Exploring dynamic embeddedness: a network analysis of the global pharmaceutical industry 1991-2012

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Abstract. We analyze the global pharmaceutical industry network using a unique database that covers strategic transactions (i.e. alliance, financing and acquisition collaborations) for the top 90 global pharmaceutical firms and their ego-network partnerships totaling 4735 members during 1991-2012. The network evolution is traced via a novel method based on the concept of dynamicity that quantifies individual network members (i.e. actors) contribution to the longitudinal period. Specifically, we observe dynamic embeddedness defined for key network centrality measures, and capture the impact of the 2007-2008 global financial crises and the subsequent global and Eurozone recession effects on the strategic transaction flows between the industry's key players as well as their partners. Results suggest the feasibility of dynamicity as a dynamic network indicator as well as the importance of constellation strategic transactions in the study of large network perturbations.

Keywords: longitudinal social network, strategic transaction, dynamicity, dynamic embeddedness

1 Introduction

Organizations are inherently embedded actors of social networks, whose structures evolve dynamically, and as a result of each actor's involvement offer important clues on organizational strategic behavior. Inside a dynamic network, organizations exist as highly mobile entities with their relationships and positional structures continuously changing in time. As such, understanding organizational behavior involves first and foremost capturing organizational dynamics often done by analyzing the longitudinal context where network dynamics is observed. While most literature on longitudinal networks focuses on a more holistic evolution of their structure [2, 4, 11], more recent studies have highlighted the contribution of each actor to the overall network dynamics [1, 6]. This actor-level approach embodied by the concept of dynamicity, relies on the assumption that capturing organization's dynamic behavior in a given network should be based on a combined analysis of both static and dynamic network topologies [12]. Additionally, dynamicity enables researchers to study the effect of specific critical events (i.e. perturbations) that greatly alter the structure of the panel network.

However, quantifying actor involvement and contribution in longitudinal networks, and modeling its behavior against specific perturbations has been limited, with research confined to the effect that organizational crisis has had on organizational communication networks [6, 13]. These few available longitudinal network studies on actor contribution have analyzed network dynamic evolution relying on embeddedness, a well-known concept in social network analysis, long considered a highly strategic resource with important impacts on firm's performance [5, 8]. On this matter, network literature has often relied on centrality-based embeddedness to provide a dynamic image of social network evolution [9, 14].

Furthermore, the majority of research on embeddedness has approached the concept from a dyadic (i.e. a group consisting of only two actors) perspective, bypassing multiple types of firm interaction. Even those studies that focus on the so-called constellation (i.e. interactions between more than two actors) perspective [3, 7], miss out at the relevance of actors engaging in constellation ties of multiple kind, by considering only a single type of collaboration. Additionally, embeddedness' studies have focused heavily on strategic alliance collaborations, a choice well-grounded by the interorganizational collaborations in any given industry, but that often fails to embrace the full picture of strategic interactions' multitude.

We fill these shortcomings by focusing on longitudinal networks generated from strategic transactions, a conceptualization of interorganizational collaborations engaged by a firm with its network partners including strategic alliances, acquisitions and financing collaborations, analyzed under both a dyadic and constellation lens. By doing so, we contribute not only to the literature of alliance collaborations but enhance the currently undernourished network literature on acquisition and financing collaborations as well which play an important role in the dynamics of strategic organizational behavior.

Our study addresses the above gaps by developing and testing a theoretical framework that links the concepts of dynamicity, embeddedness and strategic transactions. By doing so, we uncover the dynamic evolution of the global pharmaceutical industry chosen for its intensive collaboration environment. Given the novel nature of dynamicity as a concept, we attempt to examine some fundamental questions that develop a theory-based understanding of dynamicity and its relationship with embeddedness, as well as analyze the impact that strategic transactions have on such structure: How does dynamicity of centrality measures evolve in a longitudinal network? What is the role of strategic transactions in the evolution of such dynamicity? How does actor´s dynamicity behave in the presence of exogenous events that critically alter the network structure?

Specifically, we expand the actor-level approach on dynamic networks by introducing the concept of dynamic embeddedness, defined as the individual actor’s central position variability in a longitudinal network setting compared to its central position variability in a aggregated network. For the purpose of this paper, our focus is exclusively on the dynamicity of structural embeddedness and particularly on the dynamicity of key network centrality measures such as degree, betweenness and closeness. Specifically, we build on a dynamicity model [12] by exploring the critical impact that large exogenous perturbations, such as the 2007-2008 financial crisis, the subsequent 2008-2009 global recession and the more local Eurozone recession of 2011-2013 have on longitudinal networks between top-level actors and their ties in the global pharmaceutical industry.

