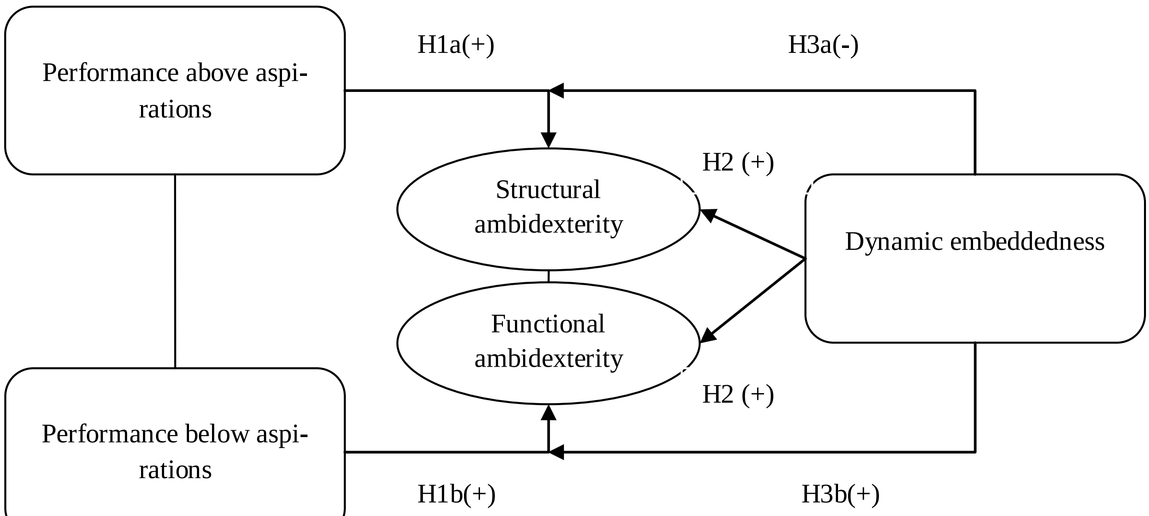
Over-performing (i.e. performing above aspirations) firms have an increased tendency to either explore due to the extra slack they have at disposal, or exploit in an effort to maintain their status-quo (Rhee and Kim, 2015). Similarly but for different reasons, underperforming (ie. performing below aspiration) firms could focus on both exploration in an effort to search for a solution to their performance-related problems (Baum and Dahlin, 2007), or exploitation in a survival rigidity scenario that focuses on existing routines considered vital for the firm (Di Lorenzo et al., 2011). On the other hand, highly embedded firms will benefit from the high number of connected firms when engaging in ambidextrous behavior (Tiwana, 2008; Lin et al., 2007).

Given that centrality is positively related to ambidexterity, a key question regards the strategic behavior of the firm if its performance exceeds or fall short of its aspirations. We hypothesize that if central firms are the ones that overperform, these will use their high network status to engage in preferential (i.e. explore or exploit) activities depending on whether they are faced with a slack search or an exploitation of their successful strategy. For an overperforming firm, "the marginal benefits of forming new linkages will be low and the marginal costs of additional links will be high" (Ahuja, 2000a: 322). In fact, Simsek (2009) propose that in a high centrality scenario, the firm could get overloaded with information that it cannot process. Thus, it makes sense for the firm to be selective and explore or exploit rather than balance these activities in both partner and alliance type selection. On the other hand, an underperforming firm will have a stronger incentive to engage in alliance ambidexterity the more embedded it is in its network of alliances. A higher centrality by default increases the chances of the firm to be ambidextrous (Lin et al., 2007; Tiwana, 2008), therefore positively impacting the firm's ambidextrous response to problemistic or threat rigidity (Iyer and Miller, 2008; Greve, 2010). More specifically, we posit the following hypotheses (see Figure 4.2 for a summary):

Hypothesis 3a (H3a): Dynamically embedded firms performing above their aspiration level will have a decreased tendency to engage in both structural and functional domains of alliance ambidexterity.

Hypothesis 3b (H3b): Dynamically embedded firms performing below their aspiration level will have an increased tendency to engage in both structural and functional domains of alliance ambidexterity.

Figure 4.2 Research model



4.3 Data and Methods

4.3.1 Research setting and sample

We test our hypotheses by examining the global pharmaceutical industry chosen due to its ubiquitous explorative and exploitative alliances between pharmaceutical firms, and the fact that these collaboration types are considered a norm for this industry. In order to capture firm´s dynamic embeddedness, we select a sample of 90 organizations by identifying those firms that have appeared at least once in the top 50 of the Pharmaceutical Executive Magazine yearly editions from the period 2002-2013 and whose ranking selection criteria is based on the firm's total sales. Subsequently, we use the Pharma and Medtech Business Intelligence database to collect all strategic alliances whose types are described in Table 3.1 that involve the top 90 firms in question between January 1, 1991 and December 31, 2012.

