

Does Performance Homophily Matter in Acquisition Decisions? Evidence From Acquisition Network in the Global Electricity Industry

Mohamed Bin Abderrazek Boukhris

Department of Accounting and Finance, College of Business Administration, Prince Mohammad Bin Fahd University, Al Khobar, Kingdom of Saudi Arabia

Abstract

In this paper I use data, that I have collected on corporate acquisition transactions among electricity companies worldwide during the period 1994-2004, to test the hypothesis of organizational performance homophily as an acquisition network-selection mechanism for firms in the electricity industry. I report clear evidence that performance considerations are taken into account by international electricity firms while choosing their network partners. The methodology used in this study is based on the stochastic actor-oriented models for social network analysis.

Keywords: Interorganizational networks; Performance homophily; Selection; Acquisition; Stochastic actor-oriented models.



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1. Introduction

It is well documented in the interorganizational literature that organizational performance considerations are taken into consideration in partner selection decisions (Dyer and Singh, 1998; Pallotti and Lomi, 2011; Podolny, 1994; Powell *et al.*, 2005). It has been argued in many empirical studies that similarity along organizational outcomes, such as performance, has a tendency to increase the likelihood of partnership relations between firms (Gulati and Gargiulo, 1999). Accordingly, these results suggest the presence of a network-embedded process that connects, as a network selection phenomenon, interorganizational network ties to organizational performance. While it has been shown that organizations related by network ties, such as strategic alliances in general and acquisition in particular, tend to perform similarly (Ahuja, 2000; Davis and Greve, 1997; Hedström *et al.*, 2000), it was also demonstrated that they are also more likely to choose as targets other organizations attaining a similar level of performance (Hinds *et al.*, 2000; Powell *et al.*, 2005). In fact, earlier comparative works have highlighted the determinacy of similarity in organizational attributes to predict the formation of social network ties e.g. (Lazarsfeld and Merton, 1954; Louch, 2000; McPherson *et al.*, 2001). Firms in the network-neighborhood are more likely to develop links with others whom they estimate proximate in attributes and characteristics to themselves. For example, it has been argued that homophily in attitudes, characteristics, and status breeds connections since it increases the predictability of network partners' behavior and generates empathy with them (Kramer, 1999; Van de Bunt *et al.*, 2005). The homophily hypothesis has received considerable support from scholars who examined the interorganizational partnership relations (Lincoln *et al.*, 1992; Podolny, 1994; Powell *et al.*, 2005; Stuart, 1998). For instance, closeness in characteristics, attributes, and a variety of organizational outcomes was revealed in the majority of partnership and alliance studies as an antecedent for network tie formation among organizations. This is because it does catalyze knowledge transfer, learning process, experience exchange, and coordination among organizations experiencing close levels of outcomes. Powell *et al.* (2005), showed that homogeneity along the dimensions of age, size, location, ownership, and status does affect positively the likelihood of inter-firm collaboration in the biopharmaceutical industry. Therefore, several empirical results are strongly in favor of the claim that outcomes of network-oriented processes of social influence frequently affect individual partner selection decisions.

To advance this line of research, I focus in my study on the role of homophily in performance, which is explained by network oriented processes, as an important selection criterion candidate for acquisition network-tie formation. The empirical framework for my study is the global electricity industry which I observed during the period 1994-2004. Using longitudinal network data generated by electricity firms' acquisition decisions, I model their individual decisions to build acquisition ties based on alters' performance attributes. Because my unit of analysis is represented by individual electricity companies, the methodology I present may be viewed as a statistical translation of the stochastic actor-oriented models for network dynamics. The model for network dynamics that I test in this paper is based on procedures that were developed mathematically in Snijders *et al.* (2007), Snijders *et al.* (2010), Snijders (2013) and Steglich *et al.* (2010).

2. Theoretical Background

Organizations have been shown to experience dissimilarities in how they perform. These differences between organizations along this specific organizational outcome (i.e., performance) have been proven to be the consequence of, among other reasons, the different positions they occupy in their respective markets (Porter, 1980), and to the unique competences and specific resources they can access (Barney, 1986; Selznik, 1957; WeRnerfelt, 1984). In

their empirical study, [Shan et al. \(1994\)](#), revealed how the variety of forms of embeddedness in networks of relationships would affect the performance differential between organizations. Furthermore, a huge volume of research on strategic alliances has argued that distinctive organizational resources are more likely to span traditional corporate borders and limits and, therefore, have tendency to be embedded in interorganizational network relationships rather than being only involved in isolated structures of individual companies ([Dyer and Singh, 1998](#); [Powell et al., 1996](#)). According to these arguments, two distinct but interrelated processes do exist and, hence, lead consequently to a dual association between organizational performance and network relations. The first is a network influence process that network relations, once established, might exert on organizational outcomes such as performance. The second is a network partner selection process that focuses basically on the antecedents of the network tie formation.

