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The Role of Firm Network Embeddedness on Merger & Acquisition Success:
A Study of the Automotive Industry

by

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Abstract

Firms build network linkages across different dimensions to access external resources provided by other network participants. These network resources are embedded within the network linkages and as such can only be access by a firm through network participation. This study extends the concept of network resources into the M&A literature stream by theorizing that network resources strategically combined lead to resource synergies and thus, an added-value through a M&A transaction. This begs the question of what combination of network configurations managers should look for. Subsequently, I determine network combinations based on two network dimensions through which a firm's access to network resources is determined: (1) Network Centrality, i.e. how central a firm is within its network and (2) Network Geographic Embeddedness, i.e. to what extend a firm is locally or globally embedded. Following the concept of strategic complementarity in which mutually supportive differences in firm resources achieve a combinational advantage, I show that the combination of network resources results in similar combinational advantages. In extension, the combination of buyer firm and target firm network embeddedness has an impact on M&A performance. I empirically test this concept on a network dataset of 5,524 linkages, including vertical, horizontal, shareholder, internal and board member subnetworks in the context of the automotive industry in North America.

Key Words: *Network Embeddedness, Network Centrality, Network Local Embeddedness, Network Resources, Network Theory, Mergers and Acquisitions, Strategic Complementarity, Merger and Acquisition Success, North American Automobile Industry*

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AV	Autonomous Vehicle
BEV	Battery Electric Vehicle
CAPM	Capital Asset Pricing Model
CAR	Cumulative Abnormal Return
EV	Eigenvector Centrality
FCA	Fiat Chrysler Automotive
GM	General Motors
IB	International Business
M&A	Mergers and Acquisitions
MNE	Multinational Enterprise
N	Firm Network
NAICS	North American Industry Classification System
OEM	Original Equipment Manufacturer
PSA	Peugeot Société Anonyme
TM	Transplant Manufacturer

iv. Preface

Whilst exploring different international business (IB) streams in search for a research field and subject, I came across a visualization of global corporate ownership networks as a part of the International Business M.S.c. curriculum. The course *Industry Analysis* directed by Prof. Ekaterina Turkina, “forced” me on the prowl for interesting data visualizations to present to the class. It was then that I stumbled upon Vitali et al. (2011)’s visualization of the global corporate ownership network. Both the visualization and extreme explanatory power behind its network analysis inspired me to further explore social network theory. Furthermore, as with years spent tumbling within the automotive supply chain in Detroit and Munich, I realized that the explanatory power of social network theory could uncover novel insights in the light of strong industry disruption. Particularly in explaining how traditionalist, like industrial manufacturing, willingly collide with the modernist, like tech start-ups in search of reviving industrialist productivity in Western economies. For that reason, I chose to explore social network theory in the context of M&A activity in the North American automotive industry.

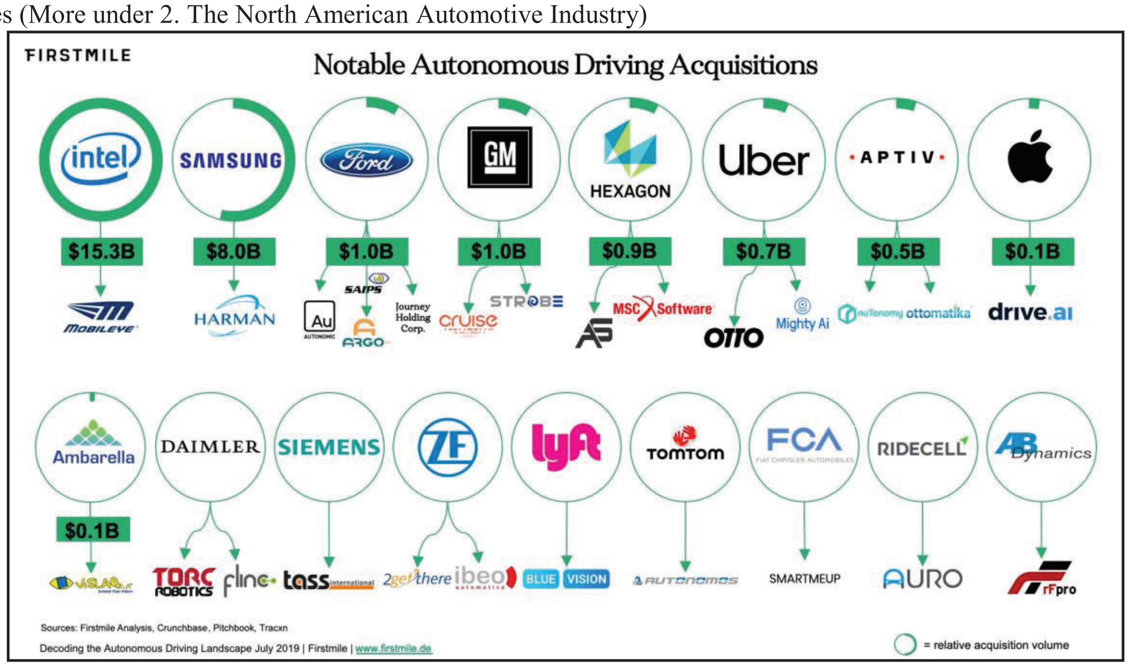
v. Acknowledgements

Throughout the process of preparing this work, I would like to thank my friends and family for their continuous emotional and theoretical support as well as Ekaterina Turkina for her academic guidance. I further would like to thank all voluntary and involuntary listeners for their comments and thoughts.

1. Introduction

"I believe that the automotive industry will change more in the next 5 years then it has in the last 50." This is what General Motor's CEO and Chairman Mary Barra said in the context of the World Economic Forum in January 2016 (WEF, 2016). Mrs. Barra's comment comes at a time where technological disruptions and social pressures are shaking the automotive industry to its foundation. The rise of battery electric vehicles (BEV), car-sharing and autonomous vehicles (AV) is leaving purebred industrialists in Detroit, Wolfsburg or Toyota scrambling for ways to adapt (The Guardian, 2018; The Guardian, 2015; BCG, 2016; The McKinsey Company, 2017). This fundamental shift does not only impact car manufacturers themselves but in the age of global value chains, this shakedown can be felt all along the automotive supply chain (Reuters, 2019; PWC, 2018). To cope, automakers are rushing to amend their existing capability portfolios to bridge knowledge gaps such as in BEV software and are often opting for inorganic growth strategies (PWC, 2019). This spike in M&A activity can be seen in the size and number of acquisitions of autonomous driving firms by established automotive players such as FCA, Aptiv or ZF as well as alternative mobility providers such as lyft or automotive industry novices such as Apple (Figure 1).

Figure 1: Visualization of "Notable Autonomous Driving Acquisitions"
Figure published by *medium.com* in cooperation with VC Fund Firstmile (*www.firstmile.com*)[1]; Transaction buyers include OEMs such as Ford, GM, and FCA, Tier 1s such as Aptiv and ZF, and auto industry novices such as Apple. This underlines that AV solutions might only be presented by incumbent players but also through new market entries (More under 2. The North American Automotive Industry)



[1] Accessed on December 10th, 2019 under *https://medium.com/@firstmilevc/avlandscape-8a21491f1f54*

The gaps to bridge may run deep as Amsterdam-based KPMG consulting and auditing laments in a 2017 study. In it, KPMG states that the automotive industry lacks the needed capabilities to manage technological disruptions such as autonomous and/or electric vehicles (KPMG, 2017). Yet, with time being short for firms to react to challenges, non-organic growth seems to be the common approach (WEF, 2016; PWC, 2019). However, "shopping" capabilities through these external growth strategies does not always yield the aspired results. Christensen et al. (2011) estimate that roughly 70-90% of M&A transactions fail to deliver on anticipated results, e.g. the Daimler Chrysler merger of 1998 to 2007 (Maynard, 2009). Yet, how can firms deliver on capability and value growth through M&A transactions?

One answer may lie in the notion of network theory. It describes networks as harboring industry-specific resources and capabilities that lay outside of the formal boundaries of the firm (Lavie, 2006). These resources are accessible for firms through their network participation (Gulati, 1999). These network resources are seen as a crucial element of a firm's knowledge creation process and their impact can be seen in the rise of firm cluster research and organizations (e.g. Porter, 1980). Researchers have rushed to study the determinants and constellation of network effects, e.g. network embeddedness or geographic embeddedness (Bathlet et al., 2004; Lavie, 2006; Lorenzen and Mudabmi, 2013). In extension, academia identifies these two structural dimensions as differentiation factors between networks: Network centrality and Network geographical embeddedness. However, current network research has only gone so far as to study network resources in non-changing static, isolated networks. Researchers have thus far neither focused on the dynamic process of two networks merging nor on the combinational effects that may arise from such a merger.

Similarly, M&A literature has struggled in explaining the pitfalls in resource-based strategies and has limited a firm's resources and capabilities into the confined formal frame of its legal entity. Combinational network effects, i.e. the effect of combining networks into one, are often reduced to simple market power advantages such as increased bargaining power towards suppliers (e.g. Chatterjee, 1986, 1991; Devos et al., 2009; Fiorentino and Garzella, 2015; Bauer and Matzler, 2014). Current research fails to address networks and their effects.

In this thesis, I bridge these existing shortcomings in academic literature by combining two streams of International Business research. I do this by confronting network theory research with the dynamic context of M&A research in which two networks are merged while expanding M&A literature's definition and scope of analysis behind the formal boundaries of a firm into a firm's external network. Through this, I will expand the prevalent academic status quo of determining whether an M&A transaction will deliver value by the dimension of a firm's external network.

Given the magnitude of changing facing the automotive industry and the heavily cooperation-based strategies it has followed in recent years, the automotive industry offers a unique opportunity to address these shortcomings (PWC, 2019).

To identify network effects, I examine the network structure of target and buyer firms within an M&A transaction and analyze the impact of combinational effects on M&A performance.

This thesis is organized as follow: First, I provide a qualitative outline of the North American automotive industry to provide background context on my testing environment. Given my testing environment is the automotive industry, it is especially important because of specific automotive industry dynamics not found anywhere else. Secondly, I outline existing literature on both network theory and M&A performances and conclude with the theoretical framework building up to the formulation of my hypotheses. Thirdly, I introduce my data sample and empirical model based on OLS multilinear regression to test my hypotheses. Next, I present my regression results and the discussion of my findings. Lastly, I conclude my thesis with implications for practitioners and an outlook for future research potential.

2. The North American Automotive Industry

I begin my thesis by providing contextual background information on the study industry: the automotive industry. Characterizing the context is important as individual firms are highly influenced by the dynamics of their industry and specifically the automotive industry exhibits highly particular (Sturgeon et al., 2008). These attributes revolve around high innovation creation, e.g. as measured in patent registration, with strong cost pressures, e.g. as measured through competition analysis. In extensions, the automotive industry is also the showplace of strong technological disruption in which it is confronted with challenges changing the nature of vehicle use and thus manufacturing. Geographically, these effects are most strongly present in mature vehicle markets, whereas North America with an existing dominance in disruptive technologies can be seen as the forefront of these changes. Century old networks in Detroit and the Windsor-Toronto corridor are teaming up to young automotive start-ups environments from Silicon Valley, Toronto and Montréal. Therefore, the automotive industry in North America is a particularly interesting area to study the effects of networks combinations.

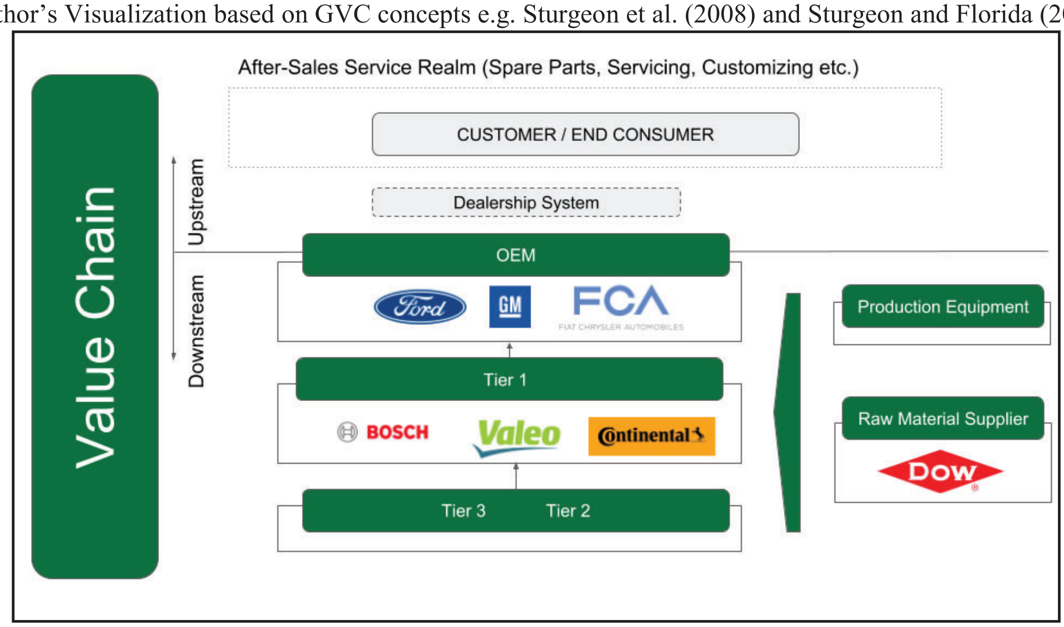
Firstly my analysis will cover an overview of the automotive value chain and its actors in North America. Secondly I provide an overview of key cluster “hotspots” with special focus on the “Motor City” of Detroit, Michigan (Bathelet et al., 2004).Thirdly I conclude my industry analysis with a look at its trends and their implications on current industry structures.

2.1. North American Automotive Value Chain

First off, an industry value chain can be seen as core dynamic “grid” of an industry and as such is vital in understanding industry dynamics (Hannigan et al., 2015). Value chains outline the creation of value from raw material to final consumption by the end customer. Graph 1 visualizes this structure in the context of the automotive industry (Sturgeon et al., 2008; Sturgeon and Florida, 2004). It divides the value chain participants into downstream and upstream actors or front-end and back-end of the automotive industry. The front-end or upstream side of the value chains describes all activities after the final production of the vehicle such as vehicle sales through traditional dealership systems or direct-sale OEM subsidiaries, e.g. Tesla, or after-sales service activities such as vehicle customization, repair or spare part sales. On the other hand, downstream or back-end activities describe all value chain steps that contribute to the production of the vehicle. In extension, OEMs function as the point of contact between the upstream and downstream activities. They represent the final customer of all manufacturing activities and the starting point for upstream activities. In my study, I will focus on the back-end or downstream activities, i.e. the manufacturing of vehicles in North America.

Graph 1: Overview of the North American automotive value chain

Author’s Visualization based on GVC concepts e.g. Sturgeon et al. (2008) and Sturgeon and Florida (2004)



The downstream value chain as shown in Graph 1 comprises primarily of original equipment manufacturers (OEMs), tier 1 to 3 suppliers, as well as supporting industries. OEMs as the pivotal point between upstream and downstream activities in the value chain play a dominant role in the dynamics of the industry (Figure 1). Generally, North American OEMs can be divided into three groups: U.S., Asian and European manufacturers. U.S. OEMs comprise of “the Big Three“, i.e. Ford, General Motors (GM) and Fiat Chrysler Automotive (FCA), as well as automotive newcomers, most well-known of which being Tesla, Inc. Generally, automotive manufacturing is based on sub-group modules. OEMs buy the majority of sub-group modules, e.g. steering wheel module, dashboard module, seat modules and then assembly them into the final car in the last production step. Tier 1 suppliers sell these in-house assembled sub-group modules to OEMs while subcontracting the actual production of parts for the sub-group modules to Tier 2 suppliers. Depending on the complexity of the modules, suppliers “pass along” easier production steps, such as the manufacturing of plastic pins of the sunroof module down the value chain. This represents a particularly strong specialization of the value chain driven by strong cost pressures that push sub-group module manufacturers to outsource components to specialized suppliers who are able to achieve higher economies of scale by focusing on said sub-component. An example of this is VERNICOLOUR Group; a French tier 2 supplier specialized on the manufacturing of plated airbag covers for steering wheel modules. This can be seen in the visual representation of Fiat Chrysler Automotive (FCA)’s list of Top US Suppliers for 2017, which categorizes suppliers within their respected value chain (FCA, 2018) [Appendix A].

Lastly, the value chain is fed by supporting industries such as production equipment suppliers or raw material suppliers, such as plastic resign or steel manufactures. These supporting industries are characterized by the fact that they often do not exclusively supply one industry, i.e. the automotive industry, but related industries as well. An example is the injection molding machine manufacturers. These firms produce machines for plastic production and although they supply the production equipment for all plastic-based components in the automotive industry, they also supply their equipment to plastic packaging or the medical devices industries. These industries can also be seen in the related clusters to the automotive industry in the U.S., in which the automotive industry is linked to metalworking, production technology, and the plastics industry (U.S. Cluster Mapping, 2018).

Geographically, the value chain spans Canada, the U.S. and Mexico through a North-South Corridor known in as the “auto alley“. This corridor spans the U.S. from Michigan in the North to Alabama in the south and could be extended by the Canadian “Windsor-Toronto Corridor“. In Mexico, vehicle production is primarily located in the heavily populated center from around Mexico City to Aguascalientes and San Luis Potosi as well as the areas surrounding the U.S./Mexican border[2].

The US remains North America’s main supply and demand market accounting for 67% of North American vehicle production, as visible in Appendix B while US automotive firms account for 79% of total automotive related turnover in North America (MexicoNow, 2018; Statista, 2019).

In Mexico, pre-NAFTA automotive production was primarily for the domestic market and driven by foreign OEMs and their investments into e.g. Sonora (Ford) and Coahuila (GM and Chrysler), as well

[2] Border States with significant vehicle production are Baja California, Sonora, Chihuahua, and Coahuila (US Cluster Mapping, 2016)

as in Aguascalientes (Nissan) and Morales (Volkswagen). With the introduction of NAFTA in 1990, Mexico's share of vehicles exported surged to roughly 80% of local production up from about 15% in 1985 (Klier and Rubenstein, 2017) [Appendix C]. Of all exported vehicles, the majority are exported to the U.S. and Canada. Despite the high intercontinental export ratio for vehicle production in Mexico, only in the case of VW does an OEM's Mexico-based facility represent its largest production facility in North America and only VW does not have any other production sites within the U.S. or Canada (Klier and Rubenstein, 2017). In recent years, additional automotive manufacturers, such as Hyundai-Kia or Honda, have opened production facilities with BMW and Toyota pleading to establish themselves by 2020.

Overall, the value chain of the automotive industry can be characterized as what Sturgeon (2008) calls a "nested structure". On the one hand side, the industry seeks to geographically disperse value chain activity to lower wage areas, i.e. Mexico, which can be seen by the rise of automotive manufacturing in Mexico in early 1990s. On the other hand, the industry is confronted with high political pressures in Canada and the United States to localize production as well as by the need to customize production to local needs (Sturgeon, 2008). Particularly in the U.S., political pressure can be enormous and its influence on the value chain can be seen in the rise of transplant manufacturers (TMs).

Generally speaking, TMs are foreign-based automotive OEMs which have established U.S.-production capabilities. Historically, TMs are associated to the growing market share of Japanese vehicle imports into the U.S. market in the 1960s and 1970s up to its peak of about 17% of total vehicle sales in the U.S. in 1970 (Bureau of Labor Statistics, 1992). During this growth period, US policy makers became increasingly concerned about the rise of Japanese automotive imports. Subsequently, policy makers introduced a limit on foreign vehicle importation (Sturgeon and Florida, 2004). In response, the 1980s saw a wave of plant installations by Japanese manufacturers to circumvent established limits. By 1989, Japanese car sales from local production reached 15% of the total car sales in the US, up from 0.5% in 1982. Follow this surge in Japanese plant installations, other OEMs emulated the Japanese "build-where-you-sell" strategy with German manufactures opening plants in the late 1990s and the Korean Kia-Hyundai group following in the early 2000s (Sturgeon, 2008). In response to the increase in local OEM production activity, the automotive industry developed a hub of specialized clusters to maximize economies of scale, in e.g. R&D, while constrained by localization factors such as political pressure and the need to adapt to local needs (Sturgeon, 2008) [Appendix D].

To analyze the industry dynamics, I next turn to Porter's five forces framework (Porter, 1980). However, I extend his original framework by an additional dimension: an institutional dimension [Appendix E]. This dimension aims at capturing the impact of the institutional environment on industry dynamics and is particularly important for the automotive industry given its high political visibility.

The market entry barriers can be analyzed through the market entry of California-based manufacturer Tesla, Inc. Founded in 2003 and taken over by prominent Silicon Valley figure Elon Musk in 2004, Tesla produces electric vehicles and with annual revenues of $21.5 billion USD is widely considered as an active player in the automotive market in 2018[3].

The first entry barrier is high capital requirements in the development, operationalization and subsequent release of a vehicle. In the case of Tesla, it took Tesla 9 years to introduce a vehicle with noticeable market penetration[4] with the Tesla S, which would later become the second most sold battery electric vehicle (InsideEVs, 2018). From 2010 to 2012, which represents half of the average Research & Development (R&D) time for vehicles, Tesla spent $243.42 million USD on R&D for its early models (Statista, 2019). In contrast for the Tesla Model 3, Tesla spent an estimated $23 billion USD on R&D (Statista, 2019). Furthermore, Tesla has been operating on a net loss since 2008 and ended the 2017 with $9.4 billion USD in outstanding debt (Bloomberg, 2018). These figures underline the high capital requirements and constraints to enter the automotive market as a new OEM and posse a serious constraint for potential new competitors. Furthermore, the production of automobiles also requires a high degree of specialized production knowledge. Tesla, for example, faced serious issues in their production process of the most recent Model 3. Despite promising a total of 200,000 produced vehicles in 2017, Tesla was only available to deliver an estimated 2,700 from 2017 to early 2018 and cumulatively was only able to manufacture 231,000 by early 2019 (Bloomberg, 2019). This shows the operational difficulty of large scale vehicle production and the specialized knowledge needed for it.

Hence as the case of Tesla shows, high capital requirements and a high degree of specialized knowledge needed in vehicle production decrease the threat of new market entry and function as high market entry barriers.

Next, I turn to study the threat of market substitutes for automotive vehicles which I analyzed through its definition and history of substitutes. Automobiles are defined as a four-wheeled, self-propelled road vehicle (Merriam-Webster, 2018). Therefore, electric or hydrogen powered vehicles are per definition also automobiles and cannot be seen as substitutes. In effect, road vehicles substitutes are limited to self-propelled vehicles with more than 4-wheels, such as trucks or commercial buses, less than 2-wheels, such as motorcycles, or non-self-propelled road vehicles, such as horse drawn carriages or bicycles. Alternatively, non-road-based vehicles can also be considered substitutes such as boats or airplanes. However, most practically vehicle substitutes comprise of alternative transportation methods such as public transport. Despite a sharp incline in public transportation spending in North America and

[3] Source: Tesla Website (*https://www.tesla.com/*)

[4] The Tesla S was not Tesla's first vehicle release. Its first was the Tesla Roadster, which sold a mere 2,700 units in active production four years (InsideEVs, 2018)

strong usage rates in populated metro areas such as Toronto, New York, Mexico City, or Montréal, stark population dispersion, e.g. in rural areas and weak public infrastructure deem public transportation a low substitute in North America as a whole. In extension and particularly valid in rural areas, the threat of direct substitutes are low. However, with increasing urbanization, alternative mobility concepts arise which indirectly affect the automotive market. Their effect is indirectly as these would not substitute the automobile but rather decrease their volumes. These concepts revolve around shared vehicles, raid hailing and autonomous driving concepts (McKinsey, 2016). Yet, while the threat of indirect substitutes could have substantial impacts on the automotive market, I do not see them as a substitute for vehicles but rather as industry trends to be discussed under 4. *Industry Trends*. Consequently, I conclude that the overall threat of direct substitution is very low in rural areas while low in urbanized communities.

Next, I analyze the bargaining power of suppliers in the industry. First, we differentiate suppliers along the value chain of the industry into tier 1 suppliers, tier 2 to 3 suppliers, and supporting industry suppliers. For tier 1 suppliers, their bargaining power has shifted from low to medium as the nature of tier 1 linkages to OEMs has changed from captive linkages in the 1980s to relational linkages in the 1990s with the spin-off of sub-system manufacturers such as Delphi and Visteon. However, at the same time more linkages turned into market linkages as OEMs, particularly valid for "the Big Three" from 2002 to 2009, increasingly used predatory supplier switching behaviors to keep supplier bargaining power low (Sturgeon, 2008) [Appendix F]. This shift is the result of an outsourcing boom with the opening of low cost labor countries such as Mexico in 1995 (Sturgeon, 2008). Furthermore, predatory supplier switching behavior is often cited as the cause for widespread supplier bankruptcies from 2000 to 2008 and laid the foundation for a risk-averse investment environment on the side of tier 1 suppliers. In contrast, Japanese TMs introduced their cultural-based habit of relational linkages with suppliers into North America, which is visible from 2004 through 2008 in Appendix F. Alongside the outsourcing and the rise of market-based linkages, came the rise of the global supplier (Sturgeon, 2008). The global supplier consists of a global manufacturing footprint with localized production alongside OEM facilities (Sturgeon, 2008). Today, 14 of 20 Top North American suppliers are also represented in the list of Top 20 global suppliers (Automotive News, 2018; 2009). Furthermore, the standard deviation of revenues by region for the Top 20 Global suppliers dropped by an average of 76% across all regions for 2018 in comparison to 2008 with similar average revenues per region (Author calculation based on data by Automotive News, 2008; 2018). This implies an increased homogeneity of regional revenues across regions in favor of the regionalization of "global supplier" (Sturgeon, 2008; Automotive News, 2018; 2009). Despite this increase in supplier power, tier 1 suppliers are still dwarfed by OEMs in sheer size. In 2018, the average sales of the three largest tier 1 suppliers to North America had an average annual sales volume of 35.6 billion USD versus an average sales volume of 140.4 billion USD for "the Big Three" OEMs (Automotive News, 2019; Ford, 2019; GM, 2019; FCA; 2019)

Furthermore, the 2008/09 crisis marked a turning point for both Japanese and U.S. OEMs as production volumes declined rapidly leaving many OEMs underfunded [Appendix F]. Subsequently after the crisis suppliers took on more and more production capacity as OEMs were keen to outsource capital intensive engineering costs. This consequently gave tier 1 suppliers more bargaining power through increased specialization on certain subsystems.

In addition, the post-crisis investment attitude of tier 1 supplies had changed. As an industry insider from a tier 1 supplier describes: "If a tier 1 was maxed out[5], an OEM would come and ask for them to build another facility to support additional capacity. Pre-crisis, a tier 1s would jump and invest with a wink of an eye. Post-crisis, that wasn't the case. Tier 1s simply didn't trust OEMs to hold volumes and had experienced what happens when volumes dropped. In 2008/09, as volumes declined, OEM pulled contracts regardless of past promises to hold volumes". Ultimately, the increasingly internalized capabilities alongside with distrust towards OEMs, shifted bargaining power more in favor of tier 1 suppliers. Despite this increase, OEM positioning and size keep supplier bargaining power low to medium. For tier 2 to 3 suppliers however, this shift has not yet taken place and their bargaining power can be largely compared to tier 1 suppliers in the early 2000s. Tier 2 to 3s are predominantly small- to medium-sized enterprises (SMEs) with captive or market-based linkages. In addition, with the increasing price competition from low cost manufactures in Asia and Mexico, tier 2 to 3 supplier's bargaining power largely diminished further than it already was. However, similarly to the power shift of tier 1s, slow movement is visible. With highly competitive pricing associated with deteriorating product quality, an increased demand for 100% part traceability, as well as increased political pressure to localized production a market has emerged for high quality, small-to medium scale global tier 2s to tier 3s. These manufacturers are still predominantly family-owned SMEs but with multiple global facilities providing localized production as well as low cost labor facilities in Eastern Europe or Mexico. Yet, despite a slowing shift, the bargaining power of tier 2 to 3 suppliers remains low.

In the case of supporting industries, the commodity-based nature of these industries, such as resign or steel manufacturing, implies a strong maturation in their industrial lifecycle. However, with the rise of automation and industry 4.0, supporting industries may see an increase in bargaining power as activities are consolidated to offer "turn-key solutions"[6]. Nonetheless, supplier bargaining power for

[5] Note by author: "maxed out" refers to tier 1 suppliers reaching the limit of their current production capacity.
[6] Phrase describes projects in which customers must only "turn the key" of the production cell to start production in contrast to less complex production systems in which the customer typically buys the machines and automation separately and would set up the projection cell himself.

supporting industries remains very low as the demand for simple parts as opposed to complex parts in need of 4.0 production remains high.

Overall, supplier-customer relationships are mainly based on relational and market linkages. This can be seen in the main motivations behind M&A activity in the automotive industry. There, KPMG identifies that the main price driver for an automotive supplier is their access to the customer base of the purchased entity (KPMG, 2010). While this is an indication of relational linkages, a second growing driver is also identified. It is technology. The rise in importance of technology as a M&A price driver can be seen as an indicator for the increasing specialization of suppliers and their upwards mobility in terms of bargaining power. Yet, despite upward momentum for tier 1 suppliers, total supplier bargaining power remains low.

The bargaining power of automotive buyers, i.e. the OEMs, is corresponding to the low to medium supplier power high. These stem partially from aforementioned predatory purchasing behaviors in the early 2000s, their pivotal positioning in the automotive supply chain (Figure 1) and there critical size.