2 Data and measures

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 appear at least once in the top 50 of the Pharmaceutical Executive Magazine yearly editions for the period 2002-2013. We then use the Pharma and Medtech Business Intelligence database to collect all the strategic transactions that involved the firms in question from 1991 to 2012. During this period, the 90 firms of the sample engaged in alliance, financing and acquisition collaborations with 4645 other firms and institutions creating a total of 12055 strategic transactions.

Due to our selection process, we consider two types of firms, the *core* firms comprised of the top 90 pharmaceuticals and the *periphery* firms including the rest of the actors, with a total population of 4735 firms whose full list is available from the authors. The obtained longitudinal data for both core and periphery firms presents missing actors, since some firms are acquired by others, or simply are not active for any particular year. Our analysis also includes financial data obtained from COMPUSTAT and DATASTREAM databases, supplying missing data when possible using company annual reports. Since the financial data concerns firms from different countries, we convert all currencies to USD with an exchange rate based on the particular year the data is retrieved.

We model each year over the sample period as a separate social network and analyze each network based on a similar approach for the global banking network analysis [10]: (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 4735 actors. In our analysis, we consider a weighted undirected tie approach, defined as an 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). Following this framework and using the software R, we build 22 symmetric 90 x 90 matrices to track the evolution of the core network and 22 symmetric 4735 x 4735 matrices to track the evolution of the full network for the period 1991-2012. Additionally, for dynamicity calculation purposes, we build two matrices which include the aggregated strategic transactions of the entire 22 years period for both types of network.

Network indicators. The network measures of our analysis include three centrality variables (degree, betweenness and closeness centrality) and the dynamicity variable representing the variability of the structural positions of an actor in all short-interval networks compared to its structural position in the aggregated network [12] as shown in equation 1:

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

where DDA^i is the degree of dynamicity 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 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 important to properly count for actors that disappear from the network due to simple inactivity or possible lack of presence due to network dynamics. The possible combination values that $\alpha_{t,t-1}$ can take are given in Table 1.

Table 1. Possible combination of presence and absence of an actor in two consecutive short-interval networks (Source: Uddin et al. 2013)

Current SIN (Present/Absent)	**Previous SIN** (Present/Absent)	$\alpha_{t,t-1}$
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

For the first short-interval network (i.e. $\alpha_{i,0}$ for t = 0) of our analysis, the value of the constant depends on the presence or absence of each actor (i.e. either 0 or 1) at that particular period. The dynamicity model [9] differentiates between two types of dynamicity 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:

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

where DDN^t is the average degree of dynamicity shown by an actor of the t^{th} short-interval network meaning the contribution of each actor to the short-interval network´s dynamicity, and w_t is the total number of actors in the t^{th} short-interval (i.e. yearly) network. Therefore, our analytical approach is based on three variables: degree dynamicity, betweenness dynamicity and closeness dynamicity constructed by substituting each obtained centrality value to equations 1 and 2.

Industry indicators. 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: (i) global crisis representing the combined effect of the 2007-2008 financial crisis and the global recession of 2008-2009 that followed as a direct consequence, and constructed as a dummy variable that takes the value of 1 for the years 2007-2009 and zero for the rest, and (ii) local crisis representing the exogenous effect of the Eurozone recession during 2011-2013, and constructed as a dummy variable that takes the value of 1 for the years 2011-2012 and zero for the rest.

Control indicators. We use several actor-specific measures such as strategic transaction frequency, R&D intensity, profitability, headquarters (HQ) location and financial leverage age and size. Strategic transaction frequency represents the relative frequency in percentage with which firms engage in strategic transactions. In the analysis, we differentiate between the frequency in percentage of firms engaging in alliance, financing and acquisition collaborations. R&D intensity represents the firm's R&D expenditure scaled by total sales while profitability is measured for each firm by computing the ratio of net income to total assets (ROA). We define financial leverage as the debt-to-total assets ratio including both short- and long-term debt and control for the age of the firms, operationalized as the foundation year minus the year considered in the 2002-2012 panel analysis, and size operationalized as the natural logarithm of company's employees. Finally, since our data consists of multinational firms and knowing that the majority of the top 90 firms are US- or EU-based, we control for headquarters (HQ) location based on two separate dummy variables representing whether firms are U.S. or EU-based.