While my main focus in this study is the second process mentioned above, i.e., the partner selection process, I believe it is worth to very briefly review some of the literature contribution to the network influence process. I do it here as a kind of preface to my main research question related to the acquisition selection process based on similarity in organizational performance. For instance, in their examination of the effects of being central in the network neighborhood on organizational performance, [Powell et al. \(1996\)](#), found that biotechnology companies that entertain a large number of exchange relations with other companies are more likely to become dominant players in the industry. [Ahuja \(2000\)](#), argued that organizations that are more popular in terms of overall volume of network ties sent or received are more likely to become associated with innovative technologies. More recent research studies focused on the importance of the in-going network ties “ego effect” in explaining outcomes such as job performance and career success ([Fang et al., 2015](#)), and salesperson performance ([Bolander et al., 2015](#)),...etc. All these studies that I have reviewed, among many others, are based on the generally accepted observation that networks influence individual organizational outcomes. However network ties are not only antecedents of individual decisions, but also their consequences. This view is expressed clearly by [Brass et al. \(2004\)](#) according to whom “[N]etworks create outcomes that are, in turn, antecedents for further network development”. In other words, network ties need to exist before they can exert any influence on individual behavior. So how do network ties form in the first place?

Partner selection has been the focus of many studies in the interorganizational literature. [McPherson et al. \(2001\)](#), reported that “[S]imilarity breeds connections”. Browsing in the literature, network evolution has been shown to be driven by several selection mechanisms among them similarity in attributes and characteristics between the organizations in the network which was well documented in many empirical researches ([Hinds et al., 2000](#); [Levin and Cross, 2004](#)). A huge volume of organizations studies based on the pioneer [Lazarsfeld and Merton \(1954\)](#) work, have reported and supported the claim that homophily among organizations’ attributes and characteristics has an impact on the tendency of the firm in the network to choose and to be chosen by other participants in the network ([Hinds et al., 2000](#)). A rich organizational literature on partner selection is available that addresses this question directly. [Gulati and Gargiulo \(1999\)](#) and [Uzzi \(1997\)](#) emphasized the role of embedded ties and endogenous network processes such as, for example, transitivity and reciprocity. [Gulati \(1995\)](#), added a fundamental temporal dimension to the general understanding of the antecedents of network ties and focused on relational inertia induced by the presence of pre-existing ties. [Podolny \(1993\)](#), unveiled the role of homophily – the increased likelihood of actors that are similar along relevant dimensions to engage in collaboration and resource exchange.

Despite the levels of consciousness with regards to the notion of homophily, it has been demonstrated to be a characteristic for individual affiliation decisions ([Leenders, 1997](#)). There was a large debate in the literature concerning the fact that social network features reflect, even partially, selection processes stimulated by homophily in individual actors’ cognition ([Friedken and Johnsen, 1990](#)), network centrality, positions, and characteristics ([Carley, 1991](#); [Ibarra and Andrews, 1993](#)). Other scholars focused on the importance of similarity as antecedent for the network ties’ formation. For example, in an old piece, [Feld \(1982\)](#) linked the dimensions and levels of homogeneity among people to social ties by introducing the term organized foci. Later, several studies demonstrated that preferential attachment based on similarities among actors constitute a principal cause for network ties’ formation. In the same line of research, [Knoke \(1990\)](#) emphasized that similarity along the dimensions of political opinions and orientations positively increases the likelihood of participation in political associations. Furthermore, homophily has also been shown to facilitate interpersonal communication ([Williams and O’Reilly, 1998](#)), and raising the chances for interactions within groups ([Carley, 1991](#)). Similarly, the dimension of gender has been demonstrated to play an important role in a number of different organizational settings ([Brass, 1985](#); [Ibarra, 1992](#)).