In addition, OEM bargaining power can be linked to industry standardization. For long, OEMs have hindered the formation of industry-wide standards in favor of OEM-specific standards (Sturgeon, 2008). The effect of which is an increased cost for suppliers to switch OEM customers and apply the products designed for OEM A onto OEM B. This is done through a system of standardization on a platform basis. Within a specific OEM, vehicles are grouped by platform in which a set of standardized components are used for a multitude of vehicles. For example, FCA's unifies, among others, the Alfa Romeo Giulietta, Dodge Dart, the Fiat Viaggio as well as the Jeep Cherokee SUV under the same platform (Reuters, 2014).

Furthermore, OEM bargaining power can be seen through the role OEMs play within the value chain. OEMs drive industry trends as the intersection between customers and the value chain. Along the value chain, the number of firms on the OEM level is 13, which is by far the lowest of any other value chain position. This further implies OEM bargaining power.

However, OEM bargaining power has recently found its limitations. Corresponding to increasing tier 1 bargaining power, OEM buyer power is challenged through the rise of "global suppliers" and the increased specialization of tier 1 suppliers. This can be seen in the network analysis of selected automotive supply chains. Despite differences in production location, country of origin and vehicle class, analyzed supply chains are increasingly centralized and homogenous and subsequently threaten OEM bargaining power [Appendix E]. Yet overall, buyer bargaining power remains high.

Next we look at competitive rivalry. Main focus is the cluster lifecycle stage as defined by Abernathy and Utterbeck (1975). The automotive industry can be characterized as a matured industry at the verge of decline. Despite continuous production growth since 2008, this can merely be seen as a recover back to pre-2008 production volumes [Appendix F]. For example, employment in the U.S. has seen an overall decline from 2006 to 2016 of roughly 17% CAGR while Canada's automotive employment dropped by 29% CAGR from 2006 to 2018 (U.S. Cluster Mapping, 2018; Canada Cluster Mapping, 2019). Meanwhile, Mexican employment has soared by 349% from 2006 to 2014 (CAR, 2014). Overall, MexicoNow (2016) predicts a growth stagnation around 17 million vehicles produced in North America annually and a CAGR of 0.5% from 2016 to 2024 [Appendix B]. The maturity phase of the cluster lifecycle is characterized with core competencies in manufacturing, process engineering and marketing. This correspond with the main price drivers in OEM M&A activity, in which marketing and technology take the top spots as price drivers (KPMG, 2010).

In effect, price is the main price driver as can be seen as early as the outsourcing boom in the 1990s with business-level strategy either cost-leadership or integration strategy and can be seen in recent times with production shifting into Mexico out of Canada and the U.S. (Sturgeon, 2008; Abernathy and Utterback, 1975). Subsequently, competitive rivalry is high.

Lastly, we analyze the institutional dimension as "sixth" dimension of Porter's five forces. In it, we explore the impact of the institutional environment, such as the political environment.

Politics have played a strong role in the development of the automotive industry in North America. Primarily driven by its largest actor, the United States, an early example of its impact is the 1980s rise of Japanese transplant manufacturers which were followed by Korean and German "build-where-you-sell" operations. In 1994, the North American Free Trade Agreement (NAFTA) between Canada, the U.S., and Mexico was introduced and Mexico's participation in the value chain rising to 23% of all vehicles produced in North America in 2018 (MexicoNow, 2018) [Appendix C]. In 2018, the North American Free Trade Agreement (NAFTA) was renegotiated as CUSMA, in which local content rules were further tightened[7]. These acts of protectionism give a steep contrast to automotive industry developments, which are characterized by price driven market mechanisms and volume decline. Since 1976, U.S. states have spent an estimated $17 billion USD in subsidies to automakers (Reuters, 2017). The 2009 bailout of GM alone cost U.S. taxpayers $11.2 billion USD and Canadian tax payers an additional $4 to $5 billion CAD (Time, 2017; Globe and Mail, 2015). Arguably, this political protection has slowed the demise of local production in the U.S. and Canada while at the same time favoring Mexico as low cost production location against other low cost countries, such as in Asia, through local content restrictions within North America.

[7] Website of the Government of Canada: (https://international.gc.ca/trade-commerce/trade-agreements-accords-commerciaux/agr-acc/cusma-aceum/index.aspx?lang=eng)

In conclusion, the automotive industry is as Sturgeon (2008) describes it, “Never fully global and never fully regional” as the industry is caught between, among others, economical pressure to globalize and political pressure to localize [Appendix D].

2.2. Automotive Clusters in North America and the “Motor City”

Geographically, we find both a dispersion of the value chain in North America as well as a clustering in particular areas. Most prominent is the “Motor-City” of Detroit, U.S.A, home of “the Big Three”. In addition to the Detroit cluster, we find clusters throughout the U.S. automation alley. Each cluster hotspot consists of one or multiple leading OEM plants with adjacent supporting industries, e.g. BMW in Spartanburg, North Carolina or FCA in Windsor, Ontario. The dispersion along the U.S. automation alley can be characterized by two trends: the rise of TMs and their installation away from "Big Three“-dominated Detroit as well as "Big Three“ plants aimed at utilizing local southern labor at lower relative costs than in the rust belt. Examples of such are the automotive cluster in Smyrna, south of Nashville, TN, led by Nissan and the Charlotte Cluster, led by BMW. Similarly, in Fremont, California, we see clustering in proximity to the Tesla facility. In Canada, the Windsor-Toronto Corridor is home to the Canadian automotive cluster with lead firms such as Ford, FCA, GM, Honda and Toyota. In Mexico, boarder states such as Sonora, Chihuahua and Coahuila De Zaragoza have historically been the target of primarily “Big Three” investments since before NAFTA with investments in Hermosillo in 1986 and Ramos Arizpe in 1981 due to their proximities to the United States (CAR, 2016). Central Mexican states such as Aguascalientes, Guanajuato and Puebla have attracted recent foreign direct investments (FDIs) through Nissan, Ford and Volkswagen (VW) and exhibit strong clustering.

The Detroit cluster is composed of OEMs such as “the Big Three”, FCA, Ford, and GM, as well as the majority of North American tier 1 and numerous suppliers along the value change. In the case of tier 1 supplier, 16 of the top 20 North American Suppliers are headquartered in the Detroit cluster. The analysis of five automobile supply chains with North America production shows that despite geographical dispersion 61% of suppliers have their North America headquarters in the Metro-Detroit area. In addition to strong private industry players, the “Motor city” cluster includes important institutional players from the North American automotive industry, such as the biggest Automotive Union in North America, the Union Auto Works (UAW), which counts 400.000 members across the U.S. and Canada[8]. Furthermore,

[8] UAW Website: *https://uaw.org/*

within the cluster we find the University of Michigan at Ann Arbor, which ranked 20th worldwide in both "Times Higher Education" and "Top Universities" 2017 rankings[9].

Overall, the Detroit cluster leads the U.S. and North America in terms of patent and overall employment, out-sizing the second placed clusters by staggering 432% and 53% respectively (US Cluster Mapping, 2016). Yet, Detroit's location quotient comes in at only 3rd place within the US at 6.4.

However, while static indicators show prosperous performance, dynamic indicators show change in Detroit. Overall employment has dropped by 3.5% since 1998 and the number establishment has dropped by 1% in the same period (US Cluster Mapping, 2016). Both dynamic indicators tell a tail of decline in production capacity in Detroit. Similarly, for growth in location quotient Detroit is outperformed by its main competitor, the nearby Toledo-area, by nearly 259% (US Cluster Mapping, 2016). In contrast, patent growth remains high at 6.6%. This showcases the evolution of the Detroit cluster. While automotive production remains high, it is in a steady decline in favor of lower cost labor locations, such as in the south of the US or in Mexico. What remains are Detroit's highly specialized R&D activities. But how does the Detroit cluster retain this R&D activity?

To analyze the Detroit cluster's ability to retain and foster R&D attractiveness despite decline production capacities, I use the Porter's diamond which highlights the availability of factors to the cluster (Porter, 1990). The framework breaks down cluster attractiveness into context for firm strategy and rivalry, factor conditions, related and supporting industries, demand conditions and government. In common approaches, "chance" is often added as an additional external component to show the probability of external changes. Yet, I follow the original depiction of Porter's diamond in which no such dimension is added. Next, I depict the context for Firm Strategy and Rivalry.

Domestic competition is strong, especially through increased specialization for formally low-cost automotive locations such as the Charlotte cluster or Montgomery cluster (US Cluster Mapping, 2016). This is further underlined by an overall maturity of the automotive industry in North America and the increase in intercontinental competition from Mexico. In contrast, Government interference remains high and most recently can be seen in the increase in local content rules as well as an artificial minimal wage for automotive workers.[10] As a result of increased regulation, long-term location planning becomes ever difficult. Furthermore, competition is largely based on price rather than innovation which can be attributed to the overall industry decline and hence has implication on R&D strategies.

[9] https://www.topuniversities.com/universities/university-michigan/undergrad
https://www.timeshighereducation.com/world-university-rankings/2019/world-ranking#!/page/0/length/25/subjects/3066/sort_by/rank/sort_order/asc/cols/stats

[10] Website of the government of Canada: (https://international.gc.ca/trade-commerce/trade-agreements-accords-commerciaux/agr-acc/cusma-aceum/index.aspx?lang=eng)

Factor conditions are access to highly specialized labor as a result of high labor specialization and access to highly skilled graduates from nearby universities, such as University of Michigan, Michigan State University or University of Detroit Mercy. However, due to periods of strong growth since the 2008/09, unemployment rates are low at 4.5% in June 2018[11]. Furthermore, high labor unionization makes labor costly (Smith, 2001). The Detroit Cluster is home to 16 of 20 top North America suppliers and serves as North American headquarters for 61% of supply chains analyzed. Cluster linkages are strongest with the metalworking industry, plastic production and production equipment. Each of which have major hubs in direct geographic proximity, such as mold making in Windsor area, metalworking in the Detroit and Cleveland area, and plastic products production in Grand Rapids, Detroit and Toledo.[12] Yet, even though authors, such as Bathelt et al. (2004), emphasize that co-location does not directly imply the transfer of tacit knowledge nor is it a sufficient condition, co-location can still be seen as a “strong temporal component” (Sturgeon, 2008). Additionally, interviewees overwhelmingly point out positive networking effects of co-location.

The Detroit cluster is at the heart of the largest automotive market in North America as well as has access to the entirety of the 17 million vehicles strong annual North American market [Appendix B]. However, demand is changing in favor of alternative propulsion methods such as electro mobility and alternative mobility concepts.

Lastly, the institutional environment is rich with special interests organizations such as the University research corridor, the Center for automotive Research, the Engines Manufacturers Association, and Alliance of Automotive Manufacturers that promote knowledge exchange and offer political access.

Overall, the factors available to the Detroit cluster highlight a past of production capabilities leveraged into the optimal R&D environment. Therefore, the core of the cluster can be seen as in its R&D capabilities, which also explain how despite industrial decline since the early 1900s, Detroit has remained at the forefront of the North American automotive industry.

2.3. Industry Trends and their Implications

2.3.1. Industry Trends

Major Key trends in the industries are battery electric vehicles (BEV), autonomous vehicles (AV), alternative mobility concepts (e.g. Car Sharing), and the inter-car connectivity (Duff and Phelps, 2018; Deloitte, 2017; McKinsey, 2016a).

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[11] Bureau of Labour Statistics Website (*https://www.bls.gov/eag/eag.mi.htm*)
[12] Based on location quotient, employment, specialization, and number of establishments taken from the US Cluster mapping Project.

The trend for electric vehicles in North America is driven by the market entrance of BEV-only manufacturer Tesla which manufactures 3 of the top 4 highest-selling BEVs in North America (InsideEV, 2018). However, globally China has seen strong growth in both supply and demand of BEVs with 43% of global BEV produced by Chinese OEMs while Japanese OEMs lead the industry in terms of industry adaptedness to BEV production (McKinsey, 2016b). Although the North American market has been a leader in the demand adaption of BEVs, which was largely driven through the popularity of Tesla, the global automotive industry has awoken and particularly Germany has made large advancements in both BEV supply and domestic demand (McKinsey, 2019a).

However, while increasing competition and rising BEV car sales, threaten traditional manufactures such as Detroit's "Big Three", this trend does not imply an existential challenge for the industry as a whole. Traditional suppliers are increasingly integrated into the North American supply chain with Tesla's supply chain of its 2016 Model X comparing surprisingly close to those of "traditional" OEMs such as GM and Ford [Appendix I]. Furthermore, continuous strict local content regulation will continue to push foreign OEMs into the Transplant Manufacturing model.

A second trend is increased uncertainty regarding the future of mobility. Alternative concepts could include the elimination of car ownership in favor of urban car shirring or ride hailing (McKinsey, 2019b). In total North America has invested an estimated $79 billion USD into mobility start-ups since 2010 alone with average valuations at staggering $170 million USD (McKinsey, 2019b). The core of the mobility shift must likely lies in autonomous driving. Traditionally, the development of new automotive technologies is driven by OEMs. In the case of autonomous cars, this has changed. Today, the primary companies investing in the development of autonomous driving are information technology companies, such as Google, Amazon, Apple, or Uber, while the invests from the traditional automotive industry are concentrated with tier 1 suppliers, such as Robert Bosch, Valeo, Aptiv or Continental (CBInsights, 2018).

The reaction of OEMs can be summarized in one word: Partnerships and acquisitions. The rise of the autonomous driving trend has seen almost every OEM teaming up either formally through M&A or informally through partnerships with a tier 1 or information technology giant to access specialized knowledge not currently developed by OEMs. Examples of which are numerous, such as partnerships between Toyota and Uber[13] or Robert Bosh and the Daimler Group[14] or GM's acquisition of Cruise[15]. This drives a shift in bargaining power in favor of tier 1s or information technology providers at the cost of OEM power.

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[13] Statement from Uber Technologies Inc. (*https://www.uber.com/newsroom/uber-toyota-team-self-driving-cars/*)
[14] Reuters, 2018 (https://uk.reuters.com/article/us-daimler-selfdriving-bosch/daimler-bosch-to-deploy-self-driving-taxis-in-california-test-program-idUKKBN1K02ZU)
[15] GM Cruise (*https://getcruise.com/*)

2.3.2. Implications for the "Motor-city"

The rise of BEVs has prompted the emergence of alternative clusters such as the San Jose Cluster in which Tesla's Fremont facility falls. This cluster has seen growth in location quotient by 31% and patent growth by 7.8% and subsequently ranking 2nd nationally after Detroit in terms of patents (US Cluster mapping, 2016).

Furthermore, the Detroit cluster is under threat as the trend for autonomous vehicles is fueled by specialized knowledge in information technology as well as traditional automotive engineering. However, similarly to the trends on the industry level, driving power is shifting in favor of automotive tier 1 suppliers as they are the ones driving change within the traditional automotive industry.

For Detroit, this constitutes an opportunity for future growth and cluster development as the majority of tier 1 suppliers are based within the Detroit cluster. The only continental competition lays in Silicon Valley and even then the trend for partnering with traditional automotive firms from the Detroit cluster is high, e.g. GM and Lyft.

All in all, while the rise of BEVs possess a need for the Detroit cluster to adapt to the changing needs within the automotive supply chain, past interactions with Tesla has proven successful and fuel expectations that the Detroit cluster will adapt to this challenges. In addition, the rise of autonomous driving brings a much brighter opportunity for the Detroit cluster as embracing change in favor of localized R&D knowledge and against simple automotive production could prove the final step in the transition of Detroit to a new Detroit based on knowledge-intensive activities. Past tier 1s have begun driving this change. Yet, now it is up to the cluster to embrace competition, foster cooperation and internalize knowledge capabilities.

This section concludes the contextual analysis of the North American automotive industry. Next, I turn to the literature review and theoretical framework of my thesis.

3. Literature Review and Theoretical Framework

To study the role of firm network embeddedness on Merger & Acquisition (M&A) performance, I first acknowledge the two main academic literature streams influencing my theoretical foundation. In isolation, no single stream of (international) business research is able to provide theoretical foundation to answer my research question. Therefore, I will merge existing network theory literature with existing M&A literature to build a theoretical bridge between them upon which I theorize the effects of firm network embeddedness on M&A transaction performance.

In a first step, I review literature from the study of social networks and network embeddedness. There, I find underlying rational for why firms engage in networks and how these interactions lead to increased capabilities and subsequently to an increase in firm performance. I structure the network literature review as follows: First, I introduce the common rational behind firm engagement in networks as an access to network-specific resources (e.g.: Freeman, 1979; Granowetter, 1985; Gulati, 1999). Second, I highlight the impact of linkage type and subsequently distinguish between the different types of firm network linkages and how their subsequent sub-networks behave (e.g.: Barney, 1991; Lavie, 2006; Turkina and Van Assche, 2018; Bathelt et al., 2004; Cano-Kollman et al., 2016). Thirdly, I acknowledge existing literature on network characteristics and their impact on a network participant's access to network-specific resources. Particularly, the impact of firm network embeddedness (e.g.; Gulati, 1999; Lavie, 2006; McEvily and Marcus, 2005; Kratz, 1998; Abuja, 2000; Turkina et al., 2019) and firm geographic embeddedness (e.g.: Barlett and Ghosal, 1988; Ghemawat, 2007; Giroud and Scott-Kennell, 2009; Turkina and Van Assche, 2018). Lastly with my review of network theory literature, I highlight the role of network complementarity.

In the second step, I review existing M&A literature to identify key drivers on M&A performance and antecedents of M&A performance. Within this portion of the review, I proceed as follows: first, I highlight current literature on the determinants of M&A success guided by the prevent theories of thought (e.g.: Bauer and Matzler, 2014; Brown and Warner, 1985; Barkema et al., 1996; Cartwright, 2006; Berkinshaw et al., 2000). Second, I review the prevalent rational of M&A transactions, transaction synergies, and how they materialize into augmented transaction performance (e.g.: Chatterjee and Wernerfeldt, 1991; Sirower, 1997; Seth et al., 2000; Kiymaz and Baker, 2008). Thirdly, I highlight the concept of strategic complementarity and how "mutually" supportive differences can create value-added synergies (e.g.: Larsson and Finkelstein, 1999; King et al, 2008; Kim and Finkelstein, 2009; Makri et al., 2010). Lastly, I review how past M&A literature has covered network linkages and network effects (e.g.: Cai and Sevilir, 2012; El-Khatib et al., 2015; Rossi et al., 2016)

This provides me with the foundation to theorize the impact of network-based determinants on the performance of an M&A transaction. Despite small overlap, generally I base my determinant-based argumentation on existing network theory ideas while their impact on M&A performance is theorized using extended and existing M&A theory concepts. Ultimately, this provides a comprehensive theoretical bridge between network theory and M&A theory.

In the following, I begin with the literature review of existing network theory literature.

3.1. Network Theory Literature Review

3.1.1. Introduction to Network Theory

In the context of analyzing the structure and effect of networks, academic literature's common approach is social network analysis (Giuliani and Bell 2005; Lorenzen and Mudambi, 2013; Turkina et al., 2016). It bases itself on Freeman (1979), in which he argues that an actor's central position affects its access to information and knowledge (Turkina et al., 2016). Subsequently, literature argues that economic activity is embedded within social relations and that networks are the sum of inter-actor connections and as such originates from the connection of individual acts (Granovetter, 1985). These actor linkages can take numerous forms and the relative position of each node within the network are not seen as random (Jackson and Rogers, 2007; El-Khatib et al., 2015). Traditionally, network theory has focused on network embeddedness as a determinant for the degree to which firms ate able to leverage their focal networks. Starting from network embeddedness of individuals within their networks, the focus has shifted on organizations and inter-organizational ties (Baker, 1990; Podolny, 1993; Gulati, 1995; Gulati, 1998; Gulati and Gargiulo, 1999).

All linkages are similar in the sense that they form inter-organizational networks in which network resources are imbedded (Gulati, 1999). A network resource in contrast to a firm resource is not located within the boundaries of an enterprise but lie embedded within the inter-organizational linkages (Gulati, 1999). Global Value Chain (GVC) framework identifying inter-firm connection through the form of coordination and the way a connection is govern, network connections differ in form and governance mechanism (Sturgeon et al., 2008). As Lorenzen and Mudambi (2013) point out, network resources are not exclusive to organizational ties but can also be linked into personal connections. These resources result from social capital, which in itself acts similar as in the creation of human capital (Coleman, 1988). Barney (1991) incorporates network resources into the firm resource-based view and differs from external capabilities as network resources lay between network nodes (Langlois, 1992). Others have gone a step further by encapsulating the idea of networks as tangible and intangible assets from which firms can draw on (e.g.: Gulati, 1999; Lavie, 2006; Turkina and Van Assche, 2018).

Furthermore, academics studies on performance-related performances of network capabilities are numerous and address a number of antecedents (McEvily & Marcus, 2005; Lieberman et al., 1990; Clark and Fujimoto, 1991; Henderson and Cockburn, 1994).

Generally, literature separates two determinants governing to what extend a firm is able to benefit from network resources: (1) the degree of network embeddedness (e.g. Freeman, 1979; Granovetter, 1985; Turkina et al., 2016) and (2) the type of network linkage (e.g. Lavie, 2006; Giroud and Scott-

Kennell, 2009). In the following, I will first review the dimensions of network embeddedness and subsequently, the dimensions of network linkage types.

3.1.2. Dimensions of Network Embeddedness

Networks embeddedness can be defined by a number of dimensions in academic literate (e.g.: Helper, 1991; Uzzi, 1997; Stuart, 1998; Andersson et al., 2007; Compston, 2013; Khanna et al., 2015). Most prominently discussed in international business research are two: network embeddedness and local embeddedness.

1. **Network Centrality** describes the centrality of a firm or node within its network (e.g. Granovetter, 1985; Gulati, 1999)
2. **Geographic Embeddedness** is the degree to which a firm is integrated within its domestic geographical boundaries in contrast to its international linkages (e.g. Giroud and Scott-Kennel, 2009; Meyer et al., 2014; Turkina and Van Assche, 2018).

3.1.2.1. Network Centrality

Granovetter (1985) argues that economic activity is embedded in firm ties and from there; Gulati (1999) argues that network resources are embedded within network ties. As such, the position a firm holds within the network it is a part of is crucial to the degree the firm can benefit from the resources a network harbors. Lavie (2006) describes this benefit as an extension of the resource-based view in which firms augment their competitive advantage by accessing information otherwise not available to them in isolation. Subsequently, the hierarchy of power distribution in networks suggests that the more central a firm within the network has better access to the advantages harbored within it (Moody and White, 2003). These advantages include:

(1) a better access to information and strategic resources (Barney, 1991; Uzzi, 1997; Stuart, 1998; Kratz, 1998; ; Gulati 1999; Abuja, 2000; Dyer and Nobeoka, 2000; McEvily and Marcus, 2005),

(2) an access to increased learning and absorption capabilities (Helper, 1991; Cohen and Levintahl, 1990; Powell et al., 1996; Stuart, 1998; Zahler and Bell, 2005) and

(3) Strong influence on the behavior of other market actors, i.e. on other firms and institutions (Gulati, 1998; Rugman and Verbeke, 2003; Easley, 2004; Andersson et al., 2007; Dhanaraj, 2007; Compston, 2013).

Firstly, network centrality allows firms to gain better access to information and strategic resources embedded within them. For example, access to network information decreases a firm's risk by decreasing asymmetric information risk through network exchange (McEvily and Marcus, 2005; Kratz, 1998). Furthermore, information sharing among ties firms also augments in the acquisition of other capabilities (McEvily and Marcus, 2005; Gulati 1999; Stuart, 1998). These capabilities can be technological, innovative but also administrational or organizational though knowledge transfers. Knowledge transfers are partially impactful when knowledge is tacit and difficult to codify (Polanyi, 1966; Teece, 1977; Zander and Kogut, 1995; Szlanski, 1996; McEvily and Marcus, 2005). Studies have focused on the effects on knowledge transfer through inter-organizational linkages (Kratz, 1998). Abuja (2000) underlines that the positive affect of network firms pool their knowledge resources together in collaborative networks. These pockets of knowledge allow firms as processors of knowledge to exchange (Kusunoki et al., 1998; Armin and Cohendet, 2004; Bathelt et al., 2004). Subsequently, the transfer of knowledge forms knowledge pockets within networks which firms can only access through participation but that are not directly located in one entity (Uzzi, 1997; Dyer and Nobeoka, 2000). Rather, knowledge pockets are made up of the combination of different internal and/or external firm resources available to the network.

In addition to a better access to information and resources, a second advantage of a central network position is a better access to learning and absorption capabilities. Studies have linked access to information through networks to a positive association of capability learning to the process of learning and absorbing capabilities (e.g.: Cohen and Levintahl, 1990; Powell et al., 1996; Stuart, 1998; Podolny and Page, 1998; Zahler and Bell, 2005 Uzzi and Gillespie, 2002; Herstad et al., 2014). For example, Helper (1991) studied the effects of information sharing between tier 1 suppliers and OEMs with the result that increased information sharing led to process improvements such as the introduction of just-in-time production, improved quality management and process and product innovation.

Thirdly, a central network position also increases a firm's influence on other economic actors (Gulati, 1998). This notion can be traced back to the theory of institutional isomorphism which states that organizations become increasingly similar in the light of uncertainty and institutional pressures (DiMaggio and Powell, 1983). Most notably in the context of firm networks, the more uncertainty a firm faces, the more a firm will mimic the behavior of successful network actors (DiMaggio and Powell, 1983). Furthermore, the more central a resource supply within the network, i.e. the more dependent a network is on a central resource provider, the more other network firms will emulate it (DiMaggio and Powell, 1983). Subsequently, central firms have a strong ability to influence other firms and drive their behavior in their favor (Rugman and Verbeke, 2003; Andersson et al., 2007; Dhanaraj, 2007*)*.

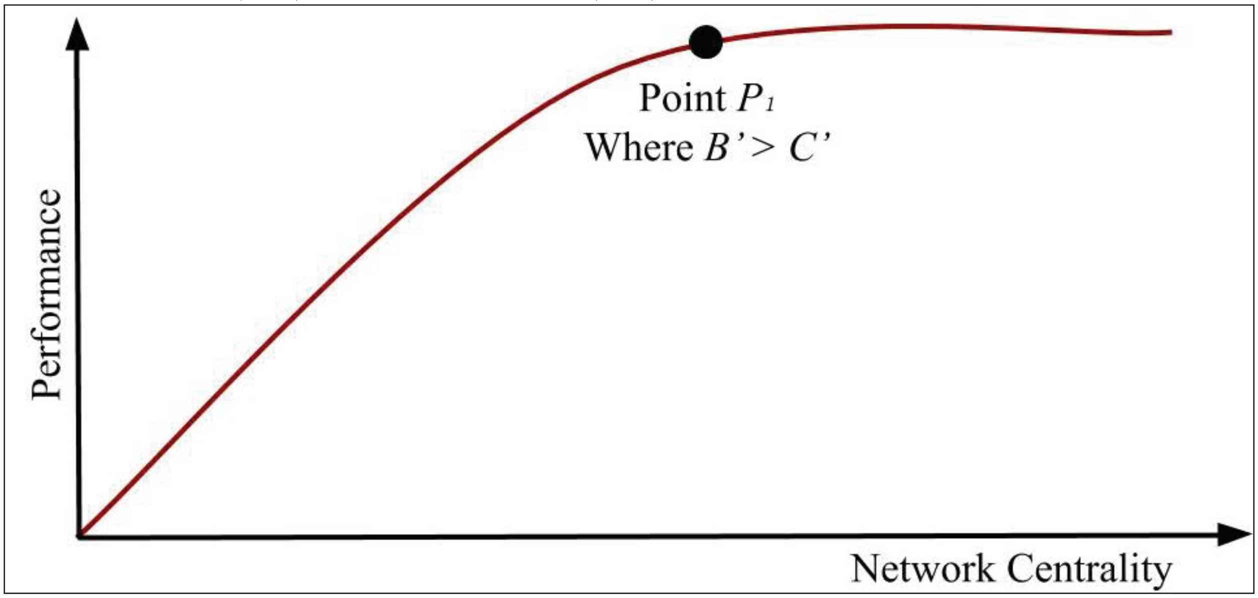
Similarly to the influence on other network firms, centrally positioned firms also have the ability to influence the institutional environment by influencing policy decisions (Easely, 2004; Compston, 2013). Given their centrality advantages through information and resource access, access to learning capabilities and their influence on other firms, firms are able to influence policy decisions by applying cumulative pressure on political actors within institutions (Compston, 2013).

All in all, these advantages show that the more central a firm, the more it benefits from the network it is embedded within. However, these advantages come at a cost of network participation and limit the positive effects of network centrality. One marginally increasing cost is the "penrose limitation", which limits an actor's capability to manage information complexity as a management resource constraint problem (Penrose, 1959). As such the amount of information a firm can access is limited by its ability to absorb the information and subsequently the more central an actor in the network, the more information it has access to. This means that the more information a firm has access to, the higher the management cost of filtering the information, deciding what to absorb and how to subsequently integrate the information are (Hutzschenreuter et al., 2011). Some scholars argue that a firm has the ability to increase its absorption capacity (Cohen and Levintahl, 1990; Powell et al., 1996; Stuart, 1998; Zahler and Bell, 2005). However, others argue that this ability increases at a rate marginally less the corresponding marginal cost of an increase in information complexity (Hutzschenreuter et al., 2011). Subsequently, this marginal cost of information absorption acts as a limitation of network centrality and defines a saturation point P_1 (Graph 2)

All in all, the relationship between network embeddedness and firm performance is strongly positive (e.g.: Bell, 2005; Mehra et al., 2006; Chiu and Li, 2009; Liu et al., 2012). However, this relationship should be seen as an inverted quasilinear function since network participation costs limit embeddedness advantages the more embedded a firm is. Based on Molina-Morales and Expósito-Langa (2012)'s description of the curvilinear relationship between R&A density and innovation and past studies on network structure and firm performance (Holm *et al.*, 1996; Andersson and Forsgren, 2000; Dhanaraj, 2007; Johanson and Vahlne, 2009; Awate and Mudambi, 2017; Turkina and Van Assche, 2018), I similarly formalize the relationship between network centrality, with marginal benefit B' and the marginal cost C', and firm performance.