These transactions used to operationalize our network variables amount to over 9,600 collaborations of which about 8,000 (84 percent) involve alliances between the top 90 pharmaceutical firms, and the rest involve alliances between these leading firms and the remaining population totaling 4,645 firms. In order to measure the organizational aspirations and control variables, we use COMPUSTAT and DATASTREAM databases supplied by annual report information whenever data is deemed incomplete. Since financial data concern the top 90 firms from Western Europe, United States, Asia, Africa and Australia, we convert all local currencies to USD with an exchange rate based on the particular year the data is retrieved.

4.3.2 Variables and measurement

4.3.2.1 Dependent variables

Based on previous contributions (Lavie and Rosenkopf, 2006; Lin et al., 2007; Lavie et al., 2011), in order to capture the structural dimension of alliance ambidexterity, we focus on the network where the firm is embedded, and particularly on the interaction between new partners and alliances formed in each year. In this stance, new partners are considered those with whom, the focal firm has no prior ties at current time t. Specifically, we operationalize *structural ambidexterity* as a continuous variable based on an exploration index defined as (total # of new partners for all of a firm's alliances in year t) / (total # of all firm's partners including new and repeated in year t). Values range from 0 to 1, with higher values indicating increased structural ambidexterity. To capture functional alliance ambidexterity, we follow similar contributions (Lavie et al., 2011; Stettner and Lavie, 2014) and focus on the content of the alliance by distinguishing between exploration and exploitation based on the type of alliance agreement that involves downward or upward business integration. Specifically, *functional ambidexterity* is calculated as the average value of a predetermined exploration categorical index across all alliances formed by the firm at time t. The exploration index takes values of 1 for typical collaborations involving R&D collaborations and 0 for partnerships not involving R&D collaborations such as licensing, marketing and production or supply alliances. Values range from 0 to 1, with higher values indicating increased functional ambidexterity.

4.3.2.2 Independent variables and moderators

Aspiration performance - To measure performance relative to aspirations, we first construct measures of both firm performance and aspirations level as seen in the current behavioral theory literature (Greve, 2003; Iyer and Miller, 2008; O'Brien and David, 2014). Organizational aspirations are usually defined with respect to a particular dimension of firm performance which in the current research has generally been associated with return on assets (henceforth, ROA) (Greve, 2010). However, as Bromiley and Harris (2014) duly note, these studies have not addressed whether other performance measures might be superior, nor have they considered the inherent issues associated with single accounting measures such as recognition of discretionary items and depreciation. Therefore, we follow Bromiley and Harris (2014) guidelines and construct a composite measure that includes ROA, return on stockholder equity (ROE) and return on sales (ROS). This measure is constructed using Stata alpha procedure that computes the interitem correlations or covariances for all pairs of variables and Cronbach's α statistic for the scale formed from them while factor analysis is used as a confirmatory method to validate its outcome.

Researchers often combine self- and social-referent aspirations into a single measure of aspirations which aligns well with corporate practice of the firm usually retaining only one set of stated goals for a given activity at a given time (Bromiley and Harris, 2014). This is because dealing with separate social and historical aspirations adds more complexity to the interpretation of the aspiration models, and due to the measurement nature, this choice is not a safe guarantee of effective concept operationalization. Therefore, similar to Greve (2003) and based on Bromiley and Harris (2014), we use a weighted proxy for organizational aspirations that combines both historical and social aspirations. Specifically, we measure historical aspiration as a weighted average of firm's past composite performance calculated as: $HA_t = 0.7(P_{t-1}) + 0.2(P_{t-2}) + 0.1(P_{t-3})$ where P is the composite performance measure that includes ROA, ROE and ROS. Social aspiration is operationalized as $SA_t = \frac{\sum P_t}{N-1}$ where P_t is the composite performance measure for any given year (t), N is the number of all firms (i.e. 90), and the final aspirations' level measure constructed as $AL = 0.8 \times SA + 0.2 \times HA$. The chosen performance and aspiration weights were the ones that gave the lowest AIC and BIC values during models' testing. Similar to Greve (2003) and O'Brien and David (2014), in order to analyze alliance ambidexterity and aspiration performance, we conduct a spline regression which sets the inflection point at P = AL. Therefore, we subtract aspirations from performance and split the results into positive and negative values meaning *Performance below Aspirations* (henceforth, PbAL) when performance < aspirations and *Performance above Aspirations* (henceforth, PaAL) when performance > aspirations. Both are continuous variables, but while PbAL takes negative values, PaAL takes positive ones.