In sociological studies, friendship relations have been demonstrated to more likely occur with others who are similar along several dimensions like age, gender, education, and status; and that this result is the outcome of homophilous preferences within groups ([McPherson and Smith-Lovin, 1987](#)). In addition, while friendship networks have been shown to be predicted by similarities along the dimensions of ethnicity and network centrality ([Gibbons and Olk, 2003](#)), homophily in personality characteristics has been also reported to predict friendship ties’ formation and centrality in advice ([Klein et al., 2004](#)). In inter-firm studies, companies that are similar along relevant dimensions and outcomes such as power, status, prominence, and performance have been shown to experience a tendency to evaluate their mutual contributions and outcomes much more than dissimilar others ([Tsui and O’Reilly, 1989](#)). Strong empirical evidence that homophily facilitates interorganizational relationships and coordination is also offered by [Powell et al. \(2005\)](#) that similarity along the dimensions of age, size, location, and ownership status affect positively the likelihood of interorganizational collaboration among organizations in the biopharmaceutical sector.

Overall, convincing evidence is available that interorganizational relations are more likely if partners have similar status, and power, are endorsed by high status supporters ([Stuart et al., 1999](#)), are affiliated with well-known

exchange partners (Benjamin and Podolny, 1999; Podolny, 1993), or with prominent organizations (Baum and Oliver, 1991), or are homophilous along other relevant dimensions (Ring and Van de Ven, 1992) such as status, prominence or performance. Then, my “*performance homophily*” hypothesis suggests that:

Hypothesis: *Firms are more likely to acquire other firms experiencing a comparable level of performance.*

3. Research Design

3.1. Data

In this study I model the acquisition of equity stakes as network ties between international electricity firms. In order to do so, given the methodology used in this paper, I only focus on the minority acquisitions (partial ownership), i.e., less than 50% of the equity shares of the target firm can be bought by the acquiring companies. I had to restrict my empirical framework to the partial ownership to intentionally deal with partnership relations rather than full ownership relations. In other words two separate companies should be maintained after the acquisition event has been accomplished between two companies. The primary data source for this study is the SDC (Securities Data Company) worldwide global acquisition database, which contains information on all international and domestic acquisitions events worldwide since 1994.

The information on acquisitions’ transactions I gathered describe: the effective date of the transaction, the identity of the firms involved in the acquisitions events, the region of both acquirers and targets firms, the status of the transactions (completed, withdrawn, pending, intended, or unknown), the primary four digit SIC codes for both acquirers and targets, and the name of industry sector for both acquirers and targets. To extract my study sample I focused on three main criteria: 1/ all the companies (both acquirers and targets) must belong to Industry Group 4911(SIC): “Electric Services”: Establishments engaged in the generation, transmission, and/or distribution of electric energy for sale. I therefore targeted only on the within-industry group relations rather than the inter-industry group relations, 2/ all the companies should be publically traded which simplified my task to collect financial variables on each company included in the sample, 3/the status of the transactions has to be effectively “completed” rather than just “announced.” I ended up with a final sample that includes information on 2240 equity investment events among 223 companies operating in 40 counties and across five continents during the period 1994-2004. I coded the acquisitions’ transaction data as one-mode network matrix. The 223 selected firms constituted the actors of my networks. The eleven network matrices constructed for each year over the period of analysis were 223 by 223 square matrices. These matrices are binary; where I put 1 in the cell (ij) if there was an acquisition event between firm i and j, or 0 otherwise. As the unit of analysis is the dyad, all possible combinations of dyads are included; $N*(N-1)$ dyads for years 1994-2004, where $N=223$.

Figure-1. Network ties generated by investment decisions

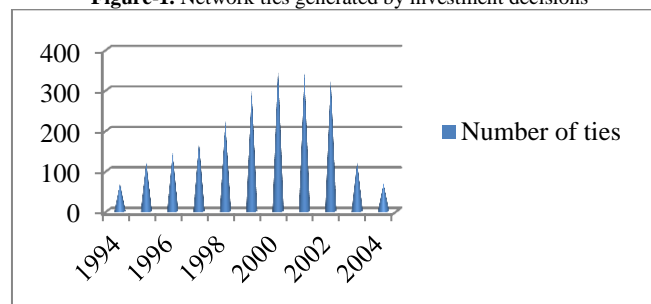
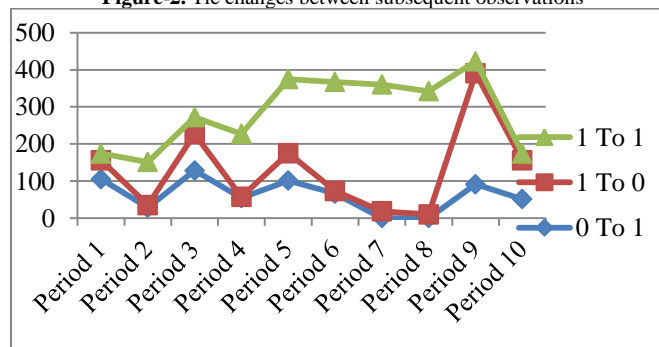