Model approach. By using a two-step approach to our analysis, first we assess the stability of dynamicity distributions in selected years to capture statistical differences throughout our data using Kolmogorov-Smirnov (henceforth, KS) tests for both core and full networks, second by controlling for firm-specific effects, we investigate the effect that the global crisis (including the 2007-2008 financial crisis and the great 2008-2009 recession), and the local crisis referring to the Eurozone recession, observed for 2011-2012, have on degree, betweenness and closeness dynamicity. For our second step, we run a panel regression model based on random effects (henceforth, RE) with robust estimations based on the model seen below:

$$Y_{it} = \beta_k X_{it} + \alpha_i + u_{it} + \varepsilon_{it}, \qquad i = 1,\ldots,90, \qquad t = 1,\ldots,10,$$

where Y_{it} is firm´s dynamic embeddedness considered as a dependent variable, X_{it} is a vector of firm and industry-specific independent variables including global and local crises, age, size, profitability, financial leverage, R&D intensity, transaction frequency and firm location, α_i is the unknown intercept for each firm, u_{it} is the between-firm error, ε_{it} is the within-firm error, β_k is the coefficient for each k independent variable, i is the number of firms (90 in total) and t is period of time considered (10 years in total or +/- 5 years window before and after the offset of the 2007-2008 financial crisis).

3 Results

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

We track dynamic embeddedness evolution by plotting the cross-sectional averages of dynamic indicators during 1991-2012 as seen in Figure 1. Both panels show that dynamicity values present relative stability before 2007 for degree centrality but vary substantially for betweenness and closeness centrality throughout the study period. Specifically, for the core network, degree and betweenness dynamicity drop respectively 20 percent and 17 percent while closeness dynamicity is almost halved by 40 percent during the global crisis. The more local Eurozone crisis of 2011-2013 (of which we analyze only one year due to sample structure) shows a similar pattern with both networks' dynamicity severely reduced. An exception is closeness centrality, whose dynamicity shows an upward trend for the core network, with signs of a more clustering-oriented tendency.

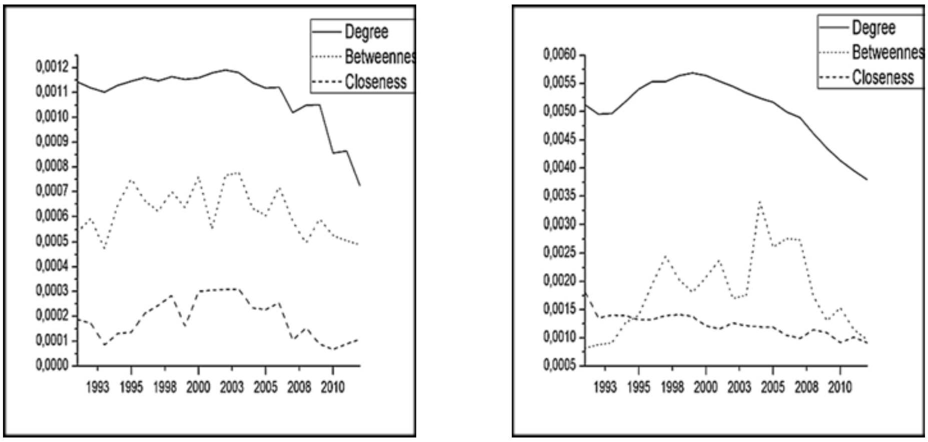

Fig. 1. Core network (left) and full network (right) dynamic embeddedness evolution

We monitor the stability of both core and full networks by comparing the dynamicity distribution in the first year of each decade including last available year's data (1991, 2001 and 2012) with subsequent years in the same decades, a procedure seen in global banking network analysis [10] and whose results are given in Table 2.

Table 2. Empirical distribution stability for dynamic embeddedness

Core networks				**Full networks**			
	1991	2001	2012		1991	2001	2012
Degree				Degree			
1991-2001	0.00	0.00	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	0.00	0.00	1.00	1991-2001	0.00	0.00	0.18
2002-2012	0.27	0.36	0.54	2002-2012	0.00	0.18	0.00
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

Table 2 shows the proportion of years when the dynamicity distribution is statistically different (at 5 percent level of significance) in each decade compared to 1991, 2001 and 2012. Values of zero mean that the distribution of a particular year compared to a particular decade are statistically close, as is the case for degree and betweenness dynamicity for the years 1991 and 2001 when compared with the 1991-2001 period. This means that in both core and full networks, the firms have kept a similar centrality structure. On the other hand, the distribution for the decade 2002-2012 is statistically different for almost all dynamicity variables in both core and full networks, meaning that the actors' dynamicity has been highly unstable for the second decade. An exception concerns betweenness dynamicity for the full network, whose results show a relatively unaffected actors' brokerage tendency, with only 18 percent of significant distribution change.

Looking at Table 3, we observe that the top five ranking for both degree and betweenness dynamicity includes the biggest pharmaceutical firms (based on their average total sales) which are not underlined, meaning that these firms score high in their centrality position during the core network evolution. Interestingly, closeness dynamicity shows only two big pharmaceuticals in the top five, with a clear tendency of smaller firms reducing their mutual proximities. However, big pharmaceutical firms' hegemony is reinstated in the core network with big pharmaceuticals scoring high in all centrality measures.