Dynamic embeddedness - Multi-agent settings such as the simulation models (Lin et al., 2007; Lazer and Friedman, 2007) oversimplify complex decision-making of specific actors (i.e. individuals or organizations) which can in turn distort real-life network evolution thus providing a generalist view of network dynamics that often fails to capture individual actor-level involvement in the longitudinal context. On the other hand, an 'actor-level dynamics' approach captures actor's positional evolution in longitudinal networks which is why we introduce the concept of dynamic embeddedness observed by an individual actor as the variability of structural positions of that actor in all short-interval networks compared to its structural position in the aggregated network (Uddin et al., 2013; Shijaku et al., 2016).

We capture our proposed moderators by modeling each year over the sample period as a separate network, formally characterized as a symmetric (i.e. square matrix that is equal to its transpose so that the main diagonal of the sociomatrix always contains zeroes in order to avoid firm self-reference ties) *N* x *N* 'weight' matrix, whose generic entry $wij = wji > 0$ measures the interaction intensity between any two actors (zero if no link exists between actor *i* and *j*). This means that ties between actors are valued according to the actual number of new alliance formations, a procedure seen in the network literature (De Montis et al., 2005). Following this framework and using software R that enables us to handle very large vectors, we build 22 symmetric 4,735 x 4,735 matrices to capture dynamic embeddedness of the firms for the given period. Dynamic embeddedness represents the variability of the structural positions (i.e. dynamicity) of an actor in all short-interval networks compared to its structural position in the aggregated network. The mathematical expression for this measure originally proposed by Uddin et al., (2013) and later modified and adapted by Shijaku et al., (2016) is given by the following equation 1:

$$DDA^{i} = \frac{\sum_{t}^{m} \alpha_{t,t-1} \times \left| OV_{AN} - OV_{t} \right|}{m} \qquad (1)$$

where DDA^{i} is the degree of dynamicity (i.e. dynamic embeddedness) shown by i^{th} actor, OV_{AN} is the observed variable (i.e. degree, betweenness, closeness centrality) for the aggregated network, OV_{t} is the observed variable (i.e. degree, betweenness, closeness centrality) for t^{th} yearly network for the i^{th} actor, m is the number of yearly networks considered in the analysis, and $\alpha_{t,t-1}$ is a constant valued according to whether the actor is present or missing in the current and previous short-interval network. The presence of this constant is of crucial importance to properly count for actors that disappear from the network due to simple inactivity or possible lack of presence due to acquisition effects. The possible combination values taken by $\alpha_{t,t-1}$ are given in Table 3.2.

For the first short-interval (yearly) network (i.e. $\alpha_{i,0}$ for t = 0), the value of the constant will depend on the presence or absence of each actor (i.e. either 0 or 1) at the particular period, a detail that marks a departure from the original model proposed by Uddin et al., (2013). Separately, we operationalize the observed variables that will be inputted to equation (1) namely degree centrality, betweenness centrality and closeness centrality. *Degree centrality* formally represents the simplest centrality measure and determines the number of ties for each actor, i.e. the number of actors that the focal actor is connected to, and modified to take into account the sum of weights in each tie (Barrat et al., 2004; Opsahl et al., 2008; Shijaku et al., 2014). *Betweenness centrality* formally represents the number of shortest paths between any two actors which pass through a specific actor (Freeman, 1980), modified to take into account the fact that in weighted networks, the actors with the highest actor strength are more likely to be connected in networks from a range of different domains (Opsahl et al., 2008; Shijaku et al., 2016). *Closeness centrality* formally represents the inverse total length of the paths from an actor to all other actors in the network, and is based on the idea that actors with a short distance (i.e. path) to other actors can spread information very productively through the network (Landherr et al., 2010). This measure is also modified to suit weighted network structure. We note that all weighted centrality measures in our analysis have been normalized and are calculated using *tnet* package available in R software.

4.3.2.3 Control variables

We control for several factors seen in both aspiration and alliance ambidexterity literature. Specifically, we control for *R&D Expenditure* measured as the ratio of R&D expenses to sales (Greve, 2003; Chen and Miller, 2007; Bromiley and Washburn, 2011; Bromiley and Harris, 2014). Including this variable in our analysis makes sense because firms who engage in alliance collaborations have an increased tendency to be innovative, with R&D expenditures being a significant determinant in this process (Ahuja, 2000b). Additionally, according to the behavioral perspective, R&D may serve as a mechanism to engage in search of more innovative channels (i.e. products, services and processes), enabling the firm to either raise prices or to reduce costs, thus closing the performance gap (O’Brien and David, 2014). Moreover, we control for several forms of *slack* since according to behavioural theory of the firm, slack (i.e.