Figure-2. Tie changes between subsequent observations



3.2. Empirical Model Specifications

The stochastic actor-oriented model examines the changes between the observations as the result of many small changes in network ties. For instance, and at random instants, actors (e.g., electricity firms) get opportunities to make small changes to their own network neighborhood (e.g., acquisition transaction). These small changes are called “micro steps”. A network micro step provides of the opportunity to add or delete one outgoing tie, i.e., firms can select a new or de-select an existing acquisition partner. Micro steps are modeled in a probabilistic choice framework and can be interpreted as maximization of underlying objective functions denoted by f which include random disturbances.

Network objective function of firm i :
$$f^{\text{net}}(x, z_i) = \sum_k \beta_k^{\text{net}} s_{ik}^{\text{net}}(x, z_i) + \varepsilon_i^{\text{net}} \tag{1}$$

where, the ‘ S ’ terms stand for statistics that may depend on the network ‘ X ’ in the neighborhood of firm i , the distribution of performance ‘ Z ’, and other partners characteristics in this neighborhood. The model dynamics assumes that firms myopically maximize their objective functions at each network micro step. For each firm the choice of probabilities for network decisions expressed in terms of the random utility functions take the familiar shape of the multinomial logit model. For network micro steps, let $x(i \rightarrow j)$ denote the network that would result from firm i changing the acquisition tie to firm j , where $x(i \rightarrow i)$ formally stands for the firm making no change at all. The probability for such a micro step is :

$$\Pr(x(i \rightarrow j) | x, z_i) = \frac{\exp\left(\sum_k \beta_k^{\text{net}} s_{ik}^{\text{net}}(x(i \rightarrow j), z_i)\right)}{\sum_{\ell \in \{1, \dots, N\}} \exp\left(\sum_k \beta_k^{\text{net}} s_{ik}^{\text{net}}(x(i \rightarrow \ell), z_i)\right)} \tag{2}$$

The parameters in the model are estimated using the method of moments. The expected values cannot be calculated exactly or numerically, but they can be approximated by Monte Carlo simulations. The resulting estimates are simulated moment estimators as defined by [McFadden \(1989\)](#). The approximate solutions of the moment equation are obtained by stochastic approximation ([Robbins and Monro, 1951](#); [Snijders, 2001](#)). By repeated continuous-time simulation of model-derived trajectories, and by comparing these trajectories to the observed longitudinal data, it becomes possible to obtain parameter estimates for these models ([Snijders et al., 2010](#); [Snijders, 2013](#)). All parameters can be tested by Z-tests applied to the t -ratio calculated as parameter estimate divided by standard error.

4. Variables and Measures

4.1. Organizational Performance Measures

In the acquisition literature, the most frequent manner of measuring both ex-post and ex-ante acquisition performance was through the usage of accounting and financial indicators ([Byrd and Hickman, 1992](#); [Finkelstein and Halebian, 2002](#); [Hayward and Hambrick, 1997](#); [Sirower, 1997](#)). The main advantage of dealing with accounting and financial measures of performance is that they are widely accessible for many organizations and they provide enormous information about a firm’s operations. For these reasons, research in strategy and strategic management mostly focused on the impact of strategy on a firm’s financial performance. Accounting approaches to characterizing a firm’s performance often rely on ratio analysis. In this paper I use two of the most important accounting ratios to measure my organizational performance variable: return on assets and retained earnings: *Return on assets (ROA)*: calculates the amount of profit that an organization produces based on its existing assets. Once the organizations’ assets are defined uniformly and the value of ROA is compared with the average of the industry, this ratio can lead to meaningful inferences. Therefore, a higher ROA is often advantageous. Commonly measured each year, ROA reflects typically the stability of the management of a given firm and determine its capability to generate profits. For software and methodology purposes, I categorized (coded) the behavioral dependent variable into 5 groups: very low, low, average, high and very high based on the boxplot distribution. *Retained earnings (RE)*: by definition it is measured as the percentage of net earnings not paid out as dividends, but retained by the company to be reinvested in its core business or to pay debt. It is calculated by adding net income to (or subtracting any net losses from) beginning retained earnings and subtracting any dividends paid to shareholders” (quoted from the financial dictionary). Mostly, firms preserve their earnings in a way to invest them into fields where it can capture and take advantage of growth opportunities, such as expending these earnings on more research and development projects or buying new equipment like machinery. Similarly, for software and methodology purposes, I categorized (coded) the behavioral dependent variable into 5 groups: very low, low, average, high and very high based on the boxplot distribution.