Along the function of network centrality and firm performance, there is a point P_1, where B' =C' and a marginal increase in centrality converges towards zero (Graph 2). At the point P_1, the effect of network centrality reaches its stagnation and subsequently its optimal point (Graph 2).

Graph 2: Function of firm performance in regards to firm network centrality
Author's conceptualized based on concepts by Holm et al. *(*1996), Andersson and Forsgren (2000), Dhanaraj (2007), Johanson and Vahlne (2009), Hutzschenreuter et al. (2011) Molina-Morales and Expósito-Langa, (2012), Awate and Mudambi (2017), Turkina and Van Assche (2018)



3.1.2.2. Geographical Embeddedness

In additional to network embeddedness, international business and economic geographers have added a geographical dimension to explain the effects of network resources (e.g.: Rugman et al., 2011; Tallman and Chacar, 2011; Schwens et al., 2011; Jensen and Pederson, 2011; Benito et al., 2011; Clark and Geppert, 2011; Figueiredo, 2011; Cuervo-Cazzurra and Genc, 2011).

This geographic dimension studies the extent to which a firm is either locally or globally embedded, i.e. the extent to which a firm's linkages are focused more in geographic periphery of its own location, like its domestic country or not.

The local context has two dimensions according to Giroud and Scott-Kennell (2009): the institutional-based and the resources-based dimension. Within the economics-based institutional view, the local context is the result of formal, e.g. legal, political, and administrational factors, and informal (e.g.: relationships and social norms) factors (North, 1990; Meyer et al. 2011). In contrast, the resource-based view focuses on what location-specific resource endowments are available (Barney, 1991).

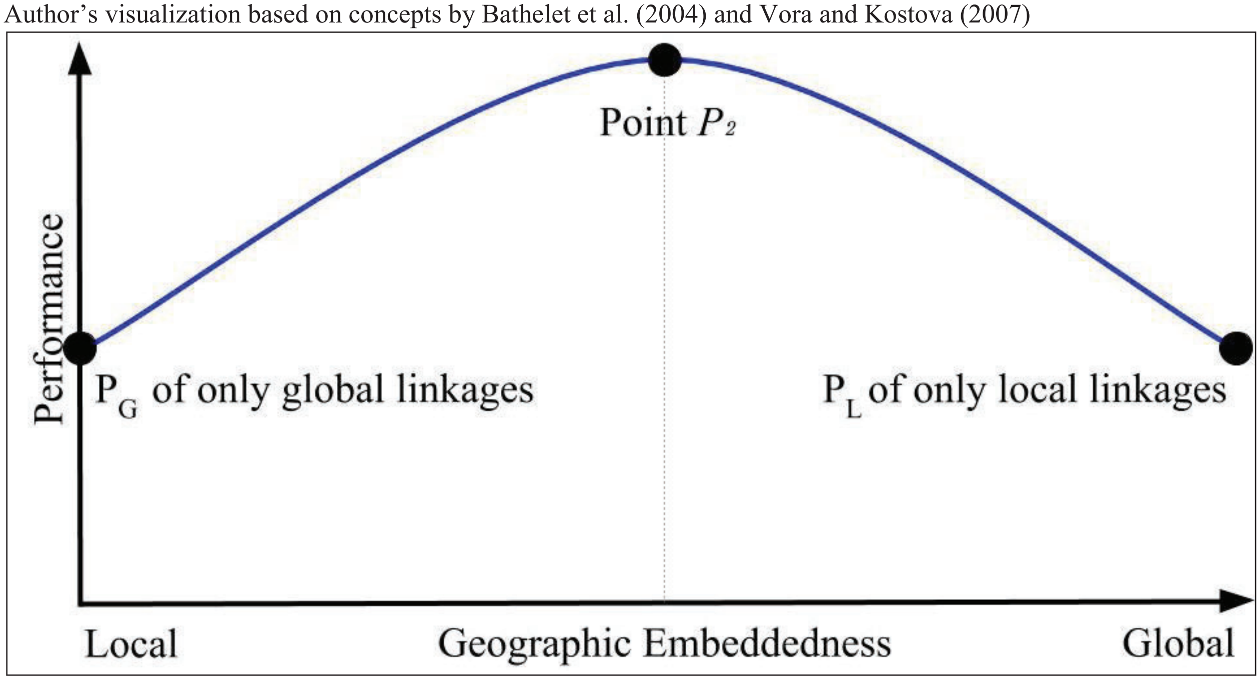
Since the portrayal of MNE networks as "integrated networks", international business research has closely focused on how MNEs structure their networks and how this structure affects MNE performance (Bartlett and Ghoshal, 1988). Particularly, scholars have examined how MNEs interact with their subsidiaries within the internationalization process (Strutzenberger and Ambos, 2014). In that context, Barlett and Ghosal (1988) introduced the concept of the "transnational firm" which describes firms that are under strong pressure for global integration as well as for local responsiveness. These firms operate their internal MNE network as independent and dispersed with joint knowledge sharing among its entities (Barlett and Ghosal, 1988). Taking the specific industry needs into account, the "transnational" concept has been positively linked to increasing MNE performance based on the ability to access both local and global resources (Birkenshaw, 2000). Such industries are characterized with strong price pressures that push for efficiency-based global integration, e.g. through economies of scale or scope, while customer and institutional heterogeneity is high across geographic boarders (Vora, 2007). A prominent example is the automotive industry (Strutzenberger and Ambos, 2014; Sturgen et al., 2008). There and in similarly characterized industries, MNEs are bound by institutional view based local institutions and benefit from resource view based local knowledge embeddedness making local responsiveness just as strong as a factor as cost factors. MNEs generate value through arbitrage accessed by the multiple embeddedness of their organizations (Meyer et al., 2011). This arbitrage can be seen as the MNE's "Raison d'être". They are in the unique organizational capacity to create and integrate global supply chains that are able to tap into the multitude of diverse location advantages (Jensen and Pederson, 2011).

Referring back to the depiction of MNE networks as "integrated networks", we are able to derive implications from the transnational solution outside of the MNE context onto the context of networks in general. "Transnational" or dually embedded networks function similar to their MNE counterparts. They are able to leverage both global and local linkages to their favor.

In the context of local embeddedness, international business research has brought up a second field of research in the study of industrial and geographic clusters. Clusters are a network of linkages that cluster industry or value chain specific knowledge within a geographically proximate group of companies or institutions (Porter, 1998). Literature prominently underlines the positive effect of direct face-to-face interactions which create knowledge spill-overs between local firms and therefore facilitate a clusters ability to localize knowledge (Storper and Venables, 2004). For instance, Ghemawat (2007) underlines that a key success factor is the knowledge of and the embeddedness within local contexts. However, an increasing local specialization within a certain area is arguably not the only contributing factor of cluster networks ability to facilitate greater innovation and job creation (Delgado et al., 2010; Delgado et al., 2014; Turkina and Van Assche, 2018). Wolfe and Gertler (2004) argue that a cluster should not be viewed as an isolated system in that it provides knowledge and resources but rather as an inter-connection with other geographic focal points. Hence, a second important factor is the access to as Bathelet (2004) calls it, "global pipelines". A "global pipeline" describes a cluster's access to other geographically separate centers of excellences and is an important driver for innovation and cluster performance. For instance, Cantrell (1989) emphasizes that technological heterogeneity across geographically dispersed knowledge pockets can be leverage to supplement local technologies. These internationally available technologies that are transferred through information exchange (McEvily and Marcus, 2005; Uzzi, 1997; Dyer and Nobeoka, 2000) might not have been available to the firm in a locally isolated setting.

A firm who is able to leverage both local and global linkages and thus access both local "buzz" and global knowledge effects while evading isolation and innovation stagnation through "global pipelines" (Bathelet, 2004). Subsequently, the network's resources would not just lie within its local network but within the interplay of global and local linkage, and are accessible through these "pipelines" (Acácer et al., 2016). Studies have found locally and globally embedded clusters to have increased innovation potential which in turn fuels an increasing globalization of clusters (e.g.: Lorenzen and Mudambi, 2013; Hannigan et al., 2015). Following the theoretical depiction of clusters as global networks by Turkina and Van Assche (2018), we are able to draw implications from cluster network research onto firm-level network research. Firm networks consisting of local and global linkages that are able to leverage local knowledge pockets while benefiting from global information and innovation "pipelines". Subsequently, I conceptualize the relationship of dual embeddedness, i.e. a network which is equally locally embedded as it is globally, and firm performance as an inverted u-curve. Hence, in the relation between dual embeddedness and firm performance, there is a point P_2 at which the combination of local and global linkages provides the highest firm performance (Graph 3).

Graph 3: Firm performance as a function of geographic embeddedness
Author's visualization based on concepts by Bathelet et al. (2004) and Vora and Kostova (2007)



As shown, network embeddedness can be seen from two dimensions: network centrality and geographic embeddedness. However, following the resource-based view, Lavie (2006) argues that the nature of the relationship might matter more than the nature of the resources embedded in the network itself. Therefore, in the following I categorize the different types of network linkages as portrayed in network theory literature.

3.1.3. The Different Categorizations of Network Linkages

Noticeably, beneficial effects of inter-organizational networks are dependent upon the transfer of information and knowledge. In extension, as Turkina and Van Assche (2018:710) state: "Different linkages with other companies lead to the transfer of different knowledge capabilities". Thus, the type of linkage is important to determine what and how knowledge is transferred among the networks (Turkina and Van Assche, 2018:710; Giroud & Scott-Kennel, 2009). Linkage terminology differs greatly along academic scholars and fields. A common approach in international business (IB) is distinguishing between organization-based linkages, i.e. linkages that stem from the organizational activities (Bathelt et al., 2004; Cano-Kollman et al. 2016) and individual-based linkages, i.e. inter personal relationships (Lorenzen and Mudambi, 2013; Cano-Kollman et al. 2016). In the context of IB, organization-based linkages are more interesting while the extent of personal connections is often neglected.

The academic IB community commonly approaches organizations-based linkages with a subdivision into *horizontal* and *vertical linkages* (e.g. Turkina and Van Assche, 2018). This distinction finds theoretical validity in the global value chain concept which distinguishes between linkages within the same value chain level and linkages that span across different value chain steps (Burt, 1997; Podolny and Baron, 1997; Gulati and Westphal, 1999; McEvily and Marcus, 2005; Giroud and Scott-Kennel, 2009; Turkina and Van Assche, 2018). In extension to these linkages, I include two other organization-based linkage types: shareholder linkages and internal linkages. Shareholder linkages describe linkages between owner and owned, and became popular in IB research in the study of global corporate control networks (e.g. Vitali et al., 2011), while internal linkages comprise of inter-firm linkages. Inter-firm linkages in the context of MNEs are widely popular in IB research (e.g. Anderson and Forsgren, 2000; Almeidea and Phene, 2004; Cantwell and Mudambi, 2005; Cantwell, 2009; Asakawa et al., 2018). In them, authors often distinguish between vertical and horizontal linkages but these are hard to separate in practice (Ghosal et al., 1994). Hence, they receive a separate classification. For individual-based linkages, I highlight existing literature on board member linkages and their impact on network resources (e.g. Kaplan and Reishus, 1990; Adams and Ferreira, 2007; Schimdt, 2015; Khanna et al., 2015).

Firstly I describe ***vertical linkages.*** *Vertical linkages* are often referred to as buyer-supplier ties or supplier ties and are characterized by an exchange among different levels of the global value chain and allows for the knowledge transfer of "inter-task knowledge capabilities" (Turkina and Van Assche, 2018). As such vertical linkages have been the focus of much of global value chain literature (e.g. Sturgeon, 2008; Timmer et al., 2014). An example of a vertical linkage is the relationship between the General

Motors Company (GM) and Henniges Automotive as described by GM Canada[16]. All vertical linkages of a firm's network make up its vertical sub-network. These vertical sub-networks allow firms to focus on their core competitive advantages and improve value chain efficiencies by leveraging other firms' complementary core competencies (Mudambi, 2008). This allows firms to access knowledge pools that are available at different value chain steps and to leverage them within their own production chain while being able to focus on core competencies (Bevan et al., 2004). The globalization and the rise of global value chain have gained popularity in academic, policy and professional fields and have been thoroughly studied in the context of the automotive industry, e.g. Sturgeon et al., (2008) or Sturgeon and Florida (2004).

In opposite to *vertical linkages*, ***horizontal linkages*** are characterized by intra-value chain position coordination (Sturgeon et al., 2008). Within these connections, firms exchange "intra-task" knowledge in the form of joint research and development (R&D) project or other lateral knowledge sharing projects (Turkina and Van Assche, 2018). An example for a horizontal linkage would be the 2019 partnership of Ford Motor Co. and Volkswagen AG (VW) to cooperate on autonomous driving research[17]. To access "intra-task" knowledge firms develop inter-firm partnerships (Powell et al, 1996; Roijakkers and Hagedoorn, 2006). Subsequently, these exchanges provide access to technological capabilities (Cantwell and Mubdambi, 2011) and to knowledge capabilities within the partner's cluster environment (Inkpen, 1998). Studies on alliance formation are numerous and are based on horizontal linkages (e.g.: Gulati et al., 1994; Powell et al., 1996; Gulati, 1998). These linkages are essentially partnerships or alliances along the same value chain level and cover "eye-level" exchanges of resources and information towards the same goal.

For the third type of inter-firm linkage, I look at firm ***shareholder linkages***. Here, I look at a firm's corporate control (Vitali et al, 2011) or ownership network. These shareholder linkages are characterized by shareholders from the financial industry or industrial conglomerate holdings, and are often defined as global ultimate shareholders of a firm (Moerland, 1995). Within them, firms do not have an exchange of inter-task knowledge but rather intra-task knowledge. However, on a shareholder network level, literature emphasizes less on knowledge transfer benefits but more on political and market power benefits (Fich and Shivdasani, 2007). A common example for a shareholder linkage is an asset management firm, like U.S.-based BlackRock Holdings Inc., and the firms they are invested in. Statista

[16] Following a press release concerning GM's 26th Supplier of the Year awards ceremony held on April 20, 2018 in Orlando, Florida, U.S.A.
[17] Press Release from July 12, 2019 about VW's investment in Ford's autonomous driving venture ARGO AI.

(2019a)[18] shows BlackRock as the main single shareholder in the German lead stock-market index DAX30. There, it owns significant stakes of at least 2.8% in each DAX30 firm and therefore links these enterprises through a shareholder linkage (Statista, 2019a). This exemplifies the beneficial effects of shareholder linkages as market and political influencers (Cheffins, 2008; Culpepper, 2010). In continuation, empirical studies have shown that corporate control networks have significant impact on institutional, i.e. policy, and market factors by excising centralized corporate control in their ownership and i.e. shareholder network (Compston, 2013). Furthermore, Massa and Rehman (2008) show empirical data from banks showing that funds or fund families increase their stakes in the firms that borrow from their affiliated banks. They attribute this adverse selection to information exchanges between the funds and their affiliates based on shareholder linkages (Massa and Rehman, 2008). Hence, a strong shareholder linkage can decrease risk uncertainty (Massa and Rehman, 2008). However, extensive shareholder networks also come at costs. Easley (2004) found that well-connected shareholders expect a higher return from investments then in the case of lesser connected shareholders. Hence, firms with well-connected shareholders face higher shareholder scrutiny with the effect that risk-decision making behavior may be biased (Easley, 2004). Furthermore, strong shareholder networks are able to influence other economic actors like other firms through what the theory of institutional isomorphism describes as institutional pressures (DiMaggio and Powell, 1983). These pressures suggests that firms emulate other firms that are more successful and that have strong resources upon which others in the network are dependent upon (DiMaggio and Powell, 1983), or which influences policy though increased political power . This is empirically test by studies such as Compston (2013) in which the author positively tests the impact of the shareholder network on the institutional policy.

A fourth type and often analyzed linkage in the context of multinational enterprises (MNEs) are ***internal linkages***. More commonly, they are referred to as MNE ties that form “inter-organizational networks”. First conceptualized by Ghosal and Berlett (1990), internal linkages are ties within a firm group consisting of subsidiary and branch ties. As such, literature often groups internal linkages into either vertical linkages, i.e. headquarter (HQ) -subsidiary ties, or horizontal linkages, i.e. between subsidiary ties (Ghosal et al., 1994). These are not to be confused with external vertical and horizontal linkages discussed prior (Turkina and Van Assche, 2018). Internal vertical and horizontal linkages differ from prior discussed external vertical primarily due to the hierarchical governance of these linkages (Gereffi et al., 2005). Internal linkages are shaped by the MNE headquarter which distributes and decides what roles subsidiaries play within the internal network and to what degree and direction information is

[18] *https://de.statista.com/statistik/daten/studie/518085/umfrage/groesste-blackrock-beteiligungen-am-aktienkapital-von-dax-unternehmen/*

exchanged (e.g.: Almeida and Phone, 2004; Andersen and Forgren, 2000; Cantwell and Mudambi, 2005; Cantwell, 2009; Asakawa et al., 2018). As such, informational flow direction and form of knowledge transfer is highly dispersed and subsequently must be viewed in separation to external vertical and external horizontal linkages (e.g. Barlett, 1988; Struzenberger, 2014). Vora and Kostova (2007) argue that subsidiaries may range from fully independent on its HQ to fully dependent on HQ decisions. Thus, subsidiaries play crucial roles within the dynamics of a group in terms of distribution and location of knowledge and innovation resources, as well as the network dynamics within the subsidiary networks (e.g. Meyer et al., 2011; Rugman et al., 2011; Figueiredo, 2011). Subsidiaries act either individually or as a collective within a firm's organization (Barlett and Ghoshal, 1986; 1988). This shows that subsidiary dynamics and individual roles differ from external linkages. For example, Rugman et al. (2011) show the degree of subsidiary integration-responsiveness is dependent upon the different stage of the value chain. Furthermore, Jensen and Pederson (2011) emphasis the role of subsidiary location in order to take advantage of local resource and capabilities. Subsequently, the more central a firm lies within its internal network, the more access it has to other subsidiary information and resources.

In addition, to the four organization-based ties, I also look at the most prominent category of personal ties: the ***board sub-network***. These comprise of ties based upon the formal connections of board members. As an example, we take Susanne Klatten[19], chairwoman of the supervisory board of the SGL Carbon SE. In addition to her duties at SGL Carbon SE, she is also a member of the board of the BMW AG, the Atlanta AG and the UnternehmerTUM GmbH, the Start-up incubator of the Technical University Munich. The precise effect of board ties is disputed. Not however, its influence. Ishii and Xuan (2014) identify two competing views. The first view describes a positive association with firm performance as enhanced social ties argument access to information and reduce exposure to asymmetric information (Gompers and Xuan, 2008; Cai and Sevilir, 2012). For example, Ingram and Roberts (2000) provides an empirical study from the hotel industry showing that hotels with a higher number of board ties earn higher revenue per room. This, they partially attribute to better access to information and is echoed by a number of other empirical studies on board room connectives and performance (Ingram and Roberts, 2000; Larcker and Wang, 2013). The opposing view encompasses the "familiarity bias" (Ishii and Xuan, 2014:345). This bias, also known as the "status quo bias" describes the preference of individuals towards choices that they are familiar with and that are closer to the status quo (Samuelson and Zeckerhauser, 1988). The "status quo bias" explains investors' tendency to prefer domestic markets versus international investing (Coval and Moskowitz, 1999; French and Poterba, 1991). Furthermore, Grinblatt and Keloharju

[19] *https://www.sglcarbon.com/en/company/about-us/supervisory-board/*; *https://www.bmwgroup.com/de/unternehmen/unternehmensprofil.html*

(2001) show that this bias exceeds geographic boundaries to include a change in preference depending on language and cultural characteristics. As a result, board members lower standards and lack diligence within the decision making process (Ishii and Xuan, 2014). One potential explanation is described by sociology as the "birds of a feather“ concept and suggests that board members with familiar ties shift from rational decision making to trust-based emotional decision making (McPherson et al., 2001; Ishii and Xuan, 2014). In extension, Uzzi (1997) suggests that board members tend to positively exaggerate each other's actions in the context of close knit board networks.

Furthermore, the effect of social ties is also heightened by herd thinking or group mentality which are particularly detrimental where social consensus is clearly wrong (Asch, 1951). This group mentality leads to insufficient decision making diligence (Janis, 1982). Additionally, board members may also find validation within board networks in favor of an increased agency problem (Jensen and Meckling, 1976). In that case, managers may engage in inorganic expansions for personal financial gain in the form of salary-based incentives or to increase their personal status within the network (Cartwright and Schoenberg, 2006; Seth et al., 2000). Reputation plays a major role in accessing information within board networks as reputation acts as signaling to other network participants that an act has valuable information to give and is worth giving information to (Mehra et al., 2006; Zajac and Westphal, 1996). Kaplan and Reishus (1990) show that board members whose firms cut dividend payouts were on average roughly 50% less likely to receive additional board mandates in comparison to board members whose firms did not reduce dividend payouts. This reputational effect is a double-edged sword: on the one hand, board member's interests might be better aligned with focal firms, as negative firm performance has a negative association with their future board engagement and thus financial and reputational gain (Kaplan and Reishus, 1990; Fich and Shivdasani, 2007). On the other hand, the probability of fraud and fraudulent cover-ups is higher with board-appointed CEOs than with non-board-appointed CEOs as board members have strong incentives to mask fraudulent CEO behavior in fear of strong reputation backlash within their board network (Khanna et al., 2015).

3.1.4. Complementarity of Networks

In extension to the definition of networks as a firm's intangible and tangible asset located within its external network connections, firms can use these additional resources to augment firm returns by acting as an addition to a firm's local resources (Gulati, 1999; Lavie, 2006; Turkina and Van Assche, 2018). For this combination to give the strongest return, the combination of internal and external resource must be optimal. In the context of merging two networks, the combination of network resources from network A and network B must be so that it yields the strongest added effect to the buyer capabilities.

Concluding the literature review of network theory, firms form networks to gain access to economic activity and resources that are embedded within them (e.g. Granovetter, 1985; Gulati, 1999; Lavie, 2006). To take advantage of these network resources, it matters where and how in the network a firm is positioned (Jackson and Rogers, 2007). Firm positioning within a network can differ in the form of how central a firm is within a network, i.e. its network embeddedness, (Holm et al., 1996; Andersson & Forsgren, 2000; Moody and White, 2003; Dhanaraj, 2007; Johanson and Vahlne, 2009; Awate and Mudambi, 2017; Turkina & Van Assche, 2018) and how geographically situated a firm is within its network, i.e. geographic embeddedness (Malmberg and Maskell, 1997; Ernst and Kim, 2002; Bathelt et al., 2004; Glückler, 2007; Vora, 2007; Coe et al., 2008; Ter, Wal and Boschma, 2009; Bathelt and Li, 2013; Turkina et al., 2016). Furthermore, networks differ in what types of linkages build a network and thus, I subdivide into five types of linkages and subsequent sub-networks: vertical, horizontal, shareholder, board, and internal linkages (e.g.: Ghosal and Berlett, 1990; Giroud and Scott-Kennel, 2009; Vitali et al., 2011; Cai and Sevilir, 2012). Lastly, I review the literature on network complementarity to show the combinational advantages of complementary resources (e.g. Turkina and Van Assche, 2018).

In conclusion of the network theory literature review, I addressed current literature reviewing network resources (Gulati, 1999), their emergence from two dimensions, network centrality and network geographic embeddedness, as well as the impact and different types of network linkages. Next I review existing M&A literature.

3.2. Review of M&A Literature

The term M&A unifies formal firm combinations to form a single legally either within the boundaries of an existing firm or within a new third firm and acquisitions, in which one company takes control of another or two companies band. Both cases describe the highest degree of integration between companies involved and are therefore studied in similar environments (Zollo and Meier, 2008). In In this context, I focus on acquisitions, in which one firm, the buyer, acquires the target in order to achieve an overarching goal to the buyer. This lies in contrast to intentions of firms involved in a merger where the union is formed for mutual benefit (Zollo and Meier, 2008).

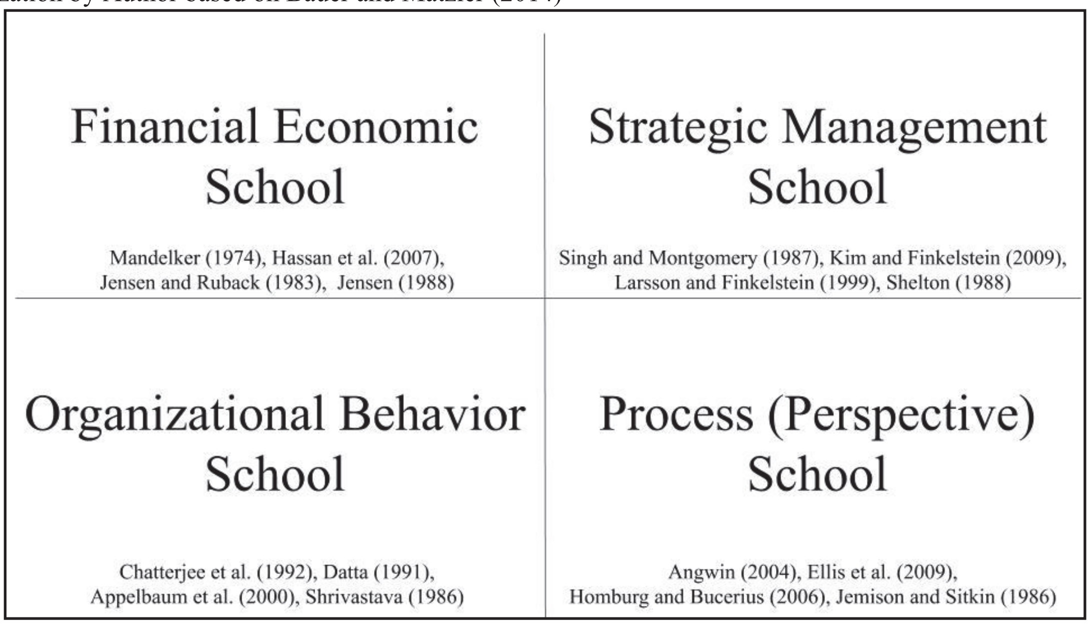
To explain how network configurations can have an impact on M&A performances, I highlight the dynamics of M&A success and explore how firms are able to realize M&A success. First, I look at the determinants of M&A success next I review the dynamics of transaction synergies that explain M&A determinants, and ultimately conclude with how past M&A literate has dealt with network configurations.

3.2.1. Determinants of M&A success

Before approaching the determinants of M&A success, I first review what constitutes an M&A success. Das and Kali (2012) review the academic landscape on M&A performance indicators and subdivide them in (a) accounting measures, (b) market measures and other subjective measures such as survey responses. While accounting measures provide of an accurate snapshot of firm pre- and post-performance, market-based mechanism best display the core definition, i.e. a combinational add-value that arises when two firms merge resources which in isolation would not be able to be achieved (Zollo and Meier, 2008).

Next, I turn to the determinants of M&A success. In sorting through M&A research on the determinant of M&A success, I follow Bauer and Matzler (2014) which categories existing literatures into four schools of thought (Figure 2).

Figure 2: Overview of the different schools of thought within M&A Literature
Visualization by Author based on Bauer and Matzler (2014)



Following Figure 2, firstly literature identifies the financial economic school, in which scholars analyze stock-based performance of buyer firms and how the announcement of mergers affect the firm's market capitalization (Brown and Warner, 1985). Secondly, there is the organizational behavior school. This view investigates the effect of a transaction on the organization itself and its culture, and includes studying the impact of cultural differences in international transactions. The organizational behavior school is most commonly analyzed in IB within the context of MNEs. An additional common intersection with IB literature is the pre-transaction investigation of cultural fit or the post-transaction degree of integration (e.g. Barkema et al., 1996). The third school of thought is the strategic management school. In it, scholars study the effects of pre-merger relatedness of target and buyer, as well as the effect of perceived complementarity and similarity on the transaction (Cartwright, 2006; Chatterjee, 2009; Larsson and Finkelstein, 1999). Lastly, the process school of thought can be seen as the symbiosis of strategic management and organizational behavior school as it focuses on the process of transactional integration as a vital determinant for transaction success (Berkinshaw et al., 2000; Angwin, 2006).

As seen in studies in which as much as 70-90% of M&A transactions fail to create an added-value, M&A literature has been struggling to identify clear determinants of M&A performance (Christensen et al., 2011). A number of authors have subsequently studied this inability by testing on the most commonly used predictors and have attested a systematic failure of common predictors which traditionally follow the financial economic school of thought (Ahmmad et al., 2016; Haleblian et al., 2009; Stahl and Voigt , 2008; Christensen et al., 2011). Authors like Weber et al. (2009) have suggested a shift beyond financial and strategic variables.