resources) is highly dependent on aspiration performance. Namely, if the firm is performing above aspirations, it will have more slack at disposal while if performance is below aspirations, slack may be lacking as a result of the firm using resources to improve its performance (O'Brien and David, 2014). Additionally, slack has been observed to affect the ability of the firm to be ambidextrous in balancing both exploration and exploitation (Greve, 2007). Specifically, we control for *unabsorbed slack* measured as cash and marketable securities divided by current liabilities, *absorbed slack* measured as the ratio of selling and administrative expenses to sales, and *potential slack* measured as the ratio of total long-term debt to total assets (Bromiley, 1991; Greve, 2003, O'Brien and David, 2014). We also control for the *age* of the firms, operationalized as the foundation year minus the year considered in the 1991-2012 panel analysis, as well as controlling for *size*, measured as the natural logarithm of firm's employees.

4.4 Analysis

Given that the structural ambidexterity and functional ambidexterity are continuous variables, we opt for a panel OLS with robust standard errors clustered for firm data, conditioned by several factors. First, Hausman's test preferential of fixed over random effects which control for unobserved heterogeneity, as well as the nature of the yearly alliance observations and new partnerships within this timeframe, obliges us to consider within-firm variation over time. Second, robust standard errors, combined with the clustering option, relax the assumption of interdependence within the cluster (Lin et al., 2007), and counter the groupwise heteroskedasticity observed by the modified Wald test using *xttest3* command in Stata. Third, all regression models show little to no autocorrelation with test significance around and above the critical value of .05 according to *xtserial* code in Stata. The slack variables contain some outliers, so we follow O'Brien and David (2014) method and winsorize their distributions at the top and bottom of 0.5th percentiles. Furthermore, to infer causality, in all models, the independent variables and controls are lagged by one year relative to the dependent variable.

4.5 Results

Table 4.1 provides descriptive statistics and Pearson correlations among the variables used in the regression analysis with observations varying across variables due to missing data. The low correlations between the independent variables are consistent with the dimensional conceptualizations of exploration and exploitation ambidexterity. The higher mean for functional ambidexterity is an indicator for such preference in the alliance formations of the global pharmaceutical in the study period. Additionally, the high correlation between the dynamic embeddedness variables is a sign of their similarity as centrality measures. The significant and positive correlation that PaAL has with both structural and functional ambidexterity is an indicator that firms increase their ambidexterity when performance exceeds organizational aspirations. The majority of the chosen control variables are significantly correlated with structural ambidexterity (at .05 significance level), while slack variables show split relevant correlations with both structural and functional domains.

Table 4.1 Means, standard deviations and correlations

	N	Mean	S.D	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Structural ambidexterity	1411	0.346	0.156	1												
2. Functional ambidexterity	1450	0.615	0.163	-0.0578*	1											
3. PbAL	1512	-0.071	0.125	-0.0602*	-0.0190	1										
4. PaAL	1738	0.461	0.243	0.0601*	0.0616*	0.0826*	1									
5. Degree dynamicity	1764	0.412	0.493	-0.1713*	0.0581*	0.0105	-0.0558*	1								
6. Betweenness dynamic ity	1764	0.077	0.201	-0.1485*	0.0871*	0.0416	-0.0235	0.8158*	1							
7. Closeness dynamic ity	1764	0.084	0.009	-0.0926*	-0.0153	-0.0203	-0.0896*	0.5335*	0.3625*	1						
8. Age	1364	77.53	66.52	-0.0113	0.0975*	0.1612*	-0.00610	0.1018*	0.1307*	-0.1001*	1					
9. R&D Expenditure	1329	0.248	4.303	0.0722*	-0.00220	-0.4700*	0.00260	-0.0327	-0.0183	0.0154	-0.0489	1				
10. Size	1313	9.048	1.785	-0.2033*	0.0213	0.2843*	0.0549*	0.5071*	0.3668*	0.2255*	0.3856*	-0.3245*	1			
11. Absorbed slack	1133	0.320	0.603	0.0885*	0.0256	-0.1597*	-0.0457	-0.00940	-0.000300	-0.0849*	0.0938*	0.0518	-0.1827*	1		
12. Unabsorbed slack	1103	1.393	2.594	0.1054*	-0.0511	-0.1710*	0.0678*	-0.0878*	-0.0852*	0.00930	-0.2271*	0.1140*	-0.4428*	0.1686*	1	
13. Potential slack	1132	0.145	0.373	0.0478	0.0770*	-0.00450	0.1103*	-0.1046*	-0.0655*	-0.1062*	-0.0375	-0.0126	-0.1226*	0.1684*	-0.0787*	1