Figure-3. Return on Assets (RAO) = (Net income+ Interest expenses)/Total assets

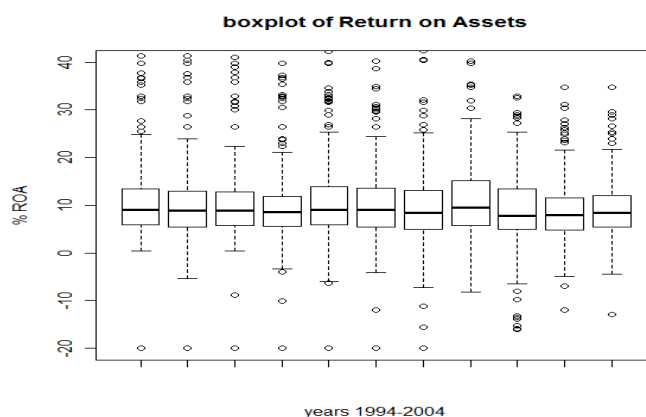
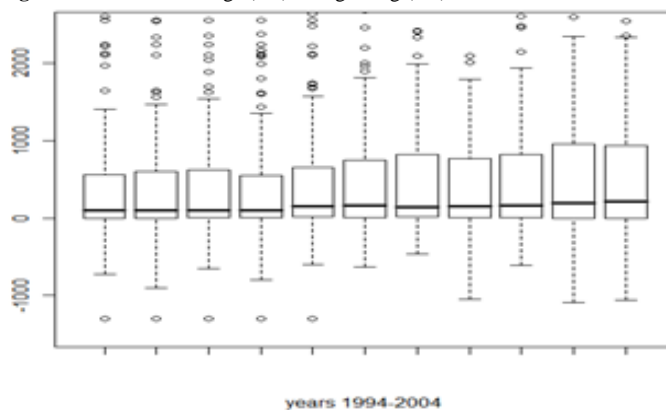


Figure-4. Retained earnings (RE) = Beginning (RE) + Net Income – Dividends



4.2. Endogenous Effects on the Network Structure

These covariates are included to control for well-known tendencies of networks to self-organize into a variety of local configurations. Endogenous network effects include: (i) density (out-degree) to control for the latent tendency of organizations to have outgoing ties (i.e., to invest); (ii) reciprocity to control for the tendency for organizations to engage in reciprocated investment relations (cross-holdings). Following studies on interorganizational networks (e.g., (Lomi and Pattison, 2006), I also allowed for the presence of more complex (triadic) dependencies by controlling for: (iii) transitivity, (iv) brokerage, which indicates the preference for keeping other at distance 2, and (v) structural equivalence, the tendency of organizations to select partners occupying the same network position. Finally, I controlled for (vi) popularity of alters to capture the preference of individual electricity companies to invest in popular other companies. The qualitative patterns and the verbal descriptions implied by the network motifs included in the model are summarized in Table 1.

Table-1. Endogenous effects for modeling network evolution For effect statistics see (Snijders et al., 2010, 2013)

Network	Effective transition in Network	Verbal description
Out-degree		Preference for ties to arbitrary partners
Reciprocity		Preference for reciprocated ties
Transitive triplets		Preference for being partner of partners' partners
Balance (Structural Equivalence)		Preference for ties to structurally similar partners
Actors At Distance 2		Preference for keeping partners at distance 2
Popularity Alter		Preference for attaching to popular partners

5. Results and Analysis

I organize the presentation of my results around the estimates reported in Table 2. I estimated a basic model 1 in which I included only the intercept effect and the endogenous network effects. I reported a negative and significant estimate of the out-degree parameter (-6.331, p-value<0.01). Actually this gives information on the implied cost associated with each acquisition transaction within the network. Given the nature of the network tie (acquisition transaction), it is obvious that reciprocity parameter would not be significant because for a firm i that buys some shares from a firm j, this does not imply a reciprocated tie from j to i. This expectation was confirmed by my result in model 1. I checked for the possibilities of triadic closure in our networks by including the corresponding endogenous network effect to the network objective function and checked whether or not they have an effect on tie formation. While the transitivity effect parameter was positive and highly significant (1.117, p-value<0.01), the geodesic distance 2 effect parameter was negative and also highly significant (-0.316, p-value<0.01). The effects of transitive triplet (positive) associated with the effect geodesic distance-2 (negative) show that there are closure tendencies, i.e., partners of partners tend to be partners. The popularity of alter parameter was positive and significant (0.986, p-value<0.01) which means that the more the shares of a target company j are being bought by other firms (k, l, m...) the more is the tendency that the focal firm i will buy shares from j. Finally, there was significance of the balance (structural equivalence) parameter. Electricity firms that occupy almost the same positions in the network have tendency to compete (e.g., initiate acquisition ties to a third firm) rather than