Thus far, these non-financial variables rarely included the impact of firm networks and if then only focus on board-based linkages (e.g. El-Khatib et al., 2015; Cai and Sevili, 2012; Ishii and Xuan, 2014). Although differentiated, all four schools of thought cannot be viewed as acting in isolation or seen as the sole cause of transaction success or failure. Numerous studies focusing on isolated aspects, e.g. on pre-merger characteristics (Haspeslagh and Jemison, 1991), or on pre-, mid-, and post-merger issues together (e.g. Barkema and Schijven, 2008) have shown that they always occur or influence the transaction in isolation. Hence, Bauer and Matzler (2014) created a holistic model to decompose the impact of network configurations testing variables from all schools of thought. More precisely, Bauer and Matzler (2014) utilize the cultural compatibility and degree of integration from the organizational behavior school, speed of integration from the process perspective school and strategic complementary and the estimation of M&A success from the strategic management school. Particularly, the concept of "strategic complementary" is a fairly novice concept in comparison to traditional M&A literature. It addresses what academic literature describes as "strategic fit" of two organizations and is emphasized as decisive for transaction performance (Homburg and Bucerius, 2006; Cartwright, 2006; King et al., 2004; Seth, 1990). For example, Cartwright (2006) argues the central rational behind the "strategic fit" argument is that a strong fit increases market power and productivity. The configuration of firm characteristics that lead to a "strategic" and strong "fit" is widely debated therefore the following summarizes the current streams of argumentation.

Proponents of market-based argue that the "fit" is a question of industry relatedness operationalized through industry codes, such as NAICS. In the case of industrial similarity, they argue that an augmented transaction performance can be the result of strong economies of scale and the reduction of redundancies that arise if two organizations come from the same industry (Capasso and Meglio, 2005). Critics however, such as Stimpert and Duhaime (1997) cite lacking robust empirical evidence for a connection between industry relatedness and M&A performance. In contrast to the market-based view, the resource-based view analyzes "strategic fit" in regards to product market, resource and/or supply chain-related similarity (Pehrson, 2006; Stimpert and Duhaume, 1997). Throughout both market- and resources-based view, traditional scholars see similarity as an indicator for potential synergy value of a transaction and subsequently similarity as value driver for transaction performance (Bauer and Matzler, 2014; Meyer and Altenborg, 2008). Numerous studies have followed suit but have brought forward inconsistent empirical results as to the validity of "strategic fit" (Capron et al., 2001; Prabhu et al., 2005; Swaminathan et al., 2008; Tanriverdi and Venkatraman, 2005; Bauer and Matzler, 2014). In attempt to further explain the variance in empirical performances, academia has introduced an alternative concept: strategic complementarity (Larson and Finkelstein, 1999; King et al., 2004). It argues that complementary difference offers valuable resource redeployment and differs in its value creation from similarity (Larson and Finkelstein, 1999).

Academic literature describes similarity as working though efficiency-based synergies, such as economies of scales and scope (Bauer and Matzler, 2014, Porter, 1999). Complementary in contrast builds on enhancement-based synergies which in addition to efficiency-synergies provide value creating through mutually supportive differences (Larsson and Finkelstein, 1999). Ultimately, this describes the added-value of achieving or combining competencies that a firm otherwise would not be able to develop on its on (Kim and Finkelstein, 2009; Capron and Mitchell, 1998; Harrison et al., 1991; King et al., 2008). Furthermore, authors argue that complementarity increases M&A success by enhancing synergy realization (Larson and Finkelstein, 1999). This has been analyzed in a multitude of dimensions such as by looking at top management complementarity (Keishnan et al., 1997), technological complementarity (Makri et al., 2010), strategic and market complementarity (Kim and Finkelstein, 2009), and product complementarity (Wang and Zajac, 2007).

To explain strategic complementarity from strategic similarity, literature refers to quoted main driver of M&A transactions: Synergies (Larsson and Finkelstein, 1999; King et al., 2004; King et al, 2008; Kim and Finkelstein, 2009; Makri et al., 2010).

3.2.2. Synergies within M&A Literature

Synergies describe any additive value created by transaction (Seth et al., 2000, Kiymaz and Baker, 2008). As such, Sirower (1997, p.20) defines synergies as "the increase in performance of the combined firm over what the two firms are already expected or required to accomplish as independent firms". As such, underperforming M&A transactions are subsequently linked to issues in realizing synergies. This can be a result of managerial over-evaluation of potential synergies in the pre-merger phase but also by an inability to delivery on expected synergies in the integration and implementation (Fiorentino and Garzella, 2015). Therefore, synergy management literature can be subdivided into three categories: (1) Pre-transaction: identification of synergies in inorganic growth strategies, (2) Mid-transaction: integration and implementation analysis, and (3) Post-transaction: capturing value creation

In this context, the literature speaks of the “synergy trap” which describes the underperformance of a transaction based on the over estimation of firstly available synergies and secondly the inability to fully realize them (Fiorentino and Garzella, 2015).

In distinguishing how strategic complementarity and similarity affects M&A performances, scholars focus on pre-transaction characteristics and their association with post-transaction M&A performance (Larsson and Finkelstein, 1999; King et al., 2004; King et al, 2008; Kim and Finkelstein, 2009; Makri et al., 2010; Bauer and Matzler, 2014). Despite implementation playing a strong role in the realization of identified synergies, Zollo and Meier (2008) argue that implementation can only be a factor if there are realizable synergies in the first place. Hence, for synergies to be realized, a transaction must identify these synergies correctly and in a sequentially secondary process, integrate and implement these accordingly.

Over time synergies have been categorized in numerous ways. Traditional authors focused have distinguished synergies as collusive, operational and/or financial synergies (Chatterjee, 1986; Chatterjee and Wernerfeldt, 1991; Schweiger, 2002). These synergy types are linked, although not exclusively, to different types of mergers (Table 1).

Table 1: Overview of different synergy typographies
Visualization and structure by Author

Chatterjee (1986), Chatterjee and Wernerfeldt (1991)	Devos et al. (2009)	Fiorentino and Garzella, (2015)	Bauer and Matzler (2014)
1. Collusive Synergies = Increase of market power 2. Operational Synergies = Realization of EoS and Scope / Decrease in operating costs 3. Financial Synergies = Reduction in the cost of capital	1. Cost-saving Synergies 2. Revenue enhancing Synergies	1. Operating synergies 2. Financial Synergies 3. Tax Synergies	1. Efficiency-based Synergies 2. Enhancement-based Synergies

Other authors distinguish between cost saving and revenue enhancing synergies (Devos et al., 2009). An additional group of studies subdivides synergies based on the organizational level they impact. Hence, distinguishing operating, financial and tax directed synergies (Fiorentino and Garzella, 2015). In continuation of Chatterjee (1986) and Chatterjee and Wernerfeldt (1991)’s categorization, scholars have distinguished between efficiency-based, i.e. synergies that create value through cost reduction in the form of capital, production or administrational redundancies, and enhancement-based synergies, i.e. synergies that act revenue or market share enhancing (Jemison and Sitkin, 1986; Kim and Finkelstein, 2009; Sarkar et al., 2001; Tanriverdi and Venkatraman, 2005; Wang and Zajac, 2007; Bauer and Matzler, 2014). This distinction of synergies is parallel to the distinction of strategic complementarity and similarity and underline the different way in which the created value-added.

3.2.3. Network-based Research in M&A Research

Within the academic research, the extent in which networks have been the focus of interest is low. There are however a growing minority of studies focusing on individual-based linkages. These studies mostly focus on the role board room ties play on M&A performances. El-Khatib et al. (2015) for instance studied the effect of CEO network centrality on Merger performance. There, they argue based on social network theory that the CEO's individual position within a social network impacts the merger performance as well-positioned CEOs would be able to access knowledge pockets (Burt, 1997; Nahapiet and Ghosal, 1998) and leverage network influence more easily (Mizruchi and Potts, 1998) . Similarly, Ishii and Xuan (2014) argue that "acquirer-target social ties lead to poorer decision making" (El-Khatib et al., 2015:p.350), while Cai and Sevilir (2012) determined that in the case of common directors between buyers and targets, takeover premiums are looker and that value generation is higher when both the buyer and the target have one director on a third's board. Furthermore, Rossi et al. (2018) determine a positive relationship between well-connected mangers and overall investment risk and subsequent returns. They state that well-connected managers are able to leverage their personal network into stronger portfolio performance and translate a greater number of manager connections into a better acquisition performance.

In conclusion of my review of M&A literature, I highlighted the antecedents of M&A success and emphasized the importance of "strategic fit" between buyer and target as key success factor (e.g.: Seth, 1990; King et al., 2004; Cartwright, 2006; Homburg and Bucerius, 2006; Bauer and Matzler, 2014). What constitutes "strategic fit" is highly debated but recent literature has brought forth the concept of strategic complementarity, in which complementary differences allows for the creation of additional synergies in comparison to strategic similarity (e.g. Larsson and Finkelstein, 1999; King et al., 2004; King et al, 2008; Kim and Finkelstein, 2009; Makri et al., 2010). The basis of the argument forms the realization of synergies. Despite limitations in M&A literature that synergy realization is dependent on pre-transaction identification, mid-transaction implementation and post-transaction capture of value creation (e.g. Chatterjee, 1986; Fiorentino and Garzella, 2015), synergies realization is primarily a sequential process, in which synergies must first be identified in order to be realized (Zollo and Meier, 2008). In contrast to strategic similarity where buyer firms daily realize efficiency-based synergies (e.g. Economies of scale, increased market power etc.), complementarity allows for the realization of enhancement-based synergies (e.g.: increased innovation, market / product diversification etc.) alongside efficiency-based synergies.

3.3. Hypotheses

Combining network theory with M&A research, I develop my theoretical framework:

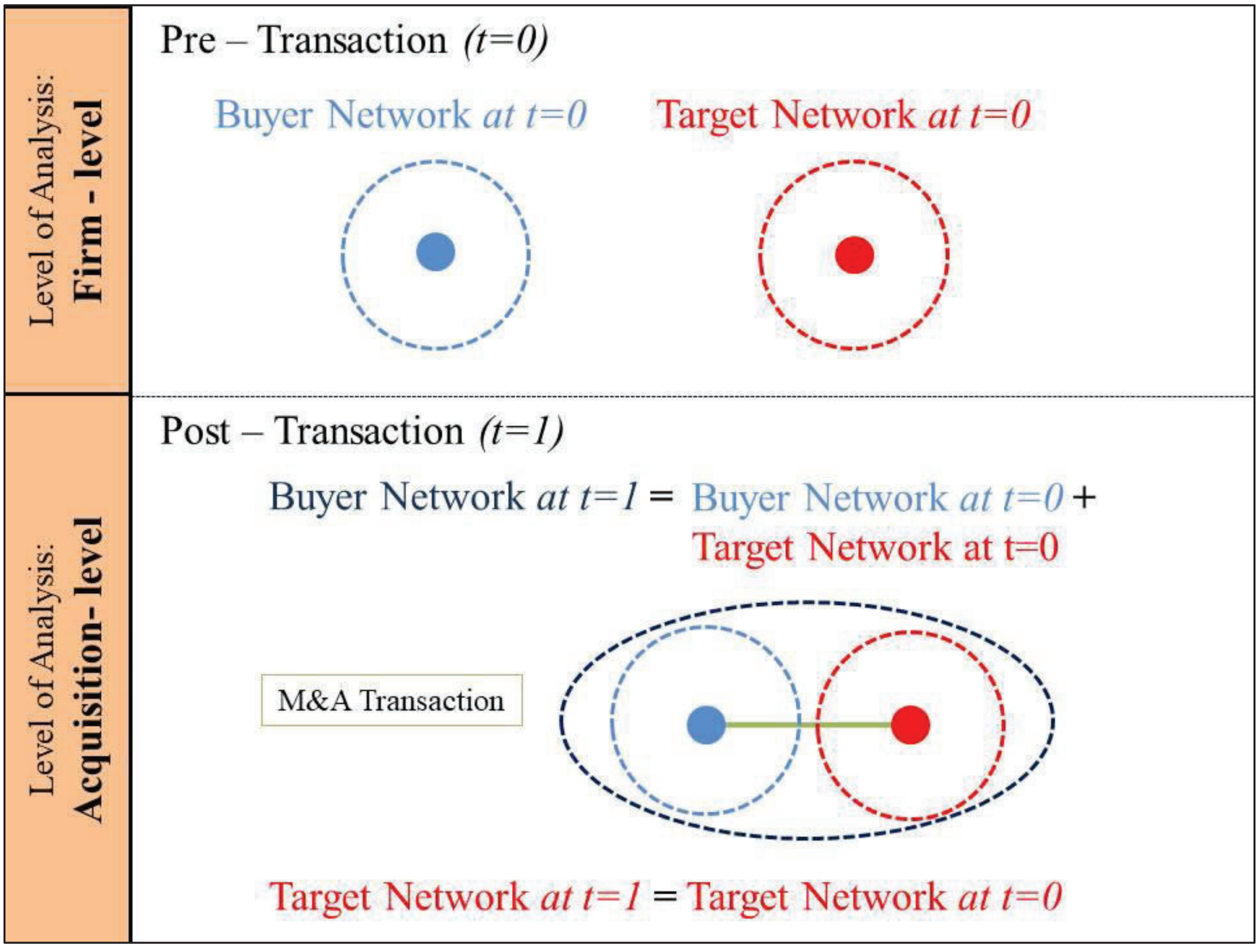
As discussed in Section *3.2. Review of M&A Literature*, M&A literature describes the combination of firm resources to the extent that they achieve an added-value not found if both resources are combined in isolation in the form of synergies (Bauer and Matzler, 2014). These combinations can take two forms based on the strategic management school of thought: strategic similarity and complementary (Larson and Finkelstein, 1999). Strategic complementarity as a combination advantage that arises from mutually supportive differences (e.g. Larson and Finkelstein, 1999; Kim and Finkelstein, 2009) and Bauer and Matzler (2014) argues that they arise from the combination of efficiency- and enhancement-based synergies in a transaction. In the following, I extend the concept of strategic complementarity of M&A transactions onto the merging of two networks and subsequently formalize the impact of firm network embeddedness on M&A performance.

For the combinational advantage of networks to provide a positive association with M&A performance, network associations must be higher post-transaction than pre-transaction. To do so the target firm post-transaction network embeddedness has to be more favorable than the pre-transaction embeddedness. As discussed in *(3.1.2.)*, network embeddedness has two dimensions: (1) Network Centrality (EV[20]) and (2) Geographic Embeddedness (λ[21]).

To determine what combinations of target and buyer network centrality and what combinations of target and buyer geographic embeddedness delivers a combinational advantage or transaction synergies, I reiterate the relationship between network centrality and firm performance as described in *(3.1.2.)*. Furthermore, to clarify the level of networks referred, Figure 7 depicts and defines the terminology used when describing the different network-levels.

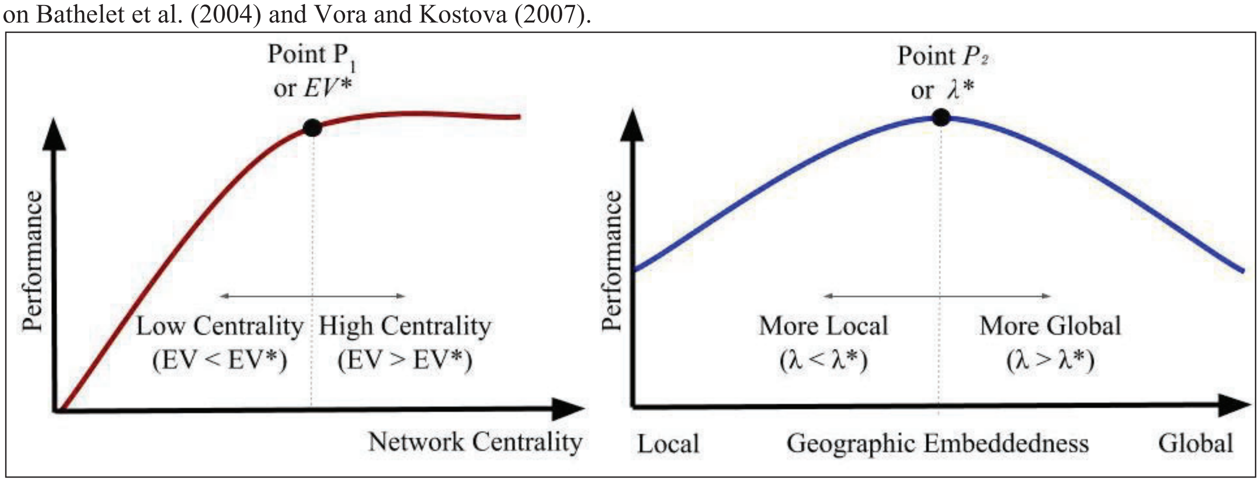
[20] "EV" is the author's chosen mathematical variable to display network centrality in reference to its measurement method (Eigenvector, see Model Description)
[21] λ is the author's chosen mathematical variable to display geographic embeddedness in reference to its measurement method (Local Embeddedness Coefficient, see model description)

Figure 3: Overview of network-levels and network terminology used
Figure 3 depicts a visualization of network-levels as conceptualized by the author.



Graph 4 summarizes the association and shows that network centrality has an inverted quasi-linear relationship with firm performance as a more central position in the network allows access to (1) information and strategic resources (Barney, 1991; Uzzi, 1997; Stuart, 1998; Kratz, 1998; Gulati, 1999; Abuja, 2000; Dyer and Nobeoka, 2000; McEvily and Marcus, 2005), (2) access to learning capabilities (Helper, 1991; Cohen and Levintahl, 1990; Powell et al., 1996; Stuart, 1998; Zahler and Bell, 2005), and (3) the ability to influence other economic actors like institutions and other firms (Gulati, 1999; Rugmann et al., 2011; Easley, 2004; Andersson et al., 2007; Dhanaraj, 2007; Dhanaraj, 2007; Compston, 2013). However, positive association of network centrality are limited by the “penrosean limitation” in which the more central a firm the higher the cost of information vetting and to a point above which no more information can be internalized (Penrose, 1959; Hutzschenreuter et al., 2011) (See section *3.1.2.1*). This translates to the more central a firm within the network, the higher the association with firm performance up until the marginal cost of network centrality is even to the marginal benefit. For geographic embeddedness the relationship is different. Geographic embeddedness has an inverted U-shaped relationship with firm performance, as the marginal advantage of localness comes at the cost of proportionally marginally reducing the advantage of global "pipelines". In section 3.1.2.2., I show that firms profit from local linkages by taking advantage of localized knowledge such as through tacit, face-to-face knowledge exchanges and overcome local institutional hurdles (e.g. Jensen and Pederson, 2011). However, full local embeddedness of a firm leads to firm isolation and hinders innovation potential (Turkina et al., 2006). Additionally, firms benefit from global linkages as global innovation "pipelines"(Bathelet, 2016). Therefore, an optimum degree of geographic embeddedness is reached at the Point P_2, where a firm is equally global as it is local and the association with firm performance is the highest. Similar, the relationship between network centrality and performance has an optimal point P_1 at which the marginal cost of additional centrality outweighs the marginal benefit of increased centrality and therefore the effect of network centrality on firm performance is the highest (Graph 4).

Graph 4: Firm Performance as a function of Network Centrality and Geographic Embeddedness
Author's visualization based on concepts by (*left*) Holm et al. (1996), Andersson and Forsgren (2000), Dhanaraj (2007), Johanson and Vahlne (2009), Hutzschenreuter et al. (2011) Molina-Morales and Expósito-Langa, (2012), Awate and Mudambi (2017), Turkina and Van Assche (2018) and (*right*) Author's visualization with concept based on Bathelet et al. (2004) and Vora and Kostova (2007).



Therefore, the combination of the pre-transaction buyer network (N_B) and the target network (N_T) has a positive association with M&A performance, if the post-transaction buyer network (N_{B+T}) is has a more favorable association on firm performance. This is given if the post-transaction buyer network centrality (EV_{B+T}) is closer to the optimal point P_1 (or Point EV*) at which network centrality has the highest association with firm performance. Vice versa, post-transaction buyer network (N_{B+T}) also has a more favorable association with firm performance, if post-transaction buyer network geographic embeddedness (λ_{B+T}) is closer to the optimal point P_2 (or Point λ^*) at which geographic embeddedness (λ) has the highest association with network performance. However, it is important to take into account the marginal degree to which network embeddedness impacts firm performance. For the case of network geographic embeddedness, the effect of local linkages versus global linkages on firm performance is a marginal trade-off in the sense that an increase in local linkages corresponds with more local geographic embeddedness. Correspondingly, an increase in global linkages increases the degree of global geographic. Theoretically, a firm A that is more locally than globally embedded may have at one point in time the association between geographic embeddedness and firm performance as a firm B that is more globally than locally embedded (Graph 4). For network centrality however, one does not have a trade-off as in the case of the inverted u-shaped relationship between geographic embeddedness and performance but rather a linear with declining marginal benefit of network centrality.

This is important in determining what network combinations are able to deliver a positive association with network centrality. To simplify, the potential combinations I categorize the degree of network embeddedness into either higher or lower than the optimal point of embeddedness (i.e. P_1 and P_2). In continuation, a firm's network centrality can thus be either *high* $(EV > EV^*)$ or *low* $(EV<EV^*)$. Correspondingly, in relation to optimal geographic dual embeddedness (λ^*), I categorize the degree of geographic embeddedness as *local* $(\lambda < \lambda^*)$ and *global* $(\lambda > \lambda^*)$ (Graph 4). This allows me to simplify the potential combinational performances of a network merger.

On the network centrality level, I group potential combinations simplified into three cases of how buyer network centrality and target network centrality stand to each other (Table 2). Network centralities can either be complementary, in which buyer and target centrality is opposite to each other as in Cases 1 and 2, or similar, in which network centrality is similarly high or similar low as in Case 3. As the relationship between firm performance and network centrality is an inverted quasilinear function, an increase in firm performance and subsequently a positive association with M&A performance based on network centrality is only given if the pre-transaction target network centrality (EV_T) is high, which the pre-transaction buyer network centrality is low (EV_B) as is in Case 1. This is conceptualized in M&A literate as strategic complementarity in that firm resources, i.e. network resources accessed through network centrality, are mutually supporting differences (e.g. Larsson and Finkelstein, 1999). Mutually supportive is the rational as to why Case 1 is theoretically able to achieve a positive impact on M&A performance and Case 2, which also displaces complementarity of the buyer and target firm's network centrality.

From the network geographic embeddedness perspective, potential performances can be grouped into two groups: similarity and complementary. For case 1, geographic network embeddedness of the buyer network is opposite to the target network and thus different. For strategic complementarity to apply, they must also be mutually supportive and this is the case give the inverted U-shape relationship between geographic embeddedness and firm performance. In contrast, case 2 displays similarity of geographic embeddedness. Again, given the inverted U-shaped relationship more "localness" to an already local does not increase firm performance more than the target network already does pre-transaction, and vice versa for "globalness" to a global network.

Similarly, this is the case when buyer and target network geographic embeddedness is complementary.

Table 2: Network combinational associations
Author's conceptualization and visualization of Network combinational associations based on network centrality (EV) and geographic embeddedness

Network Centrality (EV)					
	Target EV	**Buyer EV**	**∂ in Target EV as N_B+N_T**	**Association with Firm Performance**	**Association with M&A Performance**
Case 1	High	Low	Increase	Increase	Positive
Case 2	Low	High	Decrease	Decrease	Negative
Case 3	Low High	Low High	No change	No change	Neutral
Geographic Embeddedness (λ)					
	Target λ	**Buyer λ**	**∂ in Target λ as N_B+N_T**	**Association with Firm Performance**	**Association with M&A Performance**
Case 1	More Local More Global	More Global More Local	Increase	Increase	Positive
Case 2	More Local More Global	More Local More Global	No change	No change	Neutral

Therefore, I hypothesize for the combination of two networks based on network centrality:

H1a: *Strategic complementarity of the buyer and target network centrality has a positive relationship with M&A transaction performance.*

And subsequently for the combination of two networks based on network geographic embeddedness I hypothesize:

H1b: *Strategic complementarity of the buyer and target network's geographic embeddedness has a positive relationship with performance on M&A transaction performance.*

As described by Lavie (2006), the nature of the linkage plays a large role in how network embeddedness translates to network performance. Therefore, it is important to distinguish combinational benefits along the different sub-networks as each linkage type and subsequent sub-networks creates strategic complementarity in a different way (Turkina and Van Assche, 2019; Giroud and Scott-Kennel, 2009). Despite the nature of the relationship between network embeddedness and firm remaining the across sub-network levels, the mechanisms leading to the relationship are different.

Firstly, I examine the application my theoretical concept onto the vertical sub-network. Vertical linkages transfer “intra-task knowledge” (Turkina and Van Assche, 2018) and theorize that the combination of network resources from the vertical subnetwork leads to efficiency-based synergies (e.g. Economies of scale, increased purchasing power) (Sturgeon et al., 2008; Bauer and Matzler, 2014). Vertical linkages harbor network associations like an increased access to tacit knowledge as well as to firm knowledge pools through network centrality (Mudambi, 2008). However, firm’s ability is nonetheless limited by the "penrosean limitation“ (Hutzschenreuter et al., 2011). It is for this interplay of centrality advantages and costs that the relationship between network centrality and firm performance is an inverted quasi-linear function (Graph 4). In terms of the impact of geographic embeddedness, firms benefit from a local geographic embeddedness of the vertical sub-network by accessing localized tacit knowledge pockets and overcoming local institutional constraints (Bathelet, 2004; Lorenzen and Mudambi, 2013; Turkina et al., 2016). In contrast, global vertical linkages allow the firm to access global localization factors that leverage economies of scale (Bathelet, 2004; Lorenzen and Mudambi, 2013; Turkina et al., 2016). Therefore, the relationship between geographic embeddedness and firm performance is an inverted U-shape (Graph 4).

Subsequently, the cases of network combinations described in Table 2 are also applicable to the vertical subnetwork and therefore, I hypothesize:

H2a*: Strategic complementarity of buyer and target vertical sub-network embeddedness has a positive association with M&A transaction performance.*

H2b*: Strategic complementarity of the buyer and target vertical sub-network geographic embeddedness has a positive association with M&A transaction performance.*

Secondly, horizontal sub-networks facilitate "inter-task knowledge“ transfer (Turkina and Van Assche, 2018). As such, I theorize that network resources from the horizontal sub-network provide access to enhancement-based synergies through increased innovation and creativity potentials. However, as with vertical subnetworks, inter-task knowledge transfer is limited by the "penrosean limitation“ (Penrose, 1959; Hutzschenreuter et al., 2011). Horizontal sub-networks benefit from both local and global linkages as local linkages provides access to tacit knowledge and idea exchange, which global linkages increase innovation through increased idea diversity, as well as mitigating the risk of firm isolation which is detrimental to firm innovation (Bathelet et al., 2004; Turkina et al., 2016). Therefore, on the horizontal sub-network level, I confirm the inverted quasilinear relationship of network centrality and firm performance, and the inverted u-shaped relationship of geographic embeddedness and firm performance. Thusly, the cases of network combinations described in Table 2, are visible on a horizontal sub-network level and I hypothesize:

***H3a**: Strategic complementarity of the buyer and target horizontal sub-network embeddedness has a positive association with M&A transaction performance.*

***H3b**: Strategic complementarity of the buyer and target horizontal sub-network geographic embeddedness has a positive association with M&A transaction performance.*

Thirdly, when regarding corporate control networks or the shareholder subnetwork, the primary type of knowledge transferred is inter-task knowledge however primary benefit is the expertise of political and market control (Compston, 2013). From an M&A literature perspective, I deduce that network resources from shareholder linkages provide efficiency-based linkages as firms can utilize this knowledge to mitigate risk when dealing with other firms accessible through the shareholder sub-network and reduce cost of capital. Taking advantage of this network resource is dependent on the centrality of a firm within the shareholder sub-network (Massa and Rehman, 2008; Vitali et al., 2011; Compston, 2013). Furthermore, shareholder sub-network centrality increases the degree to which a firm can influence other economic actors like other firms through the theory of institutional isomorphism which suggests that firm emulate that are more successful and that hold strong resources upon which others in the network are dependent (DiMaggio and Powell, 1983), or policy though increased political power. However, increased centrality within the shareholder network also comes at costs. These costs are first and foremost, the "penrosean limitation" but also include an increased visibility within in turn translates to higher profitability exceptions from shareholders as well as political costs of leveraging shareholder networks. Therefore, I can confirm the inverted quasilinear relationship of shareholder network centrally and firm performance.

On the level of geographic embeddedness, localness of the shareholder network allows firms to take advantage of local institutional dimensions, which would not be possible with solely global linkages. Global shareholder linkages in contrast provide access to a broader variety of information and capital markets and as such provide a trade-off between the benefits of local versus global linkages. Therefore, for the relationship between geographic embeddedness of the shareholder network and firm performance, I confirm the inverted u-shape nature and subsequently, Table 3 finds theoretical application on the shareholder network level. Hence, I hypothesize:

H4a: *Strategic complementarity of the buyer and target shareholder sub-network embeddedness has a positive association with M&A transaction performance.*
H4b: *Strategic complementarity of the buyer and target shareholder sub-network geographic embeddedness has a positive association with M&A transaction performance.*

On an internal subnetwork-level, firms are able to materialize both efficiency- and enhancement-based synergies as internal linkages behave mechanically similar to either external vertical or external horizontal linkages. As such, internal linkages behave as a combination of the two. On the one hand, internal vertical linkages, i.e. HQ-subsidiary linkage, provide efficiency-based synergies, while internal horizontal linkages, i.e. inter subsidiary linkages bring enhancement-based synergies. Hence, internal linkages exchange both intra- and inter-task knowledge. This means that centrality in the internal sub-network takes advantage of both centrality advantages of both vertical and horizontal linkages, while being bound by both constraints. In consequence, the relationship between internal sub-network centrality and firm performance can be depicted as an inverted quasi-linear function.