Note. Coefficients are reported at p < .05 *

Table 4.2 provides the panel OLS regression results themselves. Hypothesis 1a regarding the effect of performance below aspirations receives support only within the structural dimension with an overall positive effect on structural ambidexterity in models 1 to 4. However, H1a is not supported for functional ambidexterity with the beta coefficient is mainly positive and not significant indicating possible unbalance between exploration and exploitation for upstream and downstream activities. Instead, Hypothesis 1b is supported across structural ($b = 0.05$, $p < 0.05$, model 2) in models 2 - 4 and functional dimensions of ambidexterity ($b = 0.03$, $p < 0.05$, model 9) for performance above aspirations in models 7, 9 and 10. Hypothesis 2 regarding the positive effect of dynamic embeddedness on alliance ambidexterity receives support for the structural domain in models 1 and 2 where significant results are reported for degree dynamic embeddedness: $b = 2.30$, $p < 0.05$. However we also observe a negative effect of betweenness dynamic embeddedness which is not in line with our predictions ($b = -0.73$, $p < 0.1$, model 1). On the other hand, Hypothesis 2 is not supported in the functional domain of alliance ambidexterity where mixed signs are reported for different measures of dynamic embeddedness.

Onwards to models incorporating the two-way interactions between centrality-based dynamic embeddedness and aspiration performance for each domain, conflicting results are reported for separate centrality measures. Specifically, Hypothesis 3a is supported for closeness dynamic embeddedness ($b = -6.49$, $p < 0.001$, model 4) in structural ambidexterity, and for degree dynamic embeddedness ($b = -0.524$, $p < 0.05$, model 7) in the functional domain of ambidexterity. However, the significant but opposite sign of betweenness dynamic embeddedness (($b = -0.21$, $p < 0.1$, model 3), shows an opposite behaviour of firms in brokerage roles. Additionally significant effects of the interaction terms are observed in the full models with degree and betweenness measures showing similar behaviour across domains (model 5 and 10). Due to data availability, the number of observations for each domain differs from each-other while low R-sq values are well accepted in the relevant literature (Lavie and Rosenkopf, 2006).

Table 4.2 Determinants of ambidexterity domains in alliance formations

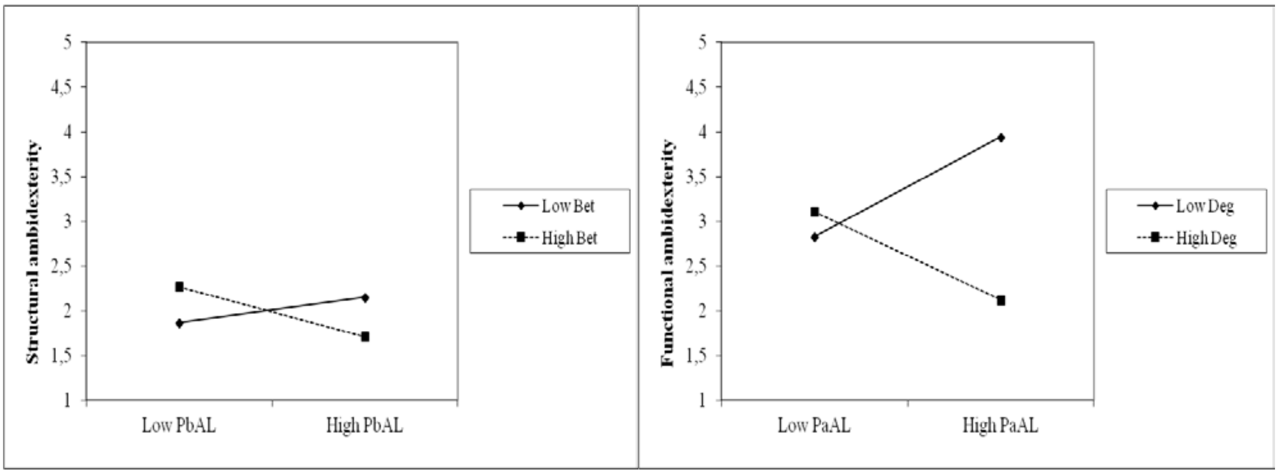
	Structural ambidexterity					Functional ambidexterity				
Model	1	2	3	4	5	6	7	8	9	10
PbAL	-0.0273+	-0.0284+	-0.0306*	-0.0260	-0.0239	0.0179	0.0144	0.0213	0.0154	0.0165
PaAL	0.0498*	0.0543**	0.0524**	0.0482*	0.0481*	0.0246	0.0322+	0.0270	0.0303*	0.0308+
Degree dynamicity	0.680*	0.730*			0.796*	-0.210	-0.384			-0.218
Betweenness dynamicity	-0.0215		0.147+		-0.114	-0.359		-0.297		-0.405
Closeness dynamicity	0.286			0.554	0.360	1.770			1.011	1.544
Age	-0.00394***	-0.00397***	-0.00354**	-0.00334**	-0.00388***	0.00411*	0.00425*	0.00388*	0.00415*	0.00420*
R&D Expenditure	0.000496	-0.000848	0.000138	0.00232	0.00291	0.00602	0.00468	0.00599	0.00674	0.00452
Size	0.0125	0.0137	0.0112	0.0113	0.0130	-0.0436*	-0.0372*	-0.0352*	-0.0377*	-0.0354*
Absorbed slack	0.00914*	0.00850*	0.00718+	0.00516	0.00755*	0.0114	0.0115	0.0123	0.0130	0.0136
Unabsorbed slack	0.00235	0.00276	0.00268	0.00268	0.00260	0.00236	0.00314	0.00276	0.00243	0.00303
Potential slack	0.0141	0.0132	0.0131	0.0145	0.0151	0.0275	0.0281	0.0288	0.0297	0.0307
Degree dynamicity x PbAL		0.620+			0.699*		0.357			0.619+
Degree dynamicity x PaAL		-0.281			-0.367		-0.524*			-0.659*
Betweenness dynamic ity x PbAL			0.0111		-0.181**			0.0377		-0.0889
Betweenness dynamicity x PaAL			-0.00274		0.134*			-0.101		0.00735
Closeness dynamicity x PbAL				5.760	4.701				-0.278	0.392
Closeness dynamic ity x PaAL				-3.732***	-3.594**				0.581	1.105
R-sq: within	0.07	0.08	0.07	0.08	0.09	0.04	0.04	0.04	0.04	0.04
N	708	708	708	708	708	733	722	722	722	722