collaborate (e.g., exchange mutual network ties). This result was shown by the balance parameter which was negative and highly significant (-0.180, p-value<0.01).

Table-2. Models and Parameter Estimates (standard errors in parentheses)

Network Selection	Model 1	Model 2	Model 3	Model 4
Out-degree (density)	-6.331** (0.348)	-5.310** (0.234)	-5.270** (0.261)	-6.387** (1.420)
Reciprocity	0.425 (0.376)	0.292 (0.405)	0.738 (0.429)	0.407 (0.719)
Transitive triplets	1.117** (0.271)	1.407** (0.296)	1.280** (0.178)	1.170** (0.236)
Balance (structural equivalence)	-0.180** (0.057)	-0.175** (0.032)	-0.180** (0.023)	-0.175** (0.031)
Number of firms at distance 2	-0.316* (0.145)	-0.259* (0.114)	-0.214* (0.102)	-0.203* (0.097)
In-degree popularity	0.986** (0.162)	0.868** (0.143)	0.910** (0.151)	0.963** (0.206)
RE alter		0.190* (0.082)		0.169* (0.068)
RE ego		-0.124 (0.090)		-0.125 (0.093)
RE similarity		1.596** (0.325)		1.532** (0.317)
ROA alter			0.052* (0.024)	0.012* (0.004)
ROA ego			-0.158 (0.096)	-0.058 (0.076)
ROA similarity			1.855** (0.365)	1.255** (0.485)

Note: Standard errors are in parentheses. **=p<.01 * = p<.05

In model 2, further to the structural network effects included in model 1, I checked whether the potential electricity firms' performance, as measured by their retained earnings, constitutes a potential predictor for acquisition transaction network tie. I included the sender (ego), receiver (alter), and average similarity effects in the model. The results I found confirm my theoretical hypothesis. In effect, the average similarity (RE) parameter was positive and highly significant (1.596, p-value<0.01). This result suggests that electricity companies are more likely to acquire others with similar levels of performance. It is worth also to mention that the receiver parameter effect (alter) was positive and significant (0.190, p-value<0.05). One possible explanation to this result is that electricity firms, and in addition to establishing partnerships with homophilous others in terms of performance, it also prefers to acquire form companies that are experiencing an improvement in their performance levels.

In model 3 I followed the same strategy as in model 2 but instead of including the (RE) as a performance measure, I tried to see whether my second measure (ROA) would generate identical results. Indeed, the results I found are quasi-identical. The average similarity (ROA) parameter was positive and highly significant (1.855, p-value<0.01) and the alter effect was in also positive and significant (0.052, p-value<0.05). The interpretation of my results in model 3 is then similar what I explained in my model 2.

Finally, in model 4 I tried to look for the interaction between my two performance measures if tested for significance together in the model. So I included (RE) and (ROA) together in model 4 jointly with the usual effects (i.e., ego, alter, similarity). I reported high significance of both similarity effects for (RE) and (ROA) with (1.532, p-value<0.01) and (1.255, p-value<0.01) respectively. However the only difference, when including my two performance measures, with models 2 and 3 is that the corresponding receiver effects remain positive but turnout insignificant.

6. Conclusion

As shown in the interorganizational literature and discussed in the theoretical part of this paper, organizational outcomes of network-oriented processes of social influence most likely affect individual partner selection decisions. Despite the majority of these empirical findings only tested the performance homophily hypothesis with cross sectional and static data, a few of them used a panel and dynamic data, but none on acquisition transactions' networks. Moreover, the studies on acquisition often examined the impact of the acquisition transactions on post-acquisition performance for both acquirers and targets. However, and as far as I know, the argument of how companies take into account performance considerations when deciding to acquire equity stakes from others has not yet been tested in an evolutionary network-selection dynamism. Therefore, I tried in this study to bridge this gap in the interorganizational literature by specifying stochastic actor-oriented models for the acquisition network-selection process in the global electricity industry based on organizational performance.

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