Correspondingly, internal sub-network geographic embeddedness, like vertical and horizontal sub-network geographic embeddedness, has an inverted u-shaped relationship with performance. Conclusively, the combinational scenarios depicted in Table 2 are applicable to the internal sub-network and thus I hypothesize:

H5a: *Strategic complementarity of the buyer and target internal sub-network embeddedness has a positive association with M&A transaction performance.*
H5b: *Strategic complementarity of the buyer and target internal sub-network geographic embeddedness has a positive association with M&A transaction performance.*

Lastly, I focus on board sub-networks. Board sub-networks exchange primarily reputation-based information and tacit knowledge about management practices. A centrality of a board member in the board sub-network has an association with reducing a firm's agency problem as the reputation-based exchanges act as a control of board member behavior. Furthermore, centrality in the board sub-network gives firms access to tacit management knowledge exchange that positively correlates with firm performance through risk mitigation (Gompers and Xuan, 2008; Ingram and Roberts, 2000; Ishii and Xuan, 2014; Cai and Sevilir, 2012). Therefore, I theorize that board linkages realize efficiency-based synergies when combined. However, this only functions to a certain extend as board members whose board-appointed CEOs conduct fraudulent behavior are more likely to be a part of fraudulent cover-ups

(Khanna et al., 2015), are more likely to mitigate other board behavior from "familiarity biases“ (Ishii and Xuan, 2014). Additionally, the “penrosean limitation” of information overflow is also valid here (Penrose, 1959; Huschtzenreuter et al., 2011). Therefore, I confirm that the relationship between board sub-network centrality and firm performance can be graphed as an inverted quasilinear function.

Geographic embeddedness of board linkages plays a role similar to vertical and shareholder linkages as localized linkages take advantage of tacit knowledge transfers and allow the location-based knowledge about e.g. the institutional environment to be exchanged. In opposite, global linkages leverage global knowledge and reputation benefits, as solely local linkages run risk of isolation effects. Hence, I confirm the relationship between geographic embeddedness and firm performance on the board sub-network level and hypothesize:

H6a: *Strategic complementarity of the buyer and target board sub-network embeddedness has a positive association with M&A transaction performance.*
H6b: *Strategic complementarity of the buyer and target board sub-network geographic embeddedness has a positive association with M&A transaction performance.*

4. Empirical Model and Data Preparation

4.1. Model Description

To investigate the association of firm network embeddedness with the success of a M&A transaction, I use a two-step estimation process using OLS multi-regression models. In a first step, I build an OLS multi regression model to determine whether there is an increased association of network embeddedness with firm performance through the M&A transaction. In a second step, I study whether the pre-transaction target network embeddedness has a similar or complementary association with firm performance. If so I am able to make assumptions that the two networks similarity in regards to the association of network embeddedness with firm performance. This two-step model will allow me to determine (1) whether there is an increase in association of the network transaction with the association of network embeddedness with firm performance which would represent a positive M&A transaction performance and (2) whether a potential an increased relationship could be explained by network configuration, i.e. the combination of network centrality and geographic embeddedness measures.

For the first step, I build a regression model estimating the association of the network embeddedness dimensions as independent variables as well as the control variables on M&A performance (I). Subsequently, I make two variations. One model variations that estimates the association of pre-transaction buyer network embeddedness on firm performance (II) and one model variations that estimates the association of post-transaction buyer network embeddedness (III). Subsequently, I preform a test of coefficients to determine whether and if how the coefficients differ and thus will be able to determine whether the combination of the buyer and target network leads to an increased association of post-transaction buyer network embeddedness with firm performance. If so then this increase would be a positive M&A performance. After regression both models, I run test of coefficients to determine whether the association of buyer network embeddedness increases through the transactions.

(I) $$FirmPerformance_{n,t} = b_0 + b_1,* EV_{n,t} + b_2 * \lambda_{n,t} + b_i * CV_i + e_{n,t}$$

with n as network position (either n=B or n=T); t time (t=1 or t=0)

(II) $$FirmPerformance_{B,0} = b_0 + b_1,* EV_{B,0} + b_2 * \lambda_{B,0} + b_i * CV_i + e_{B,0}$$

(III) $$FirmPerformance_{B,1} = b_0 + b_1,* EV_{B,1} + b_2 * \lambda_{B,1} + b_i * CV_i + e_{B,1}$$

In second step, I investigate whether pre-transaction buyer network embeddedness has a similar association as pre-transaction target embeddedness. Similar to step one, use the base model build model (IV) which describes the association of the target network embeddedness with firm performance. In a second step, I use the regression estimating pre-transaction buyer network embeddedness on firm performance. Lastly, I again run a test of coefficient analysis to determine whether buyer and target network are similar or not in terms of network centrality and network geographic embeddedness.

(IV) $$FirmPerformance_{T,0} = b_0 + b_1,* EV_{T,0} + b_2 * \lambda_{T,0} + B_i * CV_i + e_{T,0}$$

Figure 3a visualizes this two-step model with corresponding OLS equations while Figure 3b visualizes the decision tree leading from the empirical model to the rejection or non-rejection of hypotheses H1a or H1b.

Figure 4a: Visualization of Model 1 and Model 2 with corresponding OLS equations
Author visualization of the empirical model based on author conceptualization. β represents the OLS beta coefficient estimate of OLS equations (II), (III), and (IV).

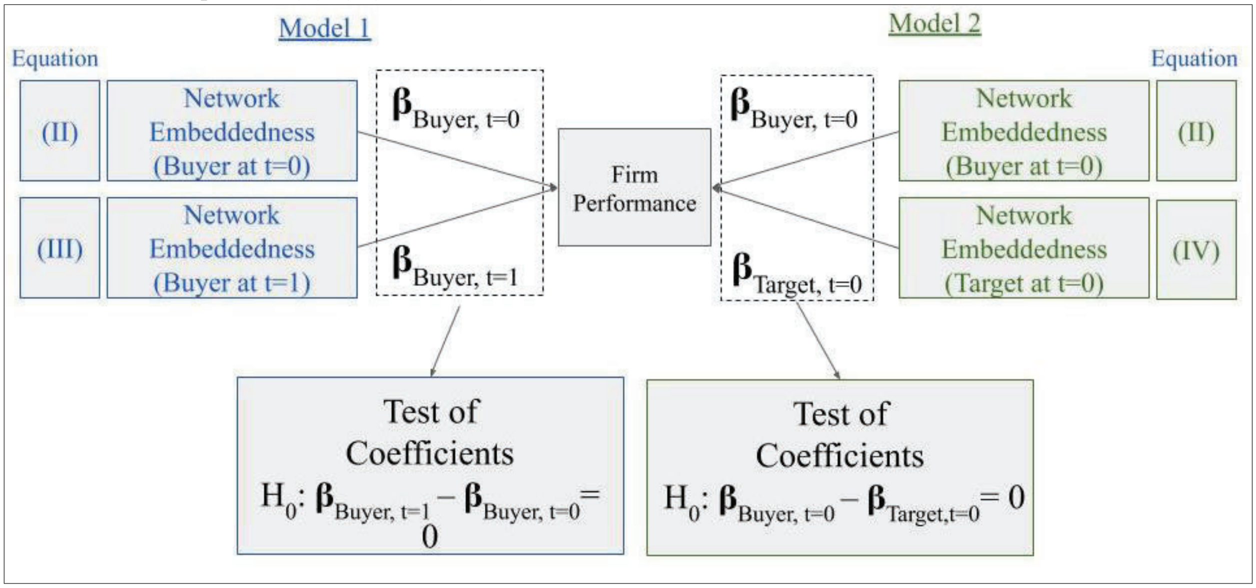
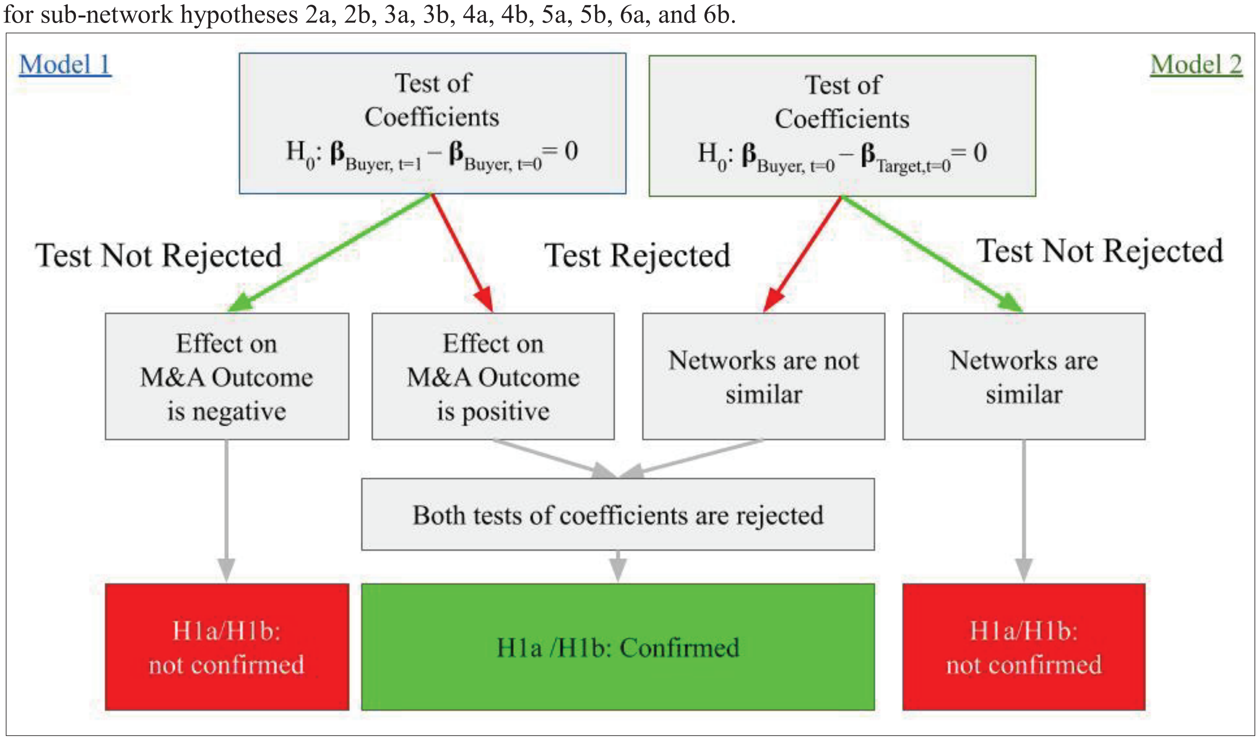


Figure 4b: Visualization of decision tree leading from model results to H1a and H1b
Author visualization of the empirical model based on author's conceptualization. The decision tree is equally valid for sub-network hypotheses 2a, 2b, 3a, 3b, 4a, 4b, 5a, 5b, 6a, and 6b.



In the decision tree from Figure 3b, I visualize that in order to confirm my hypotheses, Model 1 would pick up on a positive change of network centrality and networks geographic embeddedness while my test of coefficients would reject the zero hypothesis stating $\beta_{buyer,t=0} = \beta_{buyer,t=1}$. At the same time, Model 2 would pick of on a difference of direction, i.e. opposite associations of network centrality and geographic embeddedness. Furthermore, in the case that there is no directional change, I introduce a robustness test in which I look at the beta coefficient difference in Model 1, i.e. only in regards to the effects of the buyer network on firm performance (Δ_{Buyer}). The purpose of the beta coefficient difference test is to determine whether there are more subtle effects of the M&A transaction through changes in coefficient strength that do not translate into a change in direction. To calculate the beta coefficient difference (Δ_{Buyer}), I subtract the beta coefficient for each of the independent variables pre- and post-transaction, e.g. for the beta coefficient difference of network centrality ($\Delta_{Buyer,EV}$) as displayed in Equation (V). Correspondingly, I construct the beta coefficient difference for network geographical embeddedness (($\Delta_{Buyer,\gamma}$) as shown in Equation (VI).

(V) $\Delta_{EV,buyer} = b_{EV,buyer,t=1} - b_{EV,buyer,t=0}$

(VI) $\Delta_{\gamma,buyer} = b_{\gamma,buyer,t=1} - b_{\gamma,buyer,t=0}$

My test of coefficients would next reject the zero hypothesis stating $\beta_{buyer,t=0} = \beta_{target,t=0}$.

4.2. Data Preparation

The base data was compiled in a three-step process using the Bureau van Dijk databases ZYPHER and Orbis (Figure 4). In a first step, ZYPHER was used to choose firm pairs from a transaction-level. Sample firms needed to be based in North America, i.e. Canada, the United States of America or Mexico, with a completed 100% purchase M&A transaction post 2000 and completion before August 31st 2019. Furthermore, buyer firms were required to be publicly listed to fulfill the construct requirements of the dependent variable for M&A success. In terms of industry classification, only buyer firms needed to be from within the "Automotive Industry“ as defined by the North American Industry Classification System with codes 3361, 336211, and 3363. This was chosen to account for trend in the North American automotive industry of "autonomous vehicles“ and "electric vehicles“ in which traditional automotive firms seek non-automotive based capabilities that are not available within the industry, i.e. strategic partnership between Toyota and Uber technologies combining Toyota’s automotive capabilities with Ubers autonomous driving capabilities[22] (*See Section 2.3.*). This identified 11 individual M&A transactions with competition dates ranging from 2009 to 2019.

Next in step 2, ORBIS provided the background characteristics about the sample firms. These characteristics consisted of location, industry, size, and Bureau van Dijk Id (BvD ID). In a third step,

[22] *https://asia.nikkei.com/Business/Companies/Toyota-expands-self-driving-alliance-ahead-of-Google-s-Waymo*

background research was used to identify individual linkages based on the following linkage description: vertical, horizontal, shareholder, board, and internal linkage. These characterizations are defined in table 1 as depicted in the literature review (*See Section 3.1.3.*). From ORBIS, I was able to obtain information about shareholders, subsidiaries and affiliates. Subsidiaries were identified to be internal linkages while affiliates were researched and then classified either as internal, vertical or horizontal linkages. Furthermore, I hand collected other linkages points using the sample firm's published data, I.e. Annual or Quarterly Reports (10k), Press releases etc. Throughout my 11 transactions, I gathered a total of 5,524 linkages with 88.58% originating from the ORBIS database and 11.42% hand-gathered.

Figure 5: Overview of 3–Step data collection methodology
This figure describes the rational and conditions behind sample data collection.

4.2. Variable Description

4.2.1. Dependent Variable: Abnormal Rate of Return

To measure the success of an M&A transaction, I focus on the "success“ of the buyer in the transaction and deem a transaction as successful in which the buyer is able to generate a positive increase in the relationship between network centrality and firm performance or between network geographic embeddedness and firm performance.

Numerous measures are used developed and used depending on aim of the research. Most prominent among them are Tobin's Q and Cumulative Abnormal Returns (CAR) (Bauer and Matzler, 2015). Both measures proxies the value of a company dependent on market prices, i.e. publicly traded stocks. While Tobin's Q as a measure of market value of equity, outstanding debt, and liquidating value of preferred stock relative to total book value of assets, is a "hard asset“ fixated measure, CAR accounts for abnormal more latent effects on the profitability of the firm stock (El-Khatib et al., 2015). In effect, the CAR uses a Capital Asset Pricing Model (CAPM) to model market-predicted returns relative to the market return (Sharpe, 1964; Linter, 1965; Fama and French, 1993). These predicted returns are based on an estimation window with t being the day of the transition (Brown and Warner, 1985). Here, I use an estimation window of τ=[-60, -20], i.e. from 20 trading days to 60 trading days from the transaction completion date. This assumes that twenty days prior to the transaction event returns are not influenced by the event itself. Next, I set an event window in which I compare predicted returns to actual returns to see whether the transaction leads to returns unpredicted by the market model and that are i.e. abnormal (MacKinlay, 1997). In contrast to Tobin's Q, Abnormal returns attempt to quantify synergies produced by intangible assets, i.e. network resources.

The event window is defined as τ=[-5, +60], i.e. 5 trading days prior to the transaction completion date up until 60 trading days after the completion. In between the estimation and event window, as suggested by Thompson (1995), I allowed a separation window τ=[-20, -5]. The extended time event time is to account for the completion of post-merger integration process which on average is around 60 business days (Bauer and Matzler, 2015).

The primary difference between the CAPM and the return prediction I use is the treatment of alpha as a constant as opposed to the use of the market risk free rate. Both $ß_0$ and $ß_1$ are estimated by ordinary least squares (OLS) regression (V). The market return $R_{M,t}$ is taken as the index return from the stock exchange at which the buyer company is listed. For example in the case of the Ford Motor Company (Ticker symbol: F) listed on the New York Stock Exchange (NYSE), I use the Standard & Poor's 500 (S&P 500) index to proxy the domestic market return. Furthermore, to test for robustness, I compare the index-based market returns with data collected by Eugene Fama and Kenneth French on U.S. market returns.[23] These market returns are highly correlated with the S&P 500 at a 1%-significance level.

(V) $$E(R_{i,t}) = b_0 + b_1 \cdot R_{M,t}$$

Next, I subtract the predicted daily return $E(R_{i,t})$ from the actual daily return $R_{i,t}$ from the event window to get the daily abnormal returns (VI).

(VI) $$AR_{(i,t)} = R_{i,t} - E(R_{i,t})$$

(VII) $$AAR_t = \frac{1}{N} \sum_{i=1}^{n} AR_{i,t}$$

[23] This data is made available by Kenneth French over the Tuck School of Business, Dartmouth. *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/biography.html*

Lastly, I calculate the average abnormal return $AAR_{i,t}$ for the event window to receive the average abnormal return. This reduces potential idiosyncratic stock risk in measurement (MacKinlay, 1997) (VII).

4.2.2. Independent Variable

Network Centrality through Eigenvector Centrality ($EV_{i,t}$)

As described in the literature review, the relative position of each node in a network is not random (Jackson and Rogers, 2007; El-Khatib et al., 2015) To proxy network embeddedness, I utilize the commonly used measure of Eigenvector centrality to estimate a nodes' position within its network. The eigenvector centrality measure is an extension of the degree centrality (Freeman, 1979), which encapsulates the number of common linkages with other nodes in the network. The eigenvector measure enhances this picture by including a nodes' ability to access its network but also its ability to access resources indirectly linked to it and thus further emphasizes the position of the node within the network (Proctor and Loomis, 1951; Bonacich, 1972). Eigenvector centrality is calculated based on the number of an a firm's direct contacts, and their direct contact's structural central position in the whole network (Bonacich, 1987). Literature also utilized similar concepts such as degree centrality (Nieminen, 1974), closeness centrality (Okamoto et al., 2008) and betweenness centrality (Burt, 1992). In comparing all four centrality measures, Meghanathan (2015) found that degree centrality, closeness centrality and eigenvector centrality are highly correlated while eigenvector centrality and betweenness are lesser correlated. Despite, conceptual differences between the measures, I limit myself to eigenvector centrality as most prominent variable to depict whole network reachability (e.g.: Stuart et al., 1999; Podolny, 2001; Soh et al., 2004).

Network Geographic Embeddedness through Local Embeddedness Coefficient ($\lambda_{i,t}$)

To proxy network geographic embeddedness the degree to which a firm's linkages are local in relation to its global linkages, I use a self-constructed measure that relates the number of local linkages to the number of global linkages in a focal network. In effect, this portrays a focal firm's local embeddedness as described by Turkina et al. (2016).

(VIII) $$\lambda_{n,t} = LocalLinkages_{n,t}/GlobalLinkages_{n,t}$$

(with Network n at time t)

For example, if a firm has an equal amount of global as global linkages the local embeddedness coefficient would equal 1. If a firm is more locally then globally embedded, then the local embeddedness coefficient would be above one or $\lambda>1$. Similarly, if a firm is more globally then locally embedded, then the local embeddedness coefficient would be below one or $\lambda<1$.

4.2.3. Control Variables

Firm Size

To account for transaction firm size, I use three measures: Turnover in million USD at time of transaction, total assets in million USD at time of transaction, cashflow in million USD at time of transaction, and number of employees at time of transaction. These variables are not size variables for the linkage type but rather of the transaction firm. Each linkage is attributed with the firm size of their direct transaction linkage, e.g.: for the link between Ford Motor Company (F), a transaction firm, and Swiss SFS Intec AG, a vertical linkage, the firm size variable would take on the firm size of the transaction firm, here of the Ford Motor Co. These size variables are on the basis of common practice in empirical work on M&A transactions (Bauer and Matzler, 2014; El-Khatib et al., 2015). I test these variables against each other to establish a robust measure of firm size.

Firm Value Chain Position

Next, I include a categorical dummy variable which represents a given firms position in the value chain. The Global Value Chain framework identifies different strategies and firm behaviors dependent on firm value chain position. In the case of the automotive industry, Sturgeon et al. (2008) suggests that as firms move along the value chain, actors are more exposed to higher market pressures. This is examined in the industry analysis in *Section 2.* and an exemplary effect of these pressures is "follow sourcing“ in which suppliers are driven to follow their customer’s geographic investments (Humphrey and Memedovic, 2003). The categorical variable assigns values based on the value chain schematic devised in *Section 2.*, Graph 1, and can be seen in table 3 below.

Table 3: Values and description of value_dummy

Overview of value_dummy values and description

Value_dummy	Description
1	Original Equipment Manufacturer (OEM)
2	Tier 1 Supplier
3	Secondary Tier suppliers (Tier 2 and Tier 3)
4	Supporting Industries (e.g. Production equipment suppliers, engineering services etc.)
5	After-market Services (Aftermarket Parts and Services)

Different Country of origin variable dummy

Another variable I use aims at controlling the impact of cultural differences on the ability to utilize resources acquired through a M&A transaction. These differences arise when a buyer is based out of a different cultural area as the target and thus potential restricting access to resources (Hofstede, 1980; 2002). The variable focuses on accounting for when the buyer's country differs from the target country. Hence, the variable takes on a value of 1 if the buyer's and target's home countries are different and 0 if they are the same.

Different industry

Similarity to the different country variable above, the different industry variable identifies when in a transaction the buyer is based from a different industry as the target. In that case, the variable would have a value of 1 and 0 if otherwise.

Strategic Intent

In the realm of M&A and international expansion theories, the strategic intent behind a Merger & Acquisition is prominently highlighted (Porter, 1980). There, the transaction is partly explained by the strategic intent it wishes to fulfill. Prominently, this intent is compartmentalized by four strategic intents: natural resource seeking, market seeking, efficiency seeking, and strategic asset seeking(Porter, 1980). Natural resource seeking describes the intent to gain access to natural or infrastructure related advantages held by the target firm (Porter, 1980). Market seeking, in contrast, describes the wish to enter a market in which the target is well-established or in which the buyer could break into with the help of the target resources and capabilities (Porter, 1980). Next, efficiency seeking describes the wish to realize cost advantages through the e.g. overlapping of commercial, production or administrational activity (Porter, 1980). Lastly, strategic asset seeking describes the wish to gain access to a certain asset in the possession of the target. Often times this can be patents or knowledge assets, as well as production locations.

To categorize the transactions, I analyze all firm-issued material as well as transaction-based media coverage to identify the rationale behind the transaction.

Private Equity Vendor Dummy

To mitigate additional influences by the vendor of the transaction and the strategic orientation of the previous owner in contrast to the incoming owner, I create a dummy variable which displays the value 1 when the previous owner and seller of the target firm is a Private Equity (PE) firm and in possession of the majority at time of sale. Traditional M&A literature highlights a short-term orientation of private equity firm holdings versus a more long-term approach by corporate industrial firms (Jensen and Meckling, 1976). Therefore, as ownership of the entity switches from a potential short-term orientation, i.e. PE ownership, to a more long-term approach held by an industrial owner, there is potential effects onto the success of the M&A transaction. These differences may be visible through management of financial "hard-facts" such as cashflow management and leveraging but are most often visible in different corporate cultures (Kaplan and Störmberg, 2009). However, one could also argue a relative short-term orientation of publicly traded industrial firms, as I am dealing with in my sample, versus private ownership firms. Nonetheless, this variable attempts to account for any effects that potential arise from this change in ownership entity.

Linkage type Categorical

Following the categorization of firm linkages based on my literature review, I create a categorical variable that proxies the different linkages to account for different linkage effects on the whole network regression analysis. The categorical values corresponding to linkage type are displayed in Table 4.

Table 4: Overview of Linkage type and value of linkage categorical

Linkage Type	Value of linkage categorical
Vertical	1
Horizontal	2
Shareholder	3
Internal	4
Board	5

Year of transaction

As the transactions examined span a period of 10 years from 2009 to 2019, I include a year dummy variable which aims at isolating year-specific effects on M&A success. Despite different transaction years, I see no reason to be concerned for year-specific events and risks as my dependent variable accounts for these within the market-based prediction model, which addresses idiosyncratic risk. Nonetheless, this variable may also serve as a robustness test for the ability of the AAR to remove idiosyncratic risk.

Publicly traded dummy

Lastly, I include a dummy variable that takes into account whether a firm is publicly traded or privately held. This dummy takes on the value of 1 if publicly traded and 0 if privately held. Numerous authors have explored the effect of the increased visibility of publicly traded firms (e.g. George, 2005).

4.3. Descriptive Statistics

4.3.1. Descriptive Overview of the Network Layouts

To begin my descriptive statistics, I visualize my network and sub-networks pre- and post-transaction. Figures 5a to 5f depict the pre-transaction network on the left and the post transaction network on the right. All visualizations and network calculations were performed on *Gephi 0.9.2.*[24] Figures 5a to 5b which describe the whole network, the vertical sub-network, the horizontal subnetwork, and the shareholder sub-network, and the internal sub-network are depicted using Yifan Hu's attraction-repulsion model to arrange the data points (Hu, 2005). For the board sub-network level, I chose the Fruchterman-Reingold algorithm of mass particles as the board sub-network has a higher visualizing explanatory power at observations below 100 (Fruchterman and Reingold, 1991). Despite this limitation of 100 observations, I still use Hu (2005)'s attraction-repulsion model on my horizontal sub-network even though we have observations below 100, as the network structure benefits from visualization based on attraction-repulsion system vis-à-vis a minimized spring or "edge“ energy system as with Fruchterman-Reingold algorithm (Fruchterman and Reingold, 1991).

First, I look observe the structure properties of the whole network pre-transaction vis-à-vis the whole network post-transaction. Figure 5a showed the comparison of pre-transaction and post-transaction network as a whole. The nodes are colored by industry to highlight industry diversity within each network. In the case of the whole network, the top industries are Motor Vehicle Manufacturing (3361), Motor Vehicle Parts Manufacturing (3363), and Computer and Peripheral Equipment Manufacturing (3341). Furthermore, The structure of the whole network can be characterized as star formed with large circular elements around central lead nodes.

As for the vertical sub-network displayed in Figure 5b, I observe a distinct star shaped form with lead firms as acting as bridges to the peripheral. I find that post-transaction the network appears more dispersed and star formed then before. The top industries as seen in Figure 5b in purple, green, and blue are Motor Vehicle Parts Manufacturing (3363), Basic Chemical Manufacturing (3251), and Resin, Synthetic Rubber and Artificial and Synthetic Finer and Filaments Manufacturing (3251). Between the pre-transaction and post-transaction vertical network structure.