Table 3. Firm rankings (1991-2012) for both core and full networks

Core networks								
	Degree			Betweenness			Closeness	
Rank	Name	Value	Rank	Name	Value	Rank	Name	Value
1	Pfizer	0,879	1	Novartis	0,407	1	GlaxoSmithKline	4,68251E-05
2	Roche	0,460	2	Daiichi Sankyo	0,381	2	Baxter	4,6578E-05
3	Sanofi	0,455	3	Sanofi	0,369	3	AstraZeneca	4,42497E-05
4	Novartis	0,385	4	GlaxoSmithKline	0,344	4	MedImmune	4,31083E-05
5	Merck	0,366	5	Pfizer	0,232	5	Tanabe Seiyaku	4,14857E-05
Full networks								
1	Pfizer	0,516	1	GlaxoSmithKline	0,269	1	Pfizer	9,40487E-08
2	GlaxoSmithKline	0,384	2	Pfizer	0,231	2	GlaxoSmithKline	9,04179E-08
3	Johnson & Johnson	0,360	3	Johnson & Johnson	0,182	3	Roche	8,53981E-08
4	Sanofi	0,326	4	Novartis	0,181	4	Sanofi	8,52578E-08
5	Roche	0,311	5	Roche	0,180	5	Novartis	8,20413E-08

Table 4. Dynamic embeddedness during exogenous perturbations: regression estimates

	Dynamic embeddedness		
	Model 1	Model 2	Model 3
Variables	Degree	Betweenness	Closeness
Controls			
Age	-0.000197	-0.000325	-0.0000303
Size	0.00667*	0.0190**	0.000360
HQ location			
US firms	0.0800	-0.0233	0.00944*
EU firms	0.0416	0.00233	0.00626
R&D intensity	-0.0000478***	0.0000134	0.00000624
Profitability	-0.00748	0.0389	-0.0187*
Financial leverage	0.00216	0.0354	-0.0181*
Strategic transaction frequency			
Alliance	0.0196**	0.0131**	0.00523*
Financing	0.00786	0.00295	0.00393
Acquisition	0.0232***	0.0138	0.00251
Main effects			
Global crisis	-0.00222	-0.0154*	-0.0110***
Local crisis	-0.0220**	-0.0236**	-0.0118***
Model statistics			
constant	0.0176	-0.0932	0.0173
R^2 overall	0.0836	0.1269	0.1453
N	751	751	751

Note. Standardized coefficients are reported.
* $p < .05$ ** $p < .01$ *** $p < .001$

Looking at the main effects of the regression analysis, we observe the negative effect of the global crisis on dynamicity indicators except degree dynamicity, for which the effect is not significant, meaning that the combined effect of the 2007-2008 crisis and the subsequent global recession of 2008-2009 have not significantly affected the number of strategic transactions originating from each of the core network members. Moreover, we find strong statistical significance for the negative effect that the local Eurozone crisis has had on firms' dynamic embeddedness. Additionally, the type of strategic transaction is found to influence dynamic embeddedness. This effect is understandable considering the relatively high distribution of alliance transactions in the sample (about 75 percent). However, the positive and significant effect of acquisition transactions on degree dynamicity is interesting considering that both acquisition and financing transactions show similar distributions in the sample (about 12.5 percent each). Finally, the observed low R-squared is not necessarily a drawback for the chosen model particularly if we consider that the results present statistically significant predictors and the regressors are used in a panel setting.

4 Discussion and concluding remarks

With respect to the analyses' objective, the results on firm´s dynamic embeddedness suggest that prior to the global crises the global pharmaceutical industry has been relatively stable, with firms' centrality reflecting their market position. Specifically, the top pharmaceutical firms that rank high in terms of sales have a noticeable central position in both core and full networks as observed in the firm rankings. Dynamically speaking, the global pharmaceutical industry has reduced its activity to even lower levels than the beginning of our sampling data, year 1991. While the reduction varies for specific centrality measures, its effect is more prominent after 2007, which coincides with the offset of the 2007-2008 financial crises. The regression results confirm this by showing significant dynamicity reduction during both crises. Furthermore, the regression results indicate that the Eurozone recession has had a far deeper negative effect on global pharmaceutical industry than the global recession.

This study also highlights the importance of acquisition transactions in the expansion of the firms' importance as central hubs. Specifically, the significant effect of acquisitions on degree dynamicity demonstrates the impact that different strategic transactions have on centrality indicators and further reinforces the reasoning behind our choice to study the centrality measures evolution via the dynamicity concept. However, this also raises questions as to why comparable effects of strategic transaction types (i.e. acquisitions and financings) respond differently to centrality-based dynamicity.

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. Second, dynamicity measure calculation is based on a novel design which takes into account missing actors during network evolution using a specific constant which should be subject to further research for proper values' assignment.

Finally, the dynamicity measure could be used for 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.

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