Note. Coefficients are reported at + $p < .1$ * $p < .05$ ** $p < .01$ *** $p < .001$

In order to better understand the two-way interactions, we plot the above observed main and interaction effects for both degree and betweenness dynamic embeddedness as functions with +1 and -1 deviation from the mean. We opt to plot the interactions for these specific variables due to their significant effect in the aspiration – ambidexterity relationship across structural and functional domains. Specifically, Figure 4.3 plots are based on models 3 and 7 of the regressions showed in Table 4 and illustrate the change distances when PbAL, PaAL, and degree dynamic embeddedness measures are one standard deviation above or below their means. We observe that higher dynamic embeddedness scores are more prominent in the functional ambidexterity domain.

Additionally, averages are similar for both high and low degree dynamic embeddedness in the PbAL – structural ambidexterity relationship and PaAL – functional ambidexterity relationship.

Figure 4.3 Moderating effects of dynamic embeddedness on aspiration – ambidexterity



4.6 Robustness tests

In order to validate our regression analysis, we conduct several robustness checks. First, we performed tests on marginal effects of our regressions models which are consistent with Table 4 results and therefore are not reported. Second, we test our moderators in separate models grouped by performance above and below aspirations yielding similar significant results to our originally chosen models but showing a significant effect for degree dynamic embeddedness moderating effect on both PbAL and PaAL for structure exploration according to Hypothesis 1. Third, we added a quadratic term to each indicator of dynamic embeddedness in the main effect regression models. Prior studies have suggested a curvilinear relationship between centrality measures and alliance ambidexterity, pointing out that too many connections information will not necessarily be helpful and might, which in fact can cause centrality to become a source of confusion and information overload. (Simsek, 2009). However, we do not find support for such curvilinear relationship with quadratic terms remaining not significant throught the tested models. Finally, we added the control variable 'Tobin's Q' to account for focal firm's attractiveness as perceived by its industry partners with regression results not chaginging significantly from those shown in the results' section.

4.7 Discussion and conclusions

Organizational aspirations, alliance ambidexterity and network embeddedness are important constituents of organizational behavior with separatist contributions revealing their interdependence (Lin et al., 2007; Greve, 2010; Rhee and Kim, 2015). Despite, the current research, both theoretical and empirical questions remain unanswered as to the how these concepts simultaneously interact and what is their weight in real case scenarios. To tackle the problem, we propose a synthesized framework that connects alliance ambidexterity via a performance feedback mechanism (i.e. aspirations), and show how dynamic embeddedness affects the aspiration – ambidexterity relationship. We test our assumptions with a database containing new alliance formations of the biggest firms in the global pharmaceutical industry for the period 1991-2012. Our theoretical framework complements the separatist approaches seen by the extant literature, demonstrating that performance above and below aspirations has a positive effect on alliance ambidexterity by enhancing structural ambidexterity. In the functional ambidexterity domain, this effect is present only for the positive aspiration performance.