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Figure 6a: Visualization of the whole network

(*top*) Whole network of buyer pre-transaction (t=0); (*bottom*) whole network of buyer post-transaction (t=1); Based on author's data set and author's visualization in Gephi 0.9.2.(*n=5,524)*. Coloring of nodes by industry with top three industries: (p*urple*) Motor Vehicle Manufacturing (3361), (g*reen)* Motor Vehicle Parts Manufacturing (3363), (b*lue)* Computer and Peripheral Equipment Manufacturing (3341). NAICS code in parentheses. (NAICS, 2017)

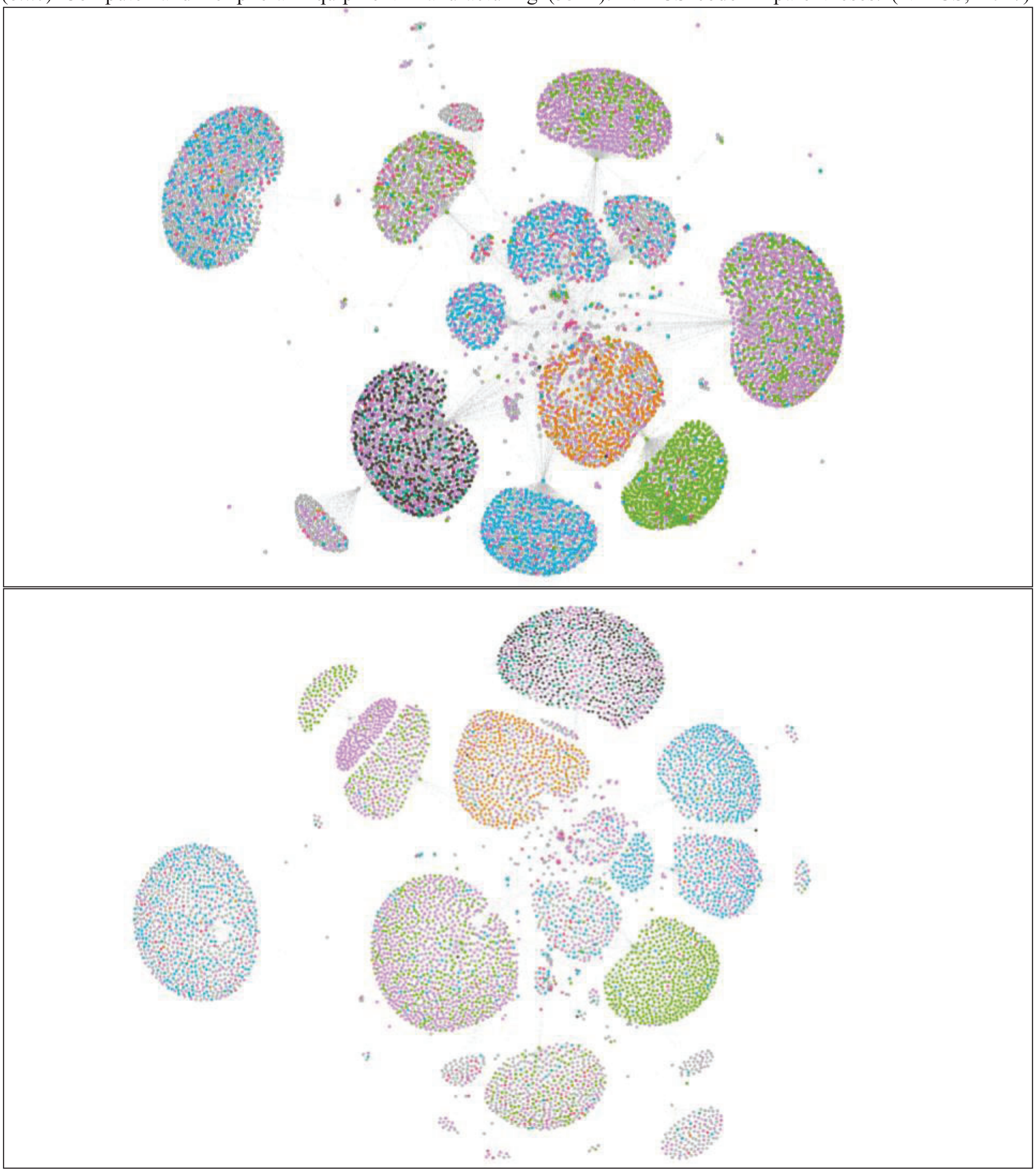


Figure 6b: Visualization of the vertical sub-network
(*left*) Vertical sub-network of buyer pre-transaction (t=0); (*right*) Vertical sub-network of buyer post-transaction (t=1); Based on author's data set and author's visualization in Gephi 0.9.2.*(n=582)* Top industries colored with top three: (*purple*) Motor Vehicle Parts Manufacturing (3363), (*green*) Basic Chemical Manufacturing (3251), and (*blue*) Resin, Synthetic Rubber and Artificial and Synthetic Finer and Filaments Manufacturing (3251). NAICS code in parentheses. (NAICS, 2017)

In the case of Figure 5c, I observe the horizontal sub-network in which the top industries are. In terms of the horizontal sub-network's shape, I observe a more collegial network with multiple cross linkages. While pre-transaction, the horizontal partnerships hotspots which are visible as peripheral clusters of firms are integrated into the overall network. The top industries as portrayed in purple, green and blue in Figure 5c are Motor Vehicle Manufacturing (3361),

Next, I turn to the shareholder sub-network displayed in Figure 5d. There, I observe a multi bow-tie like structure with multiple overlaps. These interconnections drastically increase post-transaction and displays high interconnection. The top represented industries are Investment Banks (5239), Holding or Management companies (5511), and Insurance Companies (5241).

Furthermore in Figure 5e, I analysis the network structural optically and find a loose grouping of MNE groups. These MNE groups become more proximate in the post-transition network. The top industries as seen in figure 5e in purple, green, and blue are Universities (6113), Motor Vehicle Manufacturing (3361), and Resin, Synthetic Rubber and Artificial and Synthetic Finer and Filaments Manufacturing (3251), Basic Chemical Manufacturing (3251), and Resin, Synthetic Rubber and Artificial and Synthetic Finer and Filaments Manufacturing (3251).

Figure 6c: Visualization of the horizontal sub-network
(*left*) Horizontal sub-network of buyer pre-transaction (t=0); (*right*) Horizontal sub-network of buyer post-transaction (t=1); Based on author's data set and author's visualization*(n=25);* Top industries presented in colors with top three industries: (*purple*) Universities (6113), (*green*) Motor Vehicle Manufacturing (3361), and (*blue*) Resin, Synthetic Rubber and Artificial and Synthetic Finer and Filaments Manufacturing (3251). NAICS code in parentheses. (NAICS, 2017)

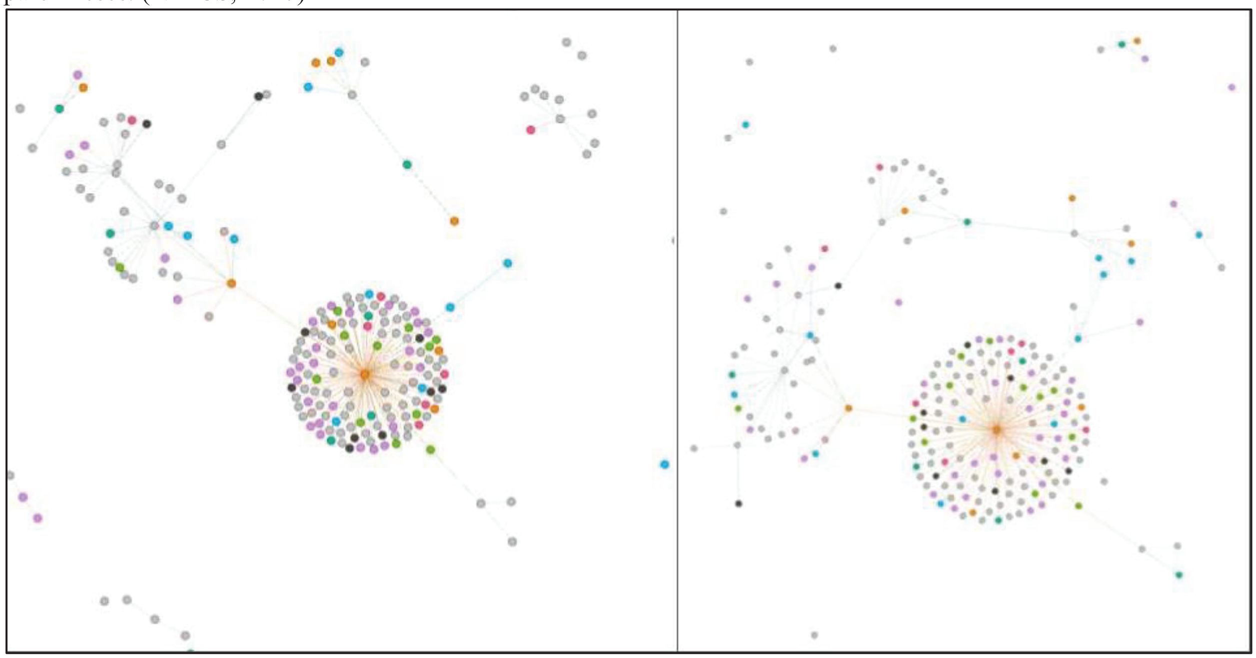


Figure 6d: Visualization of the shareholder sub-network
(*left*) Shareholder sub-network of buyer pre-transaction (t=0); (*right*) Shareholder sub-network of buyer post-transaction (t=1); based on author's data set and author's visualization in Gephi 0.9.2.*(n=732)*.Top industries presented in colors with top three industries: (*purple*) Investment Banks (5239), (*green*) Holding or Management companies (5511), and (*blue*) Insurance Companies (5241). NAICS code in parentheses. (NAICS, 2017)

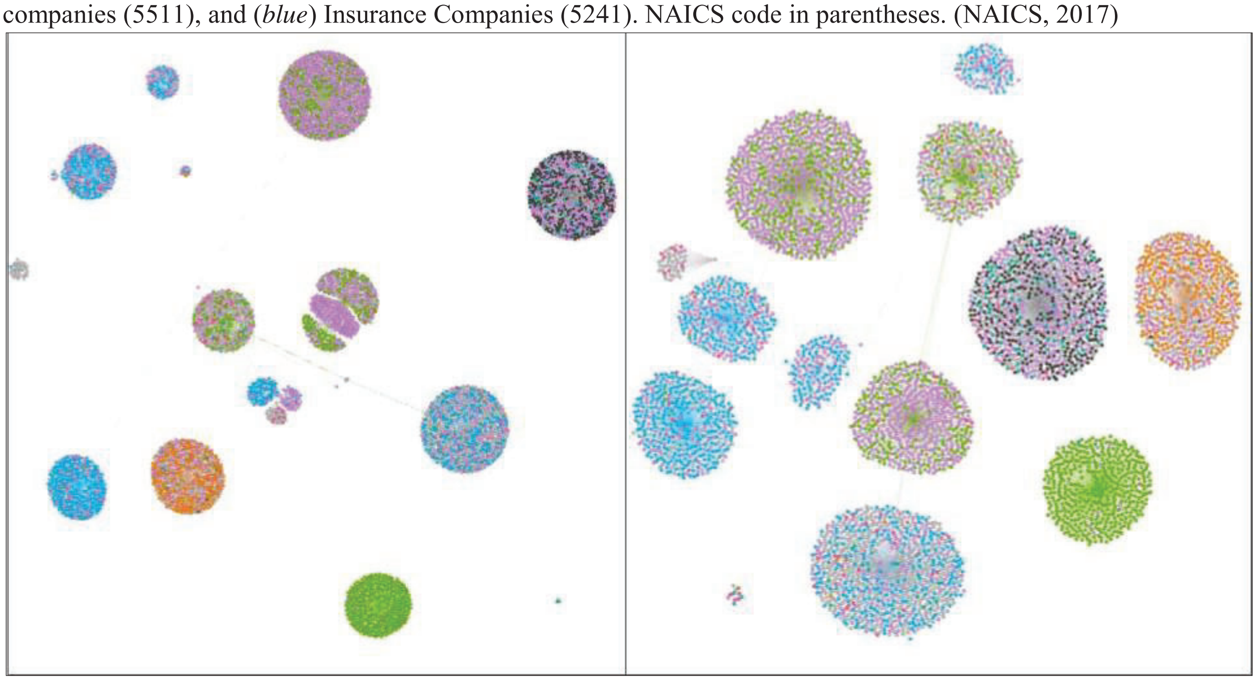


Figure 6e: Visualization of the internal sub-network

(*left*) Internal sub-network of buyer pre-transaction (t=0); (*right*) Internal sub-network of buyer post-transaction (t=1); Based on author's data set and author's visualization in Gephi 0.9.2.*(n=4,090);* Top industries colored with top three: (*purple*) Motor Vehicle Parts Manufacturing (3363), (*green*) Basic Chemical Manufacturing (3251), and (*blue*) Resin, Synthetic Rubber and Artificial and Synthetic Finer and Filaments Manufacturing (3251). NAICS code in parentheses. (NAICS, 2017)

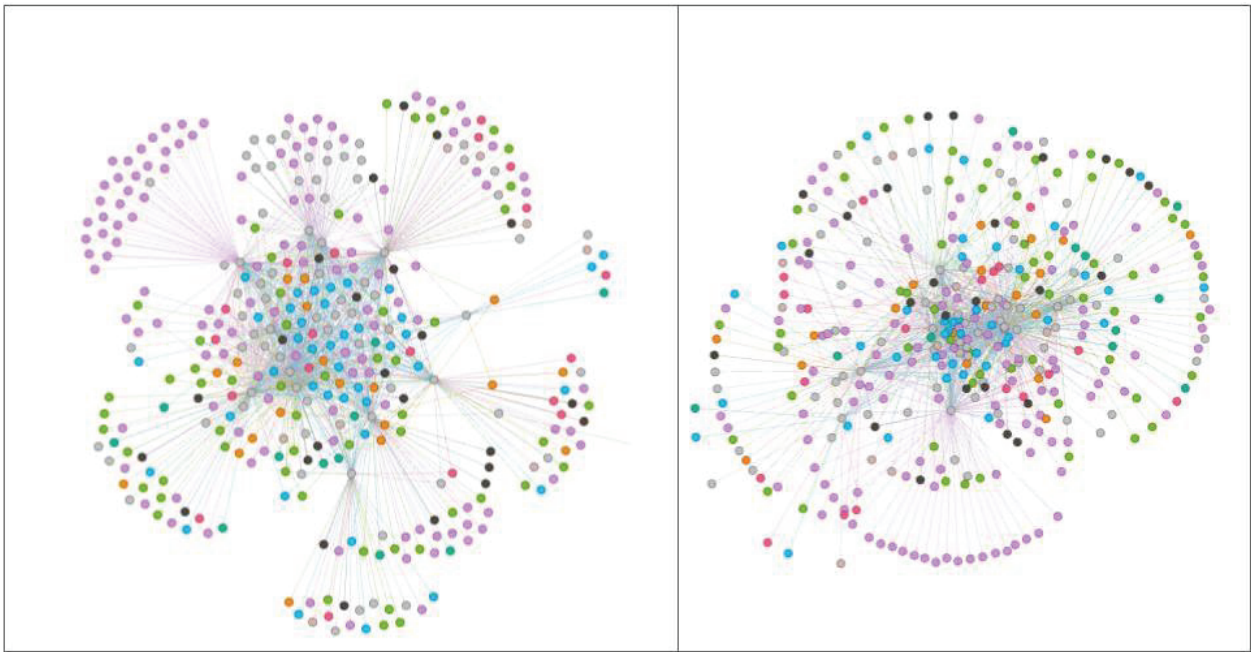
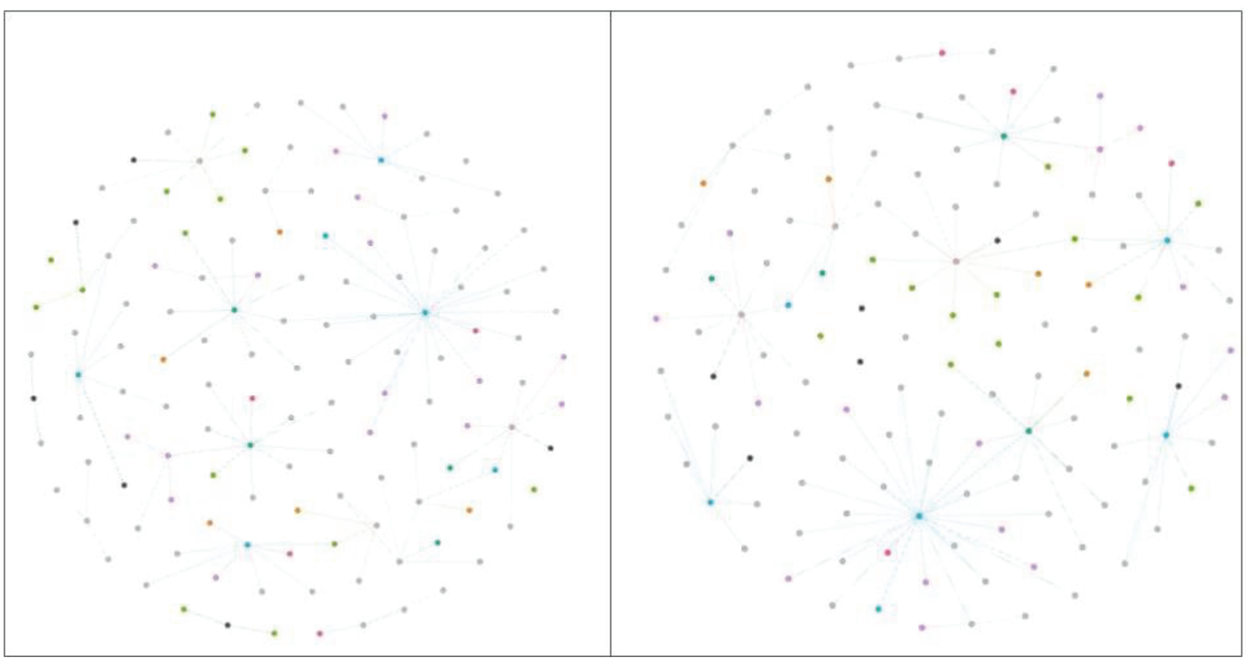


Figure 6f: Visualization of the board sub-network

(*left*) Board sub-network of buyer pre-transaction (t=0); (*right*) Board sub-network of buyer post-transaction (t=1); Based on author's data set and author's visualization in Gephi 0.9.2.*(n=95);* Top industries are displayed in color with the three industries: (p*urple*) Holding or Management company (5511), (g*reen)* Motor Vehicle Parts Manufacturing (3363), (b*lue)* Computer and Peripheral Equipment Manufacturing (3341). NAICS code in parentheses. (NAICS, 2017)



Lastly, I observe the board sub-network displayed in Figure 5f. There, I observe dispersed star shaped patterns with a low number of nodes per star that are sparsely interconnected. These star shapes become larger in the post-transaction network in that the number of nodes per stars increases. The top industries in the board network are Holding or Management companies (5511), Motor Vehicle Parts Manufacturing (3363), and Computer and Peripheral Equipment Manufacturing (3341).

4.3.2. Descriptive Statistics of the Regression Model

The data sample consists of 5,524 linkages spanning 11 transactions. All financial data is taken from the last fiscal year prior to competition. Table 5 displays the distribution of linkages by year of transaction completion while tables 6a displays the descriptive statistics for the dependent variable, 6b the for all control variables and 6c the descriptive statistics of the independent variables

Table 5: Distribution of linkages along transaction completion year

Year	Value	Freq.	Percent	Cum.
2009	1	512	9.27	9.27
2012	2	551	9.97	19.24
2014	3	1.134	20.53	39.77
2015	4	899	16.27	56.05
2016	5	819	14.83	70.87
2017	6	959	17.36	88.23
2018	7	627	11.35	99.58
2019	8	23	0.42	100.00

Table 6 displays the descriptive statistics for the dependent variable abnormal return as the firm performance proxy.

Table 6: Descriptive statistics of dependent variable

Variable	Obs	Mean	Std. Dev.	Min	Max
Abnormal Return	5.524	0.0524892	.1954751	-.1695087	.4048389

Descriptive statistics of target firm abnormal return calculated around transaction completion year based on stock price-returns.

The average abnormal return lies at 5.25% above CAPM estimated returns across all transaction. The range is from roughly -17% up to an abnormal return of +40% with a standard deviation of roughly 20 percent points. This shows that my sample transactions are heterogeneous in terms of transaction performance which means my model will be able to test its effect on over- and underperforming transactions. Next, I refer to Table 7a, in which I display the descriptive statistics for my control variables.

Table 7a: Descriptive statistics of control variables
Descriptive statistics of transaction-firm, I.e. target and buyer firm-based variables. All financial data is taken from the fiscal year prior to completion year.

Variable	Obs	Mean	Std. Dev.	Min	Max
Turnover in Mio. USD	5.509	78553.03	61042.06	306	160338
Cashflow in Mio. USD	5.480	8830.764	7855.011	-113,747	21058
Total Assets in Mio. USD	5.489	118735.9	103848.2	3,848	256540
Number of Employees	5.524	163813.1	125318	4	409881
Value Chain Position Dummy	5.524	1.752715	1.305721	1	7
Different Country of Origin Dummy	5.524	0.051231	0.220488	0	1
Different Industry Dummy	5.524	0.761042	0.426485	0	1
Strategic Intent	5.524	1.831101	0.882096	1	3
PE Vendor Dummy	5.524	0.369297	0.482658	0	1
Network Type Categorical	5.524	3.559558	0.960321	1	5
Transaction Role Dummy	5.524	0.103910	0.305172	0	1
Year Categorical	5.524	20205.81	873.8129	18240	21656

Table 7a shows that average transaction firms are very large with for example average employee number of 16,3813 employees. This can partially be explained through the average value chain position which with an average value of 1.75 lies between OEM and tier 1 supplier. As described in *Section 2.*, firms on the value chain are generally very large. Table 7b in contrast shows the descriptive statistics for the independent variables on the pre-transaction target level.

Table 7b: Descriptive statistics of independent variables from pre-transaction target networks (t=0)

TARGET at t=0; Network Centrality (EV)					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Overall Net. Eigenvector Centrality	5.524	0.056132	0.0598432	0	0.210752
Vertical Net. Eigenvector Centrality	4.625	0.008299	0.0342186	0	0.149355
Horizontal Net. Eigenvector Centrality	5.524	0.002579	0.0037367	0	0.010753
Shareholder Net. Eigenvector Centrality	4.625	0.049606	0.1391004	0	0.619777
Internal Net. Eigenvector Centrality	4.625	0.047304	0.0930123	0	0.246719
Board Net. Eigenvector Centrality	4.625	0.020722	0.0297451	0	0.091124
TARGET at t=0; Network Geographic Embeddedness (λ)					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Overall Net. Local Coefficient (λ)	5.524	7.420853	8.11434	0.14	80
Vertical Net. Local Coefficient (λ)	5.524	23.13776	39.91215	1	100
Horizontal Net. Local Coefficient (λ)	5.524	4.227708	6.574994	0	20
Shareholder Net. Local Coefficient (λ)	5.524	7.135009	8.480757	0	20
Internal Net. Local Coefficient (λ)	5.524	10.20552	9.389758	0	21.67
Board, Net. Local Coefficient (λ)	5.524	11.30051	15.21124	1	80

Descriptive statistics of the independent variables grouped by time horizon (pre- or post-transaction) and transaction position (Buyer or Target).

Table 7c displays the descriptive statistics of the independent variables from the pre-transaction buyer network level.

Table 7c: Descriptive statistics of independent variables from the pre-transaction buyer network level (t=0)
Descriptive statistics of the independent variables grouped by time horizon (pre- or post-transaction) and transaction position (Buyer or Target).

BUYER at t=0; Network Centrality (EV)					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Overall Net. Eigenvector Centrality	5.524	0.538387	0.251728	0.20650	1
Vertical Net. Eigenvector Centrality	5.524	0.425006	0.334002	0.14249	1
Horizontal Net. Eigenvector Centrality	5.012	0.012637	0.029095	0	0.08937
Shareholder Net. Eigenvector Centrality	5.524	0.553678	0.286527	0.00195	0.784027
Internal Net. Eigenvector Centrality	5.524	0.501072	0.348285	0.02180	1
Board Net. Eigenvector Centrality	5.012	0.094263	0.064002	0.01722	0.225674
BUYER at t=0; Network Geographic Embeddedness (λ)					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Overall Net. Local Coefficient (λ)	5.524	2.033403	1.477903	0.36	5.03
Vertical Net. Local Coefficient (λ)	5.524	0.797882	0.377625	0	1
Horiz. Net. Local Coefficient (λ)	5.524	1.495302	3.746168	0.37	17.6
Shareholder Net. Local Coefficient (λ)	5.524	7.864812	16.20615	0.09	52.88
Internal Net. Local Coefficient (λ)	5.524	7.877831	16.20007	0.09	52.88
Board, Net. Local Coefficient (λ)	5.524	6.796915	11.51023	1	40

Table 7d displays the descriptive statistics of the independent variables on the post-transaction buyer level.

Table 7d: Descriptive statistics of independent variables from post-transaction buyer networks (t=1)
Descriptive statistics of the independent variables grouped by time horizon (pre- or post-transaction) and transaction position (Buyer or Target). 4.4. Model Multicollinearity and Final OLS Equations

BUYER at t=1; Network Centrality (EV)					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Overall Net. Eigenvector Centrality	5.524	0.5590538	0.242360	0.245973	1
Vertical Net. Eigenvector Centrality	5.524	0.4061506	0.325874	0.100378	1
Horizontal Net. Eigenvector Centrality	5.524	0.0172343	0.028150	0	0.09268
Shareholder Net. Eigenvector Centrality	5.524	0.5600258	0.292774	0.00200	0.80679
Internal Net. Eigenvector Centrality	5.524	0.516535	0.33954	0.04341	1
Board Net. Eigenvector Centrality	5.524	0.1939002	0.262527	0.03913	1

BUYER at t=1; Network Centrality (EV)					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Overall Net. Local Coefficient (λ)	5.524	2.284365	1.682047	0.27	4.92
Vertical Net. Local Coefficient (λ)	5.524	22.10622	39.7615	0.47	100
Horiz, Net. Local Coefficient (λ)	5.524	2.381316	3.219966	0.14	10
Shareholder Net. Local Coefficient (λ)	5.524	9.107667	22.09535	0.08	70.83
Internal Net. Local Coefficient (λ)	5.524	7.978575	16.33394	0.08	53.13
Board, Net. Local Coefficient (λ)	5.524	3.911756	8.035904	1	120

4.4. Multicollinearity within the Empirical Network

To test the impact of multicollinearity in the model building, I look at correlation matrix between the dependent variable and my control variables to determine whether I find significant correlation between my dependent variable and control variables, as well as between control variables themselves (Table 8). As expected, I find significant correlations among my variable proxies for firm size, except for Number of Employees. Correlation becomes a concern for multicollinearity at a statistically significant correlation of 80% and more. Thus, I only include one firm size proxy variable and chose *Total Assets in mUSD* as firm size proxy as it shows the highest statistically significant correlation with my dependent variable *AR*. Furthermore, I find significant correlation of above 80% between *Cashflow in mUSD* and the *PE Vendor Dummy*, *Cashflow in mUSD* and *Strategic Intent*, and *Total Assets in mUSD* and *Strategic Intent*. Subsequently, as I disregard *Cashflow in mUSD* and *Cashflow in mUSD* in favor of *Total Assets in mUSD,* I remain with *Strategic Intent* and *Total Assets in mUSD* as a concern for multicollinearity and therefore I disregard *Strategic Intent*.

Table 8: Correlation matrix of dependent variables and control variables

AR (1), Turnover in mUSD (2), Cashflow in mUSD (3), Total Assets in mUSD (4), Number of Employees (5), Year (6), Different Industry Dummy (7), Strategic Intent Dummy (8), PE Vendor Dummy (9), Different Country Dummy (10), Network Dummy (11), Role Dummy (12), Value Dummy (13), Public Dummy (14); Values significant at the 0.000%-Significance level marked in with one star (*). High correlation marked with bold (Correlation Coefficient > 0.80)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	1													
(2)	-0.5997*	1												
(3)	-0.5433*	**0.9336***	1											
(4)	-0.6306*	**0.9651***	**0.9210***	1										
(5)	-0.2472*	0.4958*	0.3516*	0.3051*	1									
(6)	0.0623*	-0.1662*	-0.3539*	-0.2134*	-0.1962*	1								
(7)	0.2194*	0.2450*	0.1970*	0.1190*	0.1922*	0.5454*	1							
(8)	-0.4740*	0.7978*	**0.8192***	**0.8270***	0.0640*	-0.2147*	0.0164	1						
(9)	0.4653*	**-0.8150***	-0.7670*	-0.7730*	-0.5985*	0.1458*	-0.2819*	-0.4867*	1					
(10)	0.3356*	-0.2677*	-0.2457*	-0.2521*	-0.1843*	0.2327*	0.1302*	-0.2190*	-0.1778*	1				
(11)	0.0046	-0.0398*	-0.0344*	-0.0286*	0.0040	-0.0727*	-0.0461*	-0.0519*	0.1100*	-0.1901*	1			
(12)	0.1898*	-0.4261*	-0.3610*	-0.3619*	-0.4142*	0.1858*	-0.1250*	-0.2657*	0.3676*	-0.0495*	0.0802*	1		
(13)	0.4344*	-0.5119*	-0.4786*	-0.5072*	-0.1850*	0.1358*	0.0467*	-0.4422*	0.3969*	0.0440*	0.0935*	0.7116*	1	
(14)	0.0233*	-0.0577*	0.0383*	0.1117*	-0.7979*	0.0264*	-0.2469*	0.4042*	0.3494*	0.0822*	-0.0388*	0.0566*	-0.0883*	1

Next, I analyze correlation among my independent variables and derive my regressions from it. Naturally, my independent variables can be subdivided across a network-level, a time and transaction level and a network characteristic level (Table 9).

Table 9: Overview of independent variable levels and their potential "values"

Dimensions of the IVs	
1. Network-level	Network, Vertical, Horizontal, Shareholder, Internal, and Board
2. Transaction time / position	Target Network at time t=0, Target Network at time t=1, Buyer Network at time t=0,
3. Network Characteristics	Network embeddedness (EV) and Geographic embeddedness (λ)

Table 10a displays the correlation matrix between the independent variables and network centrality proxies.

Table 10a: Correlation matrix of independent variable for network centrality (EV)
Significant Values are marked in bold with stars (**** at 0%; *** at 1%; ** at 5%, and * 10% -significance level) distinction by transaction time / position and network characteristic (EV, λ). Corr. Coeff. Over 0.80 in bold.

BUYER at t=0; Network Centrality (EV)						
	Network	**Vertical**	**Horizontal**	**Shareholder**	**Internal**	**Board**
Network EV	1.0000					
Vertical EV	**0.8630********	1.0000				
Horizontal EV	-0.1127****	0.2509****	1.0000			
Shareholder EV	0.2704****	0.4939****	0.1664****	1.0000		
Internal EV	**0.8816********	0.5947****	-0.2196****	-0.1986****	1.0000	
Board EV	0.0158***	-0.2270****	0.0498****	**-0.9320********	0.4580****	1.0000
BUYER at t=1; Network Centrality (EV)						
	Network	**Vertical**	**Horizontal**	**Shareholder**	**Internal**	**Board**
Network EV	1.0000					
Vertical EV	**0.8977********	1.0000				
Horizontal EV	-0.0831****	0.0550****	1.0000			
Shareholder EV	0.3400****	0.4723****	0.0269****	1.0000		
Internal EV	**0.8603********	0.6341****	-0.1749****	-0.1667****	1.0000	
Board EV	-0.2952****	-0.1876****	0.0982****	-0.4080****	-0.1576****	1.0000

BUYER at t=1; Network Centrality (EV)						
	Network	**Vertical**	**Horizontal**	**Shareholder**	**Internal**	**Board**
Network EV	1.0000					
Vertical EV	0.5725****	1.0000				
Horizontal EV	0.0844****	-0.2227****	1.0000			
Shareholder EV	0.6279****	**0.9944********	-0.1632****	1.0000		
Internal EV	0.7908****	-0.0158***	0.5449****	0.0467****	1.0000	
Board EV	-0.1722****	-0.0285****	0.0112***	-0.0333****	-0.1203****	1.0000

Following Table 10a, I conclude that along the sub-network level, variables exhibit high statistically significant correlation. Furthermore, correlation dependent on transaction position-/ time-level and network characteristic is highly heterogeneity. Subsequently, in an effort to reduce complexity and multicollinearity, I subdivide each sub-network level into a separate model.

Table 10b: Correlation matrix of independent variable for geographic embeddedness (λ)
Significant Values are marked in bold with stars (**** at 0%; *** at 1%; ** at 5%, and * 10% -significance level) distinction by transaction time / position and network characteristic (EV, λ). Corr. Coeff. Over 0.80 in bold.

BUYER at t=0; Local Embeddedness Coefficient λ						
	Network λ	Vertical λ	Horizontal λ	Shareholder λ	Internal λ	Board λ
Network λ	1.0000					
Vertical λ	-0.1987****	1.0000				
Horizontal λ	-0.4673****	-0.4880****	1.0000			
Shareholder λ	0.7949****	-0.1280****	-0.7308****	1.0000		
Internal λ	0.7943****	-0.1282****	-0.7306****	1.0000****	1.0000	
Board λ	-0.1069****	-0.1403****	0.2088****	-0.1244****	-0.1249****	1.0000
BUYER at t=1; Local Embeddedness Coefficient λ						
	Network λ	Vertical λ	Horizontal λ	Shareholder λ	Internal λ	Board λ
Network λ	1.0000					
Vertical λ	0.0465****	1.0000				
Horizontal λ	0.7400****	-0.2254****	1.0000			
Shareholder λ	0.4957****	-0.2005****	-0.0306****	1.0000		
Internal λ	0.5892****	-0.2328****	0.1005****	**0.9913********	1.0000	
Board λ	0.0777****	-0.1928****	0.1755****	0.0037***	0.0244***	1.0000

Target at t=0; Local Embeddedness Coefficient λ						
	Network λ	Vertical λ	Horizontal λ	Shareholder λ	Internal λ	Board λ
Network λ	1.0000					
Vertical λ	0.2169****	1.0000				
Horizontal λ	0.0624****	-0.2723****	1.0000			
Shareholder λ	-0.2166****	-0.3080****	0.3482****	1.0000		
Internal λ	0.2626****	-0.4596****	0.6016****	0.6650****	1.0000	
Board λ	0.0210***	-0.3727****	0.1760****	0.2363****	0.1854****	1.0000

Similarly to 4.4.2.1., I analyze the correlation matrix of IV based on transaction time / position to determine to what extent I am able to bundle variables in one model as displayed in Table 10b. Table 11 shows that as expected multicollinearity may be an issue between buyer network IVs from before and after the transaction. In contrast, I only find selected correlation between buyer network IVs (both t=1 and t=0) and target network IVs. These correlations appear on the board subnetwork level for t and t1, and on the vertical subnetwork level for t with t1. Subsequently, I separate my regression models along transaction time / position as including it would increase multicollinearity concerns.

Table 11: Correlation matrix of independent variable along transaction time/position dimension
Significant Values are marked in bold with stars (**** at 0%; *** at 1%; ** at 5%, and * 10%-significance level) by sub-network level and network characteristic (EV, λ). Corr. Coeff. Over 0.80 in bold.

	1. Network Embeddedness (EV)		
EV	**Buyer at t=0 vs. Buyer at t=1**	**Target at t=0 vs. Buyer at t=1**	**Target at t=0 vs. Buyer at t=0**
Network	**0.9975********	-0.2261****	-0.2553****
Vertical	**0.9851********	-0.2247****	0.2242****
Horizontal	**0.9873*******	0.1610***	0.0194
Shareholder	**0.9981********	-0.0659****	0.0263*
Internal	**0.9983********	-0.0828****	-0.1381****
Board	**0.7877********	**0.8088********	-0.1846****

	2. Geographic Embeddedness (λ)		
EV	**Buyer at t=0 vs. Buyer at t=1**	**Target at t=0 vs. Buyer at t=1**	**Target at t=0 vs. Buyer at t=0**
Network	**0.9234******	0.4334****	0.3468****
Vertical	-0.0270**	**0.9738******	-0.1277****
Horizontal	0.1053****	0.4633****	-0.5853****
Shareholder	**0.9948******	0.5442****	0.5007****
Internal	**0.9952******	0.4559****	0.3986****
Board	0.1338****	0.5352****	-0.0866****

Lastly, I explore correlations between network characteristics. I find that within my independent variable set there are no highly significant corrections (CorrCoeff.>0.80) indicating collinearity issues, I bundle network embeddedness (EV) and geographic embeddedness (λ) into one regression model. The prior explorations on multicollinearity and the theoretical foundation leads me to the following model (Visualized in Figure 6) with CV_i representing the control variables Total Assets in mUSD, Year, Different Industry Dummy, Strategic Intent Dummy, PE Vendor Dummy, Different Country Dummy, Network Dummy, Role Dummy, Value Dummy, and Public Dummy :

(IX) $$AR_{n,t} = b_0 + b_1 * EV_{n,t} + b_2\lambda_{n,t} + b_i * CV_i + e_i$$

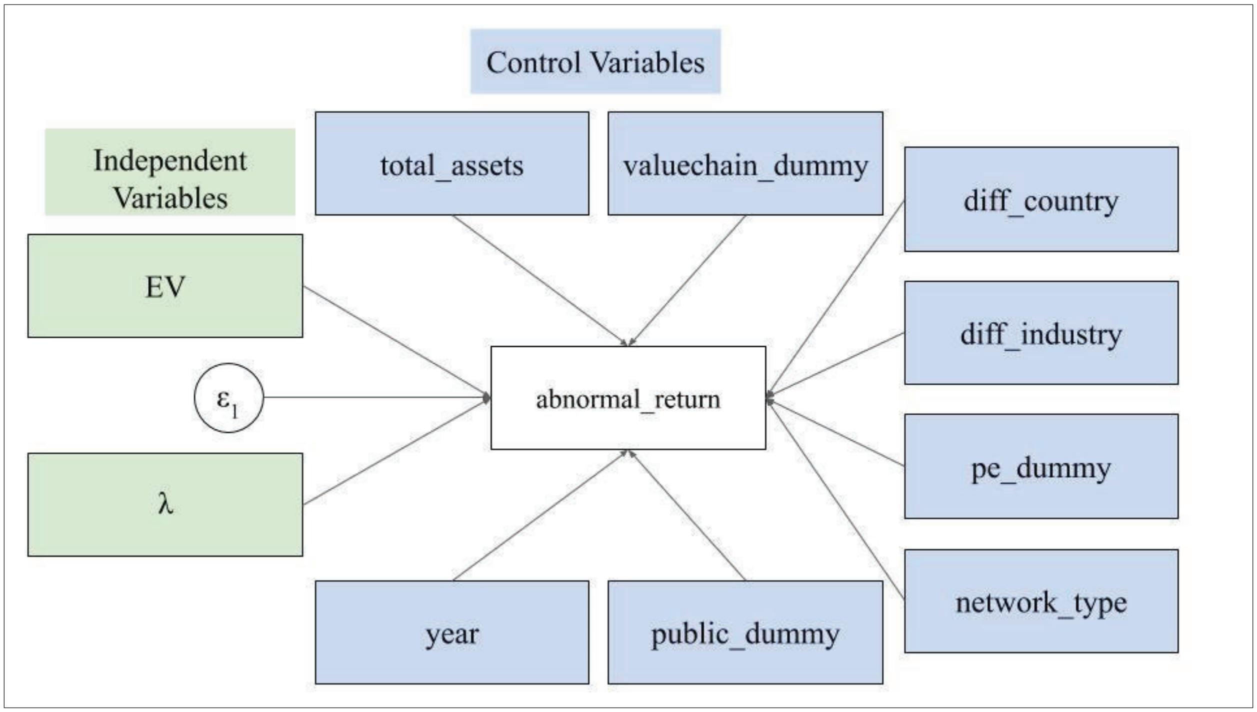
Equation (IX) includes *n* as representing transaction role which can either value target or buyer network. Similarly t representing either pre- (t=0) or post transaction (t=1). Furthermore, in the cases of the horizontal and board sub-networks, or any other regression in which network embeddedness (EV) and geographic embeddedness (λ) materialize to cause multicollinearity, I subdivide the model into (X) and (XI):

(X) $$AR_{n,t} = b_0 + b_1 * EV_{n,t} + b_i * CV_i + e_i$$

(XI) $$AR_{n,t} = b_0 + b_1 * \lambda_{n,t} + b_i * CV_i + e_i$$

Figure 7 displays the visualization of equation (IX) as a Structural Equation Model to visualize the OLS regression equation serving as base equation for my empirical study.

Figure 7: Visualization of the base OLS equation (IX) for models 1 and 2
Visual figure displaying the regression model (I), in which network embeddedness (EV) and geographic embeddedness (λ) are both included.



5. Data Evaluation and Limitations

5.1. Results and Findings

After running my model 1 and model 2 regressions, I find that despite preliminary attempts to curb multicollinearity that my models were exposed to multicollinearity through my control variable construction as determined by the variance inflation factor (VIF) analysis. However, I was able to eliminate multicollinearity by removing certain control variables. Nonetheless, for equation (III) on a vertical sub-network level I was forced to separate vertical buyer post-transaction network centrality ($EV_{B,1}$) from the vertical buyer post-transaction local embeddedness coefficient independent variable ($\lambda_{B,1}$) to curb multi collinearity. After this, all regressions pass variance inflation factor (VIF) analysis in that no individual or mean VIF is above a value of 10.

Next, I start the evaluation of my regression results on the whole network level. Table 12a shows the regressions for testing hypotheses H1a and H1b which are:

***H1a:** Strategic **c**omplementarity of the buyer and target network centrality has a positive relationship with M&A transaction performance.*

H1b: *Strategic complementarity of the buyer and target network's geographic embeddedness has a positive relationship with performance on M&A transaction performance.*

All regressions on the whole network level are significant at full significance or the 0.00%-significance level. The regressions for Model 1, i.e. equations (II) and (III), in which I compare the relationship between pre-transaction (at t=0) buyer network centrality and network geographic embeddedness on firm performance (*equation II*) with the relationship between post-transaction (at t=1) buyer network centrality and geographic embeddedness on firm performance. The preliminary regression as displayed in table 12a shows that pre-transaction buyer eigenvector centrality has a statistically negative relationship with firm performance while post-transaction buyer network centrality and pre-transaction target centrality has a statistically positive relationship with firm performance. This by itself is not sufficient to validate whether the M&A transaction lead to an increase in the relationship between network centrality on firm performance which subsequently deems the M&A transaction to have a positive performance. However, a visual comparison of beta coefficients shows the statistically significant at a 0%-level negative relationship between network centrality and firm performance with a *beta* of -0.4570 versus a statistically significant at a 0%-level positive relationship between network centrality on firm performance with a *beta* of 0.0381. Thus, I observe a directional change pre- and post-transaction. For network geographic embeddedness, I observe a statistically significant positive relationship between buyer pre-transaction (t=0) network geographic embeddedness on firm performance at a 0% significance level (*beta*=0.0272) while (III) shows also shows a statistically significant positive relationship between geographic embeddedness and firm performance (*beta*=0.0734). Thus, for geographic network embeddedness we have no directional change.

To validate whether the M&A performance is positive, I perform a test of coefficients between the network centrality coefficients of equation (II) and (III) to reject equality of coefficients. Table 12b shows the result of the test, in which I am able to rejects the zero hypothesis of coefficient equableness at full significance ($p<0.0000$). Similarly for the test of coefficients between the buyer network local embeddedness coefficient pre- and post-transaction, I can reject the zero hypothesis at a 0% significance level. Thus, my model shows that the M&A transaction has a positive impact on the relationship between network centrality and geographic embeddedness on firm performance. Therefore, my M&A transaction performance is positive.

In a second step, I turn to Model 2, in which I test whether the buyer's pre-transaction (t=0) network has similar relationship on firm performance as the target's pre-transaction (t=0) network. If the association is similar, I deduce that the buyer and target networks are similar in their association with firm performance. Analyzing the regression results of equations (III) and (IV) or the relationship between the buyer pre-transaction (at t=0) network centrality and geographic embeddedness with the relationship between target pre-transaction (at t=0) network centrality and geographic embeddedness on firm performance, I find global significance of the models at a 0%-significance level (Table 12a: (II) with (IV)). Equation (II) shows a statistically significant negative relationship between buyer pre-transaction (t=0) network centrality on firm performance at the 0%-significance level (*beta*= -0.4570), while equation (IV) shows a positive statistically at the 0%-level significant relationship between network centrality and firm performance (*beta*=1.21*82).* For geographic embeddedness, equation (II) shows a statistically significant positive relationship between of the buyer pre-transaction (t=0) local embeddedness coefficient and firm performance at a 0%-significance level (*b*=0.0272). In comparison, equation (IV) shows a statistically significant positive relationship between the target pre-transaction (t=0) local embeddedness coefficient and firm performance at a 0%-significance level (*b*=0.0110). In effect, this can be interpreted as the network of the buyer is non similar in its network centrality while similar for geographic embeddedness to the target firm's network.

Table 12b shows the results of the test of coefficients for Model 2 between (II) and (IV) which leads me to reject the zero hypothesis that the association between buyer's pre-transaction and the target's pre-transaction network centrality has the same association at a 0%-significance level. Correspondingly for geographic embeddedness, I can reject the zero hypothesis in which the association of the buyer's pre-transaction local embeddedness coefficient on firm performance equals the association of the target's pre-transaction local embeddedness coefficient on firm performance at a 0%-significance level. Therefore, in reference to my theoretical model, I can say that the buyer and target network embeddedness relationships are not similar and subsequently complementary as the M&A transaction has had a positive performance.

Therefore I can confirm my hypothesis H1a that strategic complementarity of buyer and target network centrality has a positive association with M&A performance. For 1b however, I cannot confirm my hypothesis H1b that strategic complementarity of buyer and target network geographic embeddedness has a positive association with M&A performance. Despite a positive movement of the association between the buyer's geographic embeddedness post-transaction in comparison to pre-transaction, I do not find non-similar associations of geographic embeddedness and M&A performance for the buyer pre-transaction and target pre-transaction firms.

Table 12a: Regression results for the whole network level
Significant results marked at 10% -(*) 5%- (**) 1%- (***) or 0%- (****) level with total number of observations: (n=5,524) and SE in parentheses. Results grouped by Target network at time t=0 (Pre-transaction), Buyer network at time t=0 (Pre-transaction) and Target at time t=1 (Post-transaction).

Equation ***WHOLE NETWORK LEVEL***	**(II)** **Buyer at t=0**	**(III)** **Buyer at t=1**	**(IV)** **Target at t=0**
Global (p-Value)	*0.0000*	*0.0000*	*0*
R^2	*0.5713*	*0.6719*	*0.8692*
n	*5,524*	*5,524*	*5,524*
Eigenvector Centrality (EV)	–0.4570**** (0.014)	0.0381**** (0.017)	1.2182**** (0.032)
Localness Coefficient (λ)	0.0272**** (0.002)	0.0734**** (0.001)	0.0110**** (0.000)
Year	-0.0947**** (0.002)	-0.0652**** (0.002)	-0.0331**** (0.001)
Diff Industry Dummy	0.4749**** (0.009)	0.1562**** (0.009)	0.1307**** (0.004)
Strategic Intent	-	-0.1784**** (0.004)	0.0868**** (0.003)
PE Vendor Dummy	0.2177**** (0.005)	-	-
Diff Country Dummy	-	-	0.3709**** (0.006)
Network Categorical	–0.0192**** (0.002)	-0.0165**** (0.002)	0.0057**** (0.001)
Role Dummy	0.0454**** (0.009)	-0.1193**** (0.009)	-0.2238**** (0.006)
Total Assets in mUSD	-	-	-0.000**** (0.000)
Value Chain Position	0.0158 (0.002)	0.0346**** (0.002)	0.0432**** (0.005)
Public Dummy	0.0039**** (0.007)	0.0751**** (0.006)	-0.070**** (0.005)
_constant	0.2289**** (0.014)	0.2911**** (0.012)	-0.0913**** (0.006)

Table 12b: Test of coefficients results for the whole network level

EV	Model 1: (II) and (III)	Model 2: (II) and (IV)
H_0:	$B_{(II)} - B_{(III)} = 0$	$B_{(II)} - B_{(IV)} = 0$
Chi2(1)	2493.92	92.65
Prob > chi2	0.0000	0.0000
Interpretation	Reject H_0 at full significance	Reject H_0 at full significance
λ	**Model 1: (II) and (III)**	**Model 2: (II) and (IV)**
H_0:	$B_{(II)} - B_{(III)} = 0$	$B_{(II)} - B_{(IV)} = 0$
Chi2(1)	65827.97	4297.14
Prob > chi2	0.0000	0.0000
Interpretation	Reject H_0 at full significance	Reject H_0 at full significance

Next, I turn to the analysis of H2a and H2b:

***H2a**: Strategic complementarity of buyer and target vertical sub-network embeddedness has a positive association with M&A transaction performance.*

***H2b**: Strategic complementarity of the buyer and target vertical sub-network geographic embeddedness has a positive association with M&A transaction performance.*

To test them, first I regress equations (II) and (III) within my model 1 on a vertical sub-network level and receive the results displayed in Table 13a. All regression results are globally significant at the 0%-level. Table 13a shows that the association of (II) or buyer pre-transaction network centrality with firm performance is statistically significantly negative at a 0% level (*beta*=-0.0966). In comparison, (IIIa) shows that network centrality has a statistically significant negative association with firm performance at a 0% significance level (*beta*= -0.1221). At first glance, we find no directional change between the association of the buyer pre-transaction (t=0) networks centrality with firm performance and the buyer post-transaction (t=1) networks centrality on firm performance. For the association of geographical embeddedness, I find that buyer pre-transaction (t=0) local embeddedness coefficient has a statistically significant positive association with firm performance at a 0%-significance level (*beta*=0.0075). In comparison, the association of target pre-transaction (t=0) local embeddedness coefficient is negative at 0%-significance level on firm performance (*beta*=-0.0031). A first comparison of the network centrality and geographic embeddedness *beta*s of (II) versus (III) show no change in direction for network centrality while there is a negative directional change for geographic embeddedness. To validate these findings, I run the test of coefficients for Model 1 and am able to reject the zero hypotheses at a 0% significance level for both network centrality and geographic embeddedness. Subsequently, I am able to confirm that the M&A transaction has a positive association with the association of geographic embeddedness, for network centrality, I am able to able to confirm a change in association based on my test of coefficients rejection. However, given the lack of direction change for network centrality versus a negative directional change for geographic embeddedness, I cannot confirm that the M&A transaction performance is successful on the vertical subnetwork-level.

Next I test my Model 2. There, for equation (IV) I find a statistically significant negative association of the target pre-transaction (t=0) network centrality with firm performance at a 0% significance level (*beta*=-3.6741). In contrast, for geographic embeddedness I find statistically significant positive results of the target pre-transaction (t=0) local embeddedness coefficient on firm performance at a 0% significance level (*beta*=0.0016). Comparing these beta coefficients with the coefficients from (IIIa) and (IIIb), I find no directional change for network centrality, while I find a negative directional change for geographic embeddedness. Thereafter, I confirm my results using the test of coefficients which rejects the zero hypotheses for network centrality as well as for geographic embeddedness. With that, I am able to confirm that the associations are not the same. However, for network centrality, I see no directional change. Thus, I cannot conclude that the networks are complementary on a network centrality level. On the other hand, for network geographic embeddedness, I find no change along with the rejection of the test of coefficients. Subsequently, I can confirm that the buyer and target pre-transaction networks are non-similar for the geographic embeddedness category not however conclusively for network centrality. Uniting the results of Model 1 and Model 2, I am not able to confirm H2a as there is no positive M&A transaction = relationship. However, this is not in contrast to my hypotheses but rather in its favor. Without implying causality, I observe that the association of buyer and target pre-transaction network centrality and geographic embeddedness are both in the same direction while there is no M&A success through an increase in the association of network embeddedness with performance.

Table 13a: Regression results for the vertical sub-network level

Significant results marked at 10% -(*) 5%- (**) 1%- (***) or 0%- (****) level with total number of observations: (n=5,489) and SE in parentheses. Results grouped by Target network at time t=0 (Pre-transaction), Buyer network at time t=0 (Pre-transaction) and Target at time t=1 (Post-transaction).

Equation	(II)	(IIIa)	(IIIb)	(IV)
VERTICAL SUBNETWORK	**Buyer at t=0**	**Buyer at t=1**		**Target at t=0**
Global (p-Value)	*0.0000*	*0.0000*	*0.000*	*0.0000*
R2	*0.6893*	*0.6989*	*0.7605*	*0.6911*
n	*5,489*	*5,489*	*5,489*	
Eigenvector Centrality (EV)	-0.0966**** (0.010)	-0.1221**** (0.009)	-	-3.6741**** (0.0771)
Localness Coefficient (λ)	0.0075**** (0.000)	-	-0.0031**** (0.000)	0.0016**** (0.000)
Year	-0.05934**** (0.001)	-0.0650*** (0.001)	-0.1036**** (0.002)	-0.0006 (0.001)
Diff Industry Dummy	0.3311 **** (0.007)	0.3474*** (0.007)	0.5203**** (0.007)	-
Strategic Intent	-	-	0.0919**** (0.004)	-0.0370**** (0.005)
PE Vendor Dummy	-	-	-	0.3131**** (0.001)
Diff Country Dummy	-	0.1658**** (0.008)	0.2069**** (0.007)	0.4374**** (0.011)
Network Categorical	-0.002 (0.002)	-0.0019 (0.002)	-0.0033** (0.001)	-0.0040** (0.002)
Role Dummy	0.0151* (0.008)	0.0306**** (0.001)	0.1645**** (0.008)	0.1703**** (0.012)
Total Assets in mio.USD	-0.0000**** (0.000)	-0.0000**** (0.000)	-0.0000**** (0.000)	-
Value Chain Position	0.0129**** (0.002)	0.0099**** (0.002)	-0.0189**** (0.002)	-0.0086*** (0.003)
Public Dummy	0.1793**** (0.005)	0.1819**** (0.005)	0.1909*** (0.004)	0.0600*** (0.019)
_constant	0.0600**** (0.009)	0.0800**** (0.008)	0.0589**** (0.008)	-0.0991**** (0.023)

Table 13b: Test of coefficients results for the vertical sub-network level

EV	Model 1: (II) and (III)	Model 2: (II) and (IV)
H_0:	$B_{(II)} – B_{(III)} = 0$	$B_{(II)} – B_{(IV)} = 0$
Chi2(1)	156.26	156.26
Prob > chi2	0.000	0.000
Interpretation	Reject H_0 at full significance	Reject H_0 at full significance
λ	**Model 1: (II) and (III)**	**Model 2: (II) and (IV)**
H_0:	$B_{(II)} – B_{(III)} = 0$	$B_{(II)} – B_{(IV)} = 0$
Chi2(1)	478.89	478.89
Prob > chi2	0.000	0.000
Interpretation	Reject H_0 at full significance	Reject H_0 at full significance

Thirdly, I turn to the horizontal sub-network and the testing of hypotheses H3a and H3b:

H3a*: Strategic complementarity of the buyer and target horizontal sub-network embeddedness has a positive association with M&A transaction performance.*

H3b*: Strategic complementarity of the buyer and target horizontal sub-network geographic embeddedness has a positive association with M&A transaction performance.*

First I evaluate the results of Model 1 (Table 14a). For (II), I find that the buyer pre-transaction (t=0) network centrality has a negative association with firm performance at a 0%-significance level (*beta*=-2.2336). In comparison, equation (III) finds that buyer post-transaction (t=1) centrality to have a negative association at the 0%-significance level (*beta*=-2.7403). A first comparison of coefficients shows no directional change. For geographic network embeddedness, equation (II) finds a statistically significant negative network of buyer pre-transaction local embeddedness coefficient with firm performance at a 0% significance level (*beta*=-0.1289). Equation (III) on the other hand finds a statistically significant positive impact of the buyers post-transaction (t=1) local embeddedness coefficient on firm performance at a 0% significance level (*beta*=0.0576). A first comparison of coefficients shows a positive directional change. The test of coefficients, displayed in Table 14b, finds that I am able to reject the zero hypothesis of Model 1 and I am able to interpret no successful M&A performance for network centrality as there is no positive directional change of the beta coefficients. In contrast, for geographic embeddedness, the test of coefficients in Model 1 rejects the hypothesis at a 5% significance level while showing a positive directional change. Therefore, the M&A transaction has a successful performance in terms of geography embeddedness while for network centrally the M&A transaction performance is not conclusively positive.

In Model 2, I explore how the buyer and target networks relate to each other. Equation (IV) finds that target pre-transaction (t=0) network centrality has a statistically significant negative association with firm performance at a 0% significance level (*beta*=-5.1657). For geographic embeddedness, equation (IV) finds a statistically significant association of target pre-transaction (t=0) network geographic embeddedness with firm performance at a 0% significance level (*beta*=0.0267). Comparing these beta coefficients with (II), I find that there is no change in direction of network centrality, while for geographic embeddedness there is a positive directional association. Next, I preform my test of coefficients and am able to reject the zero hypotheses at a 0% significance level for both network centrality and network geographic embeddedness Therefore, I can deduct that on a horizontal sub-network level the buyer and target networks pre-transaction (t=0) in terms of network centrality are similar and in terms of network geographic embeddedness are non-similar.

In conclusion of my horizontal sub-network level regressions, I cannot confirm my H3a hypothesis as I am not able to determine non similarity nor positive M&A performance as a whole. However, I am able to confirm H3b as Model 1 concludes that the buyer horizontal network was able to increase the network of geographic embeddedness due to strategic complimentarily as shown in Model 2 .

Table 14a: Regression results for the horizontal sub-network level
Significant results marked at 10% -(*) 5%- (**) 1%- (***) or 0%- (****) level with total number of observations: (n=5,489) and SE in parentheses. Results grouped by Target network at time t=0 (Pre-transaction), Buyer network at time t=0 (Pre-transaction) and Target at time t=1 (Post-transaction).

Equation	**(II)**	**(III)**	**(IV)**
HORIZONTAL SUB-NETWORK	**Buyer at t=0**	**Buyer at t=1**	**Target at t=0**
Global (p-Value)	*0.0000*	*0.0000*	*0.0000*
R2	*0.4588*	*0.8802*	*0.9168*
n	*5,489*	*5,489*	*5,489*
Eigenvector Centrality (EV)	-2.2336**** (0.117)	-2.7403**** (0.037)	-5.1657**** (0.307)
Localness Coefficient (λ)	-0.1289**** (0.012)	0.0576**** (0.000)	0.02677**** (0.000)
Year	-0.0364**** (0.003)	-	-0.1355**** (0.000)
Diff Industry Dummy	0.2020**** (0.009)	-0.0739**** (0.003)	0.3514**** (0.002)
Strategic Intent	-	0.0724**** (0.002)	-0.0234**** (0.002)

Equation	(II)	(III)	(IV)
HORIZONTAL SUB-NETWORK	**Buyer at t=0**	**Buyer at t=1**	**Target at t=0**
PE Vendor Dummy	0.2014**** (0.008)	-	-
Diff Country Dummy	-	0.4153**** (0.005)	0.3434**** (0.004)
Network Categorical	-0.0112**** (0.002)	-0.0025** (0.001)	-0.0048**** (0.001)
Role Dummy	-0.0472**** (0.012)	-0.1677**** (0.004)	0.1076**** (0.004)
Total Assets in mio.USD	-	-	-0.0000**** (0.000)
Value Chain Position	0.0395**** (0.003)	0.0389**** (0.001)	-0.0211**** (0.001)
Public Dummy	-0.0076 (0.007)	-0.2349**** (0.004)	-
_constant	0.0950**** (0.023)	0.0173*** (0.005)	0.5526**** (0.006)

Table 14b: Test of coefficients results for the horizontal sub-network level

EV	Model 1: (II) and (III)	Model 2: (II) and (IV)
H_0:	$B_{(II)} - B_{(III)} = 0$	$B_{(II)} - B_{(IV)} = 0$
Chi2(1)	2554.13	4853.09
Prob > chi2	0.0000	0.0000
Interpretation	Reject H_0 at full significance	Reject H_0 at full significance
λ	**Model 1: (II) and (III)**	**Model 2: (II) and (IV)**
H_0:	$B_{(II)} - B_{(III)} = 0$	$B_{(II)} - B_{(IV)} = 0$
Chi2(1)	4.33	231.85
Prob > chi2	0.0374	0.0000
Interpretation	Reject H_0 at 5%- significance level	Reject H_0 at full significance

Fourthly, I turn to the shareholder sub-network and the testing of hypotheses H4a and H4b:

H4a: *Strategic complementarity of the buyer and target shareholder sub-network embeddedness has a positive association with M&A transaction performance.*
H4b: *Strategic complementarity of the buyer and target shareholder sub-network geographic embeddedness has a positive association with M&A transaction performance.*

First I evaluate the results of Model 1 (Table 15a). For (II), I find that the buyer pre-transaction (t=0) network centrality has a negative association with firm performance at a 0%-significance level (*beta*=-0.2216). In comparison, equation (III) finds the buyer post-transaction (t=1) association of network centrality with abnormal return to be negative at a 0%-significance level (*beta*=-0.2204). A first comparison of coefficients shows no directional change but the delta of both coefficients shows an increase in coefficient strength through the transaction (Coefficient **Δ=**0.0192). This suggests a positive association on M&A transaction performance. For geographic network embeddedness, equation (II) finds a statistically significant positive association of buyer pre-transaction local embeddedness coefficient on firm performance at a 0% significance level (*beta*=0.0066). Equation (III) on the other hand also finds a statistically significant positive impact of the buyers post-transaction (t=1) local embeddedness coefficient on firm performance at a 0% significance level (*beta*=0.005). Thus, a comparison of coefficients shows that there is no directional change. Yet, the coefficient delta is negative suggesting a negative effect on M&A transaction performance (Coefficient **Δ=**-0.0106). The test of coefficients, displayed in Table 15b, finds that I am able to reject the zero hypothesis of Model 1 and I find that the M&A performance is not positive in terms of network centrality as there is no positive directional change of the beta coefficients. In contrast, for geographic embeddedness, the test of coefficients in Model 1 rejects the hypothesis at a 0% significance level while showing no directional change. Despite this, a view onto the beta coefficient suggests that for the shareholder subnetwork level there is the M&A transaction has a positive outcome for network centrality while a negative outcome for geographic embeddedness.