Our findings also reveal that the traditional balance within functional and structural domains of ambidexterity is advantageous for performance above or below aspirations echoing similar contributions on the subject (Greve, 2007; Rhee and Kim, 2015). It appears, that overperforming big pharmaceutical firms have a tendency to seek alliance ambidexterity via both partner and alliance type selection. However, we do not know whether this behavior is due to the slack search effect predicted by the behavioral theory of the firm (Cyert and March, 1963; Greve, 1998; 2011; Rhee and Kim, 2015) or due to the exploitation of their successful strategy (Rhee and Kim, 2015).

It is surprising that the effect of negative aspiration performance is not significant in the functional domain of alliance ambidexterity. An explanation to this lack of support could be the impossibility to include additional control variables that affect firm's negative aspiration performance such as organizational rigidity and problemistic search. Therefore a discussion on the underperforming firm's ambidextrous behavior in alliance type selection should be cautious, and the affirmations given by extant literature further investigated.

From the network perspective, our findings confirm that dynamic embeddedness provides conflicting results in its reincarnations of degree, betweenness and closeness dynamic embeddedness across ambidexterity domains. These results show that the categorization of dynamic centrality measures into degree, betweenness and closeness indicators, and their separate effect on structural and functional ambidexterity is a confirmation that while highly correlated, each centrality measure should receive specific attention as each enhances the structural view in the actor-oriented perspective of dynamic networks. Specifically, we find that only degree dynamic embeddedness appears to have a positive effect on structural ambidexterity, while betweenness and closeness appear to not be significant vectors of importance. Additionally, we observe that perhaps righteously dynamic embeddedness has an important saying in the structural ambidexterity where partner selection is crucial but less so if alliance types (i.e. functional ambidexterity) are concerned.

From a moderator's perspective, all three centrality measures moderate the aspiration – ambidexterity relationship albeit separately and in different domains. The fact that coefficient signs of degree and closeness dynamic embeddedness are similar across domains shows the consistency of organizational behavior when central firms that fall or exceed aspirations increase their actions to exert explorative or exploitative efforts. Dynamic embeddedness is consistent with our prediction especially in the functional domain where central firms seem to prefer alliance types as a precursor to their ambidextrous activity. Our prediction is confirmed for closeness dynamic embeddedness in the structural domain showing that for positive aspiration performance, the focal firm's proximity to other partners increases the firm's tendency to rely on partner selection for ambidextrous behavior in alliance networks. However, the fact that betwenness dynamicity behaves in opposite manner to the other dynamic centrality measures should be cause for reflection on how indirect ties affect alliance ambidexterity for performance departing organizational aspirations. From our results, it seems betweenness dynamicity shows an inverse trend by instead reducing alliances for both positive and negative aspiration performance.

Having said this, it is important to note that our analyses are not free of limitations. First, we do not test for interdependence of partners in different years, meaning we treat each year as a base reference for new partners in alliance formations which future research may address. Second, the dynamic embeddedness measure should be further researched with respect to the introduced constant that counts for missing actors in any yearly network. Third, the extrapolation of this study's results to other industries should be carefully motivated as the pharmaceutical industry evolution has historically depended on interorganizational alliances which might be sparse and of different strategic nature in other industries. Fourth, new dynamic measures could be proposed that help us understand the antecedents and consequences of other organizational behavior concepts (e.g. absorptive capacity, mindfulness, attention) in the network level, providing insights on their potential role in the aspirations of a dynamically embedded firm to explore or exploit. Finally, other financial indicators such as market value or pricing performance could affect our result which is why we think a revision of the classic aspiration models is long due and necessary.

Nevertheless, this study contributes to the extant literature in several ways. First, from a threefold perspective, we contribute to the strategic decision making behavioral theory (Cyert and March, 1963; Greve, 1998; Lin et al., 2007) by analyzing the factors that influence alliance ambidexterity viewed from both aspiration performance and social network perspectives. We propose an intricate relationship where the concepts of ambidexterity, aspiration performance and dynamic embeddedness clearly overlap with significant consequences. Our findings show that the aspiration – ambidexterity relationship in new alliance formations is moderated by the presence of dynamic centrality measures. Furthermore, we echo similar findings in literature about firm behavior for performance above and below aspirations via slack search or threat rigidity behavior (Greve, 2007; Iyer and Miller, 2008; Greve, 2010; Rhee and Kim, 2015). Additionally, we show that the relationship between performance and ambidexterity is similar when performance feedback models are considered. The significance of such similarity provides new insights on the deterministic role that firm's past performance plays on the balance between interorganizational strategic alliance exploration and exploitation.

While emphasizing our theoretical contributions, we acknowledge that practical contributions integrating our framework are more difficult to implement. The nature of aspirations is not only affected by firm's past performance and competitor's performance but also by the nature of the CEO and/or board of directors, firm ownership, and other measures which rather complicate the implementation of an alliance explorative or exploitative strategy. Furthermore, firm's idiosyncratic features embodied by the attribute domain should be considered in the context of bimodal networks that combine alliance formations with firm characteristics. However, simple models are sometimes necessary to trigger research which is why we hope our study is the first contribution of many to come in this interdisciplinary field of organizational behavior.