In Model 2, I explore how the buyer and target networks relate to each other. Equation (IV) finds that target pre-transaction (t=0) network centrality has a statistically significant negative association with firm performance at a 0% significance level (*beta*=-0.5880). For geographic embeddedness, equation (IV) finds a statistically significant association of target pre-transaction (t=0) network geographic embeddedness with firm performance at a 0% significance level (*beta=-0.0073)*. Comparing these beta coefficients with (II), I find that there is no change in direction of network centrality, while for geographic embeddedness there is a positive directional association. Conducting the test of coefficients, I am able to reject the zero hypotheses at a 0% significance level for both network centrality and geographic embeddedness.

Therefore, I can deduct that on a shareholder sub-network level the buyer and target networks pre-transaction (t=0) in terms of network centrality are similar and in terms of network geographic embeddedness are non-similar.

In conclusion of my shareholder sub-network level regressions, I cannot confirm my H4a hypothesis as I am not able to determine non similarity despite a positive M&A performance. Correspondingly, I am not able to confirm H4b as Model 1 concludes that the buyer shareholder network was not able to increase the association of geographic embeddedness despite strategic complementarity.

Table 15a: Regression results for the shareholder sub-network level
Significant results marked at 10% -(*) 5%- (**) 1%- (***) or 0%- (****) level with total number of observations: (n=5,524) and SE in parentheses. Results grouped by Target network at time t=0 (Pre-transaction), Buyer network at time t=0 (Pre-transaction) and Target at time t=1 (Post-transaction).

Equation	**(II)**	**(III)**	**(IV)**
SHAREHOLDER SUB-NETWORK	**Buyer at t=0**	**Buyer at t=1**	**Target at t=0**
Global (p-Value)	*0.0000*	*0.0000*	*0.0000*
R2	*0.7962*	*0.7784*	*0.7021*
n	*5,524*	*5,524*	*5,524*
Eigenvector Centrality (EV)	-0.2216**** (0.009)	-0.2024**** (0.009)	-0.5880**** (0.0197)
Localness Coefficient (λ)	0.0066**** (0.000)	0.005**** (0.000)	-0.0073**** (0.000)
Year	-0.1160**** (0.002)	-0.1177**** (0.002)	-0.070**** (0.001)
Diff Industry Dummy	0.4292**** (0.005)	0.4507**** (0.005)	-
Strategic Intent	-	-	0.0196**** (0.004)
PE Vendor Dummy	0.5039**** (0.005)	0.4977**** (0.006)	0.2881**** (0.007)
Diff Country Dummy	0.6575**** (0.008)	0.6406**** (0.008)	0.3874**** (0.011)
Network Categorical	-0.0054***** (0.001)	-0.0052***** (0.001)	-0.0045* (0.002)
Role Dummy	0.1545***** (0.007)	0.1513**** (0.007)	0.1594**** (0.012)
Total Assets in mio.USD	-	-	-
Value Chain Position	-0.0147**** (0.002)	-0.0129**** (0.002)	-0.0073*** (0.003)

Equation	(II)	(III)	(IV)
SHAREHOLDER SUB-NETWORK	**Buyer at t=0**	**Buyer at t=1**	**Target at t=0**
Public Dummy	-0.0420**** (0.007)	-0.0275**** (0.007)	0.0681**** (0.019)
_constant	0.1243**** (0.008)	0.1031**** (0.008)	-0.0770*** (0.022)

Table 15b: Test of Coefficients results for the shareholder sub-network level

EV	**Model 1: (II) and (III)**	**Model 2: (II) and (IV)**
H_0:	$B_{(II)} - B_{(III)} = 0$	$B_{(II)} - B_{(IV)} = 0$
Chi2(1)	248.07	15.08
Prob > chi2	0.0000	0.0001
Interpretation	Reject H_0 at full significance	Reject H_0 at a 1%- significance level
λ	**Model 1: (II) and (III)**	**Model 2: (II) and (IV)**
H_0:	$B_{(II)} - B_{(III)} = 0$	$B_{(II)} - B_{(IV)} = 0$
Chi2(1)	1289.40	2481.94
Prob > chi2	0.0000	0.0000
Interpretation	Reject H_0 at full significance	Reject H_0 at full significance

In a fifth step, I turn to the internal sub-network and the testing of hypotheses H5a and H5b:

***H5a**: Strategic complementarity of the buyer and target internal sub-network embeddedness has a positive association with M&A transaction performance.*
***H5b**: Strategic complementarity of the buyer and target internal sub-network geographic embeddedness has a positive association with M&A transaction performance.*

First I evaluate the results of Model 1 (Table 16a). For (II), I find that the buyer pre-transaction (t=0) network centrality has a positive association with firm performance at a 0%-significance level (*beta*=-0.0770). In comparison, equation (III) finds the buyer post-transaction (t=1) association of network centrality to be positive at a 0%-significance level (*b=0.1754*). A first comparison of coefficients shows no directional change but we see an increase in coefficient strength. For geographic network embeddedness, equation (II) finds a statistically significant positive association of buyer pre-transaction local embeddedness coefficient with firm performance at a 0% significance level (*beta*=0.0062). Equation

(III) on the other hand also finds a statistically significant positive impact of the buyers post-transaction (t=1) local embeddedness coefficient on firm performance at a 0% significance level (*beta*=0.0070). A first comparison of coefficients shows that there is no directional change. However I find an increase in coefficient strength. The test of coefficients, displayed in Table 16b, finds that I am able to reject the zero hypothesis of Model 1 and I find that the M&A performance is positive in terms of network centrality despite no positive directional change of the beta coefficients because we have an increase in coefficient strength. Again, for geographic embeddedness, the test of coefficients in Model 1 reject the hypothesis at a 0% significance level while showing no directional change but whilst showing an increase in coefficient strength. Therefore, the M&A transaction for geography embeddedness and for network centrality has a positive M&A transaction performance.

In Model 2, I explore how the buyer and target networks relate to each other. Equation (IV) finds that target pre-transaction (t=0) network centrality has a statistically significant positive association with firm performance at a 0% significance level (*beta*=2.1473). For geographic embeddedness, equation (IV) finds a statistically significant negative association of target pre-transaction (t=0) network geographic embeddedness with firm performance at a 0% significance level (*beta=-0.0027)*. Comparing these beta coefficients with (II), I find that there is no change in direction of network centrality, while for geographic embeddedness there is a positive directional association. Conducting the test of coefficients, I am able to reject the zero hypotheses at a 0% significance level for both network centrality and geographic embeddedness.

Therefore, I can deduct that on an internal sub-network level the buyer and target networks pre-transaction (t=0) in terms of network centrality are similar and in terms of network geographic embeddedness are non-similar.

In conclusion of my internal sub-network level regressions, I cannot confirm my H5a hypothesis despite a positive M&A performance as the networks are not complementary to each other. However, I am able to confirm H5b as Model 1 concludes that the buyer internal network was able to increase the association of geographic embeddedness due to strategic complimentarily. However, the non-confirmation of H5a does not go against my theoretical foundations per-se M&A performance was nonetheless positive and hence there is a combination advantage of combining buyer and target network. In the case of the internal subnetwork however, the combination is unclear. This is not surprising as internal linkages per my definition include internal vertical and horizontal linkages. As I was not able to confirm H2a and H2b, there could be a too broad definition of internal linkages with two different mechanisms governing its reaction in network combinations.

Table 16a: Regression results for the internal sub-network level
Significant results marked at 10% - (*) 5%- (**) 1%- (***) or 0%- (****) level with total number of observations: (n=5,524) and SE in parentheses. Results grouped by Target network at time t=0 (Pre-transaction), Buyer network at time t=0 (Pre-transaction) and Target at time t=1 (Post-transaction).

Equation	**(II)**	**(III)**	**(IV)**
INTERNAL SUB-NETWORK	**Buyer at t=0**	**Buyer at t=1**	**Target at t=0**
Global (p-Value)	*0.0000*	*0.0000*	*0.0000*
R2	*0.7741*	*0.7985*	*0.9410*
n	*5,524*	*5,524*	*5,524*
Eigenvector Centrality (EV)	0.0770**** (0.011)	0.1754**** (0.010)	2.1473**** (0.012)
Localness Coefficient (λ)	0.0062**** (0.000)	0.0070**** (0.000)	-0.0027**** (0.000)
Year	-0.1033**** (0.002)	-0.1005**** (0.002)	-0.0267**** (0.004)
Diff Industry Dummy	0.3372**** (0.008)	0.2938*** (0.008)	omitted
Strategic Intent	omitted	omitted	0.1571**** (0.002)
PE Vendor Dummy	0.4897**** (0.006)	0.5076**** (0.005)	0.2964*** (0.003)
Diff Country Dummy	0.7177**** (0.010)	0.7864**** (0.009)	0.7027**** (0.006)
Network Categorical	-0.0030** (0.001)	-0.0024** (0.001)	-0.0030**** (0.001)
Role Dummy	0.1027**** (0.007)	0.0929**** (0.007)	-0.0995**** (0.001)
Total Assets in mio.USD	omitted	omitted	omitted
Value Chain Position	-0.0009 (0.002)	-0.0000 (0.002)	0.0189**** (0.001)
Public Dummy	-0.1612**** (0.005)	-0.1503***** (0.004)	-0.2703**** (0.008)
_constant	0.0567**** (0.011)	-0.0023 (0.011)	-0.1314**** (0.0109

Table 16b: Test of coefficients results for the internal sub-network level

EV	Model 1: (II) and (III)	Model 2: (II) and (IV)
H_0:	$B_{(II)} - B_{(III)} = 0$	$B_{(III)} - B_{(IV)} = 0$
Chi2(1)	1112.71	21901.14
Prob > chi2	0.0000	0.0000
Interpretation	Reject H_0 at full significance	Reject H_0 at full significance
λ	**Model 1: (II) and (III)**	**Model 2: (II) and (IV)**
H_0:	$B_{(II)} - B_{(III)} = 0$	$B_{(II)} - B_{(IV)} = 0$
Chi2(1)	8.68	6395.28
Prob > chi2	0.0032	0.0000
Interpretation	Reject H_0 at a 5% significance level	Reject H_0 at full significance

Lastly, I turn to the board sub-network and the testing of hypotheses H6a and H46:

***H6a**: Strategic complementarity of the buyer and target board sub-network embeddedness has a positive association with M&A transaction performance.*

***H6b**: Strategic complementarity of the buyer and target board sub-network geographic embeddedness has a positive association with M&A transaction performance.*

First I evaluate the results of Model 1 (Table 17a). For (II), I find that the buyer pre-transaction (t=0) network centrality has a negative association with firm performance at a 0%-significance level (*beta*=-1.0235). In comparison, equation (III) finds the buyer post-transaction (t=1) association of network centrality to be negative at a 0%-significance level (*beta=-0.4228*). A first comparison of coefficients shows no directional change but we see a decrease in negative coefficient strength and thus an increase in the positive association. For geographic network embeddedness, equation (II) finds a statistically significant positive association of buyer pre-transaction local embeddedness coefficient with firm performance at a 0% significance level (*beta*=0.0114). Equation (III) on the other hand also finds a statistically significant positive impact of the buyers post-transaction (t=1) local embeddedness coefficient on firm performance at a 0% significance level (*beta*=0.0046). Therefore, a comparison of coefficients shows that there is no directional change. However I find a decrease in coefficient strength allowing me to assume a negative positive association of buyer pre-transaction local embeddedness coefficient with firm performance. The test of coefficients, displayed in Table 17b, finds that I am able to reject the zero hypothesis of Model 1 and I find that the M&A performance is positive in terms of network centrality despite no positive directional change of the beta coefficients because we have an increase in coefficient strength. Again, for geographic embeddedness, the test of coefficients in Model 1 reject the hypothesis at a 0% significance level while showing no directional change but whilst showing a decrease in coefficient strength. Therefore, the M&A transaction for geography embeddedness shows a positive M&A transaction performance while showing a negative M&A transaction performance for network centrality.

In Model 2, I explore how the buyer and target networks relate to each other. Equation (IV) finds that target pre-transaction (t=0) network centrality has a statistically significant positive association with firm performance at a 0% significance level (*beta*=1.8468). For geographic embeddedness, equation (IV) finds a statistically significant negative association of target pre-transaction (t=0) network geographic embeddedness with firm performance at a 0% significance level (*beta=-0.0067)*. Comparing these beta coefficients with (II), I find that there is no change in direction of the effect of network centrality as well as for the effect of geographic embeddedness. Conducting the test of coefficients, I am able to reject the zero hypotheses at a 0% significance level for both network centrality and geographic embeddedness. Therefore, I can deduct that on a board sub-network level the buyer and target networks pre-transaction (t=0) are not similar in terms of network centrality network geographic.

In conclusion of my board sub-network level regressions, I can confirm my H6a hypothesis while I am not able to confirm hypothesis H6b as I do not find a positive impact of the transaction on the association between local embeddedness and M&A performance.

Table 17a: Regression results for the board sub-network level
Significant results marked at 10% -(*) 5%- (**) 1%- (***) or 0%- (****) level with total number of observations: (n=4,625) and SE in parentheses. Results grouped by Target network at time t=0 (Pre-transaction), Buyer network at time t=0 (Pre transaction) and Target at time t=1 (Post-transaction).

Equation ***BOARD SUB-NETWORK***	**(II)** **Buyer at t=0**	**(III)** **Buyer at t=1**	**(IV)** **Target at t=0**
Global (p-Value)	0.0000	0.0000	0.0000
R2	*0.7356*	*0.7032*	*0.7791*
n	*4,624*	*4,624*	*4,624*
Eigenvector Centrality (EV)	-1.0235**** (0.028)	-0.4228**** (0.008)	1.8468**** (0.1453)
Localness Coefficient (λ)	0.0114**** (0.000)	0.0046**** (0.000)	-0.0067**** (0.000)
Year	-0.0477**** (0.001)	-0.0740**** (0.0012)	-0.3830**** (0.001)

Equation	(II)	(III)	(IV)
BOARD SUB-NETWORK	**Buyer at t=0**	**Buyer at t=1**	**Target at t=0**
Diff Industry Dummy	0.4657**** (0.007)	0.1451**** (0.005)	0.3092**** (0.005)
Strategic Intent	-0.1346**** (0.002)	-0.1274**** (0.002)	-
PE Vendor Dummy	-	-	0.3393**** (0.004)
Diff Country Dummy	0.2349**** (0.007)	0.2345**** (0.007)	0.3661**** (0.008)
Network Categorical	-0.0000 (0.001)	0.003** (0.002)	-0.0011 (0.002)
Role Dummy	0.1329**** (0.008)	-0.0308**** (0.007)	-
Total Assets in mio.USD	-	-	-
Value Chain Position	-0.006** (0.002)	0.0282**** (0.002)	-0.1960**** (0.014)
Public Dummy	-	0.1680**** (0.005)	-0.1961**** (0.014)
_constant	0.1447**** (0.0115)	0.3401**** (0.010)	0.0467**** (0.0160)

Table 17b: Test of coefficients results for the board sub-network level

EV	**Model 1b**	**Model 2b**
H_0:	$B_{(II)} – B_{(III)} = 0$	$B_{(II)} – B_{(IV)} = 0$
Chi2(1)	1268.57	32348.62
Prob > chi2	0.0000	0.0000
Interpretation	Reject H_0 at full significance	Reject H_0 at full significance
λ	**Model 1: (II) and (III)**	**Model 2: (II) and (IV)**
H_0:	$B_{(II)} – B_{(III)} = 0$	$B_{(II)} – B_{(IV)} = 0$
Chi2(1)	839.03	23501.61
Prob > chi2	0.0000	0.0000
Interpretation	Reject H_0 at full significance	Reject H_0 at full significance

Table 18 displays an overview of the interpretation of regression results and their impact on hypothesis confirmation.

Table 18: Overview of regression results and hypotheses performances
Schematic overview of Hypotheses testing based on the results displayed in Tables 12a to 17a as well as 12b to 17b.

	Network Centrality (EV)			Network Geographic Embeddedness (λ)		
	Model 1	**Model 2**	**Hypothesis**	**Model 1**	**Model 2**	**Hypothesis**
Whole Network	Positive M&A Performance	Networks not similar	H1a: Confirmed	Positive M&A Performance	Networks similar	H1b: Not Confirmed
Vertical Sub-network	No pos. M&A performance	Networks similar	H2a: Not Confirmed	No pos. M&A performance	Networks similar	H2b: Not Confirmed
Horizontal Sub-network	No pos. M&A performance	Networks similar	H3a: Not Confirmed	Positive M&A Performance	Networks not similar	H3b: Confirmed
Shareholder Sub-network	Positive M&A Performance	Networks similar	H4a: Not Confirmed	No pos. M&A performance	Networks not similar	H4b:Not Confirmed
Internal Sub-network	Positive M&A Performance	Networks similar	H5a: Not Confirmed	Positive M&A Performance	Networks not similar	H5b: Confirmed
Board Sub-network	Positive M&A Performance	Networks not similar	H6a: Confirmed	No pos. M&A performance	Networks not similar	H6b Not: Confirmed

In conclusion, as Table 18 depicts, I am able to confirm a number of hypotheses and show that there is in fact a statistically significant connection between strategic complementary and M&A success. However, the heterogeneity on the association of network centrality emphasis a need to further refine and conceptualize what role similarity plays within a M&A transaction and especially along the lines of the different subnetworks. However, such a conceptualization is not in competition to my theoretical framework developed her but rather an extension. My contribution to academic literature is to provide a first theoretical framework and give empirical data on how complementarity has an impact on M&A performance. Furthermore, I was able to confirm 4 out of 12 hypotheses while finding positive M&A performance impacts in 7 out of the 12 cases. This underlines the theoretical complexity of unraveling the combinational network effects.

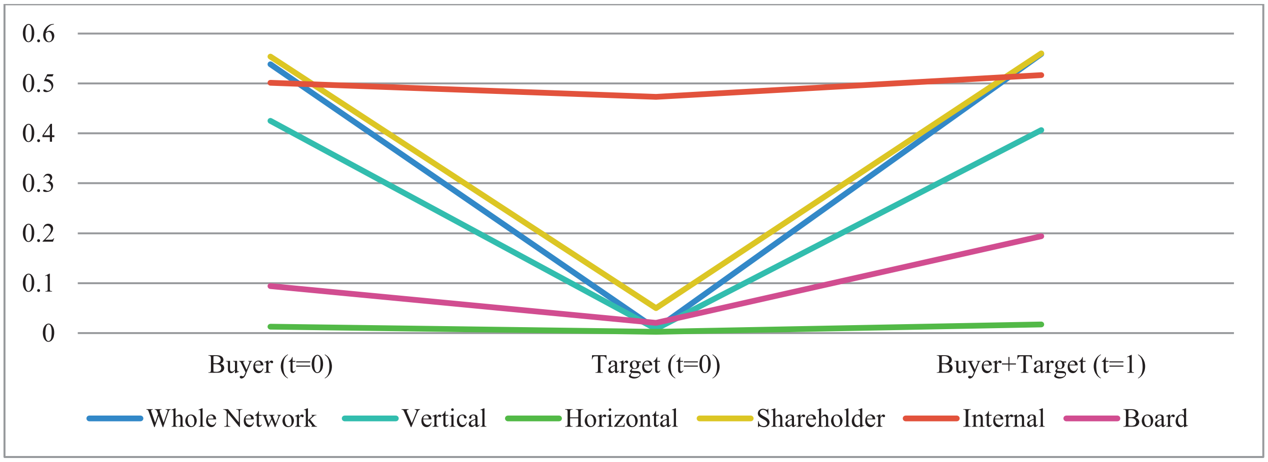
To further validate my results, I next perform a robustness test by comparing the absolute values of the mean estimated eigenvector values for the pre-transaction buyer network, pre-transaction target network and post-transaction buyer network with the outcomes of the regression for hypotheses H1a to H6a. Similarly, I will compare the mean local coefficient values for the pre-transaction buyer network, pre-transaction target network and post-transaction buyer network with the outcomes of the regression for hypotheses H1b to H6b.

5.2. Robustness Tests

First, I refer to Graph 8a and 8b. Graph 8a and 8b depicts the average eigenvector and local coefficient values for buyer firms pre-transaction at time t=0 (*left*), for target firm pre-transaction firms at time t=0 (*middle*), and for the buyer firm post-transaction, i.e. the combined network, at time t=1 (*right*).

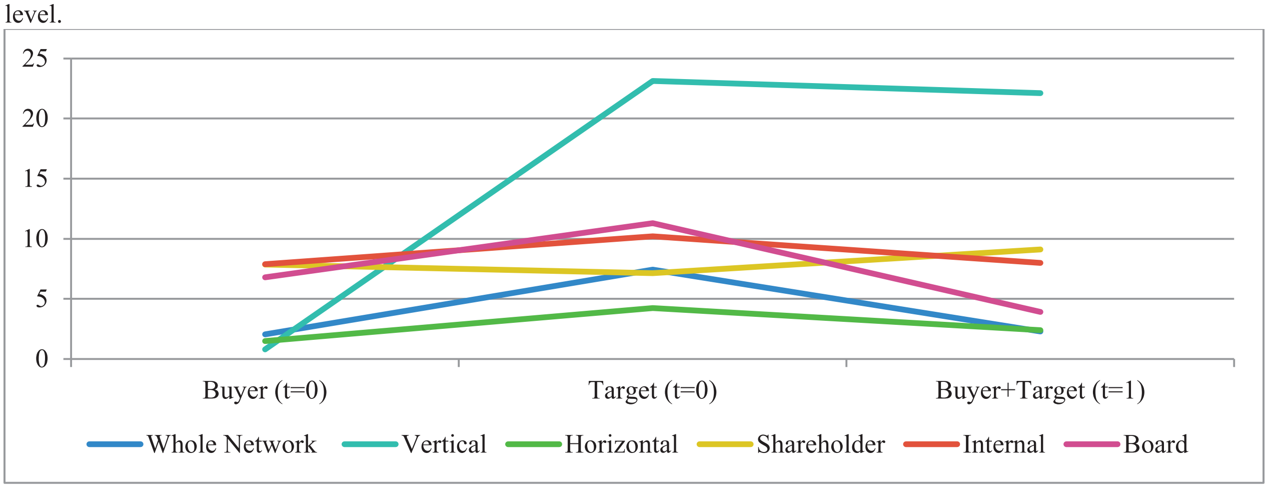
Graph 8a: Average firm eigenvector centrality values

Line graphs display the mean Eigenvector centrality values for the buyer firms at t=0, the target firms at t=1 and the buyer firms at t=1. Dark blue displays the values on the whole network level, light blue the values on the vertical sub network level, green the values on the horizontal sub network level, yellow the values on the shareholder subnetwork level, red the values on the internal sub network level and purple the values on the board sub network level.



Graph 8b: Average firm local coefficient values

Line graphs display the mean local coefficient values for the buyer firms at t=0, the target firms at t=1 and the buyer firms at t=1. Dark blue displays the values on the whole network level, light blue the values on the vertical sub network level, green the values on the horizontal sub network level, yellow the values on the shareholder subnetwork level, red the values on the internal sub network level and purple the values on the board sub network level.



In a first step, I focus on the network embeddedness characteristic, i.e. the eigenvector centrality measure and hypotheses H1a to H6a. I compare the characteristics of the line graphs in Graph 8a and 8b with the outcome displayed in Table 18. The absolute values feeding into Graph 8a and 8b are displayed in Table 19. Primarily, I focus on the regression results from Model 2 which is designed to determine whether the pre-transaction buyer network is similar to the pre-transaction target network. The model determines this by estimating whether the network characteristics of the buyer firm at t=0 has the same directional effect on performance as the network characteristics of the target firm at t=0. These results are displayed in Table 12a to 17a. Table 18 shows that H1a is confirmed. This corresponds with the dark blue line graph in Graph 8a which shows a “check mark”-shaped curve that implies a difference in mean pre-transaction buyer eigenvector centrality (EV=0.538387) with the mean pre-transaction target eigenvector (EV=0.008299) while the mean post-transaction buyer eigenvector rose to 0.5590538 versus the pre-transaction eigenvector centrality. Therefore, the underlying values confirm the results in Section 5.1.

Next, I compare the light blue curve from Graph 8a representing the eigenvector centrality values within the vertical subnetwork. Table 18 shows that for the eigenvector centrality on the vertical sub network level, model 2 deems the networks as similar, i.e. finds no directional change. This lays in contrast to visual interpretation of Graph 8a and argues in favour of the interpretation of the beta coefficients from Table 13a. In Graph 8a, the light blue curve shows a similar “check mark”-shape as displayed by the whole network curve and the absolute values as listed in Table 19 show the mean pre-transaction buyer eigenvector centrality in stark contrast (EV=0.425006) with the mean pre-transaction target eigenvector values (EV=0.008295). This argues in favor of the buyer and target networks pre-transaction not being similar and rather underlines that despite a non-similar degree of centrality, this difference does not impact the effect on firm performance enough to make a direction change. Subsequently, this underlines the relationship between centrality and M&A performance is not linear but rather curvilinear.

Next I look at the green curve in Graph 8a displaying the horizontal subnetwork eigenvector values. There, I find a very flat u-shaped curve which stands in confirmation of the results in Table 18. The mean pre-transaction buyer firm eigenvector centrality (EV=0.425006) is similarly low to the mean pre-transaction target eigenvector centrality (EV=0.0029759).

Fourth, I look at the yellow curve associated with the shareholder eigenvector centrality values. This curve exhibits as similar “check mark”- shape as displayed by the vertical and whole network curves. This curve confirms the results of Model 1 in that there is a positive transactional effect. However, I do not find significant directional change in the pre-transaction association of centrality and M&A performance for the buyer and target firms. However, this is similar to the situation in the vertical sub network. On the one side, we have strongly different values for the mean pre-transaction buyer firm eigenvector centrality (EV=0.553678) and the mean pre-transaction target eigenvector centrality (EV=0.049606). On the other side, this difference is not enough to result in directionally different associations between centrality and M&A performance. As with the vertical sub-network, this stands in favor of a curvilinear relationship between centrality and M&A performance in the place of a marginally linear one.

Fifthly, I turn to the red curve in Graph 8a displaying the internal subnetwork mean eigenvector centrality measures. There, I find a curve similar to the horizontal sub network curve in that it is a very flat u-shaped curve with a low degree of change between mean pre-transaction buyer eigenvector centrality value (EV=0.50172) and the mean pre-transaction target eigenvector centrality value (EV=0.47304). This confirms the results in Table 16a and Table 18 in which the network associations are similar for centrality characteristics.

On the last sub network, the board sub network, I turn to the purple curve in Graph 8a. It shows a flat but visible “check mark”-shape. This shape underlines that the centrality measure for the mean buyer firm changes increases pre- to post-transaction (EV=0.193900). Yet, the flatness of the curve speaks in favor of similar effects of the mean pre-transaction buyer eigenvector centrality value (EV=0.094263) and the mean pre-transaction target eigenvector centrality value (EV=0.020722). Despite this seemingly similar mean value, the regressions in Model 2 in Table 17a and Table 18 show a directional change in the association between centrality and performance for the buyer firm in relation to the target firm. This further underlines the curvilinear association of centrality and performance as a seemingly small difference in eigenvector centrality results into directional change in their associations.

Secondly, I turn to Graph 8b which shows the average firm local coefficient values for the different subnetworks. In contrast to Graph 8a where I look for a step “check mark”-shaped curve to underline my hypotheses, for the local coefficient I look for the same shape or the “check mark” inverted. Overall comparing the mean local coefficients with their respective regression results in Tables 12b to 17b, I find more sub network based variation in associations. On the whole network level (blue), Graph 8b shows a “check mark”-shaped curve with mean pre-transaction buyer local coefficient values (λ=2.033103) different to mean pre-transaction target local coefficient values (λ=7.420843). However, the Model 2 outcomes cannot confirm H1b meaning that there is no directional change in the association between network geographic embeddedness and performance. Similar to the interpretation of this discrepancy, it rather underlines the curvilinear shape of local coefficient and performance.

Just as this discrepancy exists for the whole network level, it also arises when comparing the vertical (light blue), horizontal (green), internal (red) and board (purple) sub networks to Table 18. In contrast, I only find parallels for the shareholder (yellow) sub network where the mean pre-transaction buyer local coefficient values (λ=0.553678) is non similar to the mean pre-transaction target local coefficient values (λ=0.496600) in parallel to a directional change in the association between network geographic embeddedness and