5. Final remarks

5.1 Concluding comments and future research

The consistent sigil of dynamic embeddedness across various paradigms of organizational behavior is the critical peak elevated by this dissertation. In this regard, our aim is to revitalize robust constructs such as centrality measures under a dynamic light that enables their evolution and brings traditional SNT analysis under a new perspective. We use dynamic embeddedness to explore various stages of firm behavior, from firm's response to exogenous shocks within and across industry to its behavioral aspiration based mechanisms to strategic decision making to engage in interfirm collaborations and pursue explorative or exploitative endeavors.

The first study tracks the dynamic evolution of actor´s structural embeddedness by extrapolating it from the micro world of human connections (Uddin et al., 2013) to the macro environment of interorganizational collaborations. By considering both top firms and especially their ego-network partners, our study gives an enhanced view of the global pharmaceutical industry dynamics. Additionally, it contributes to the research on strategic collaborations, by considering the multiple impacts of alliances, acquisitions and financing transactions on the global pharmaceutical network. From the practical point of view, this study is a novel approach to the analysis of a highly convoluted industry such as the pharmaceuticals shedding light on industry´s key players as well as highlighting the movement of smaller firms on the overall network structure. Additionally, our results show the true impact of both global and more regional recession effects on the pharmaceutical network, suggesting the importance and at the same time fragility of strategic transactions toward exogenous perturbations of critical nature.

The second study is motivated by a limited research in understanding performance-based aspiration mechanisms of firm strategic behavior in a dynamic network context. We propose an integrated framework bridging such concepts as performance feedback, and dynamic social networks to test our hypotheses in our database on the global pharmaceutical industry. In this sense, we integrate the concept of dynamic embeddedness in performance-based aspiration models, and show that organizational behavior in the form of strategic transaction formation is more visible the closer the distance between firm performance and its aspirations' level, but less visible the further firm performance departs from its aspirations both above and below, these results being in line with current literature on the topic (Greve, 2011; Baum et al., 2005; Kim and Rhee, 2014). In this sense, both the 'beauty' and the 'beast' firms seem to encounter a similar pattern of rigidity behavior and reduced network dynamism albeit for different reasons. Additionally, we confirm that dynamically embedded firms moderate the relationship between strategic transaction formation and performance related aspirations. From a practical perspective, this study could help managers to focus their attention on tracking the network in which their firm is dynamically embedded by analyzing the performance-based aspiration consequences of organizational processes and practices that involve strategic transaction formation. Such analysis could potentially yield managerial insights on the crafting of strategic activities that focus on collaborative networks, and avoid threat rigidity behavior that despite its survivalist intentions could isolate the firm in the long run.

Our third study continues the exploration of the organizational behavior mechanisms by proposing an intricate relationship where the concepts of ambidexterity, aspiration performance and dynamic embeddedness overlap with significant consequences. Even though alliance ambidexterity has an established unidirectional relationship with firm's financial performance, little is known on the reverse effect of performance feedback (i.e. organizational aspirations) on firm ambidextrous behavior. We posit that performance based aspiration models in strategic alliance networks have a positive effect on organizational ambidexterity, and probe the impact of dynamic network centrality measures (i.e. dynamic embeddedness) on firm's tendency to balance alliance exploration and exploitation. Through a multidimensional (i.e. structural and functional) approach, we find support for the determinant effect of organizational aspirations on alliance ambidexterity for both structure and function domains of decision-making as well as observe the significant moderating effect of dynamic network centrality measures in the aspiration – ambidexterity relationship. Our study provides a new theoretical perspective that integrates aspirations, ambidexterity and network embeddedness as well as enhances previous literature on the effect of dynamic centrality measures.

We believe this dissertation has explored a tiny fraction of the tip of the iceberg formally known as organization's 'black box'. The next logical step is the inclusion of such fuzzy constructs as organizational attention, mindfulness, and memory into our framework in an attempt to go further into the cold depths of organizational behavior. Specifically, we would like to know how CEO attention affects the firm's decision to engage in new alliance formations and whether these alliances are explorative or exploitative in nature. In this sense, the effect of previous strategic alliances in partner selection should be taken into consideration. Moreover, how memory (i.e. the ability of the firm to remember its actions) influences organizational attention and its aspirations could open the path for interesting organizational behavior scenarios. In this vein, the additional analysis of the networks from a bimodal perspective could yield important answers on partner assortativity and partnership preference that ultimately affects alliance ambidexterity formation. This is an exciting area which we believe is ripe for further investigation with potential implications for the academia in particular and management practitioners in general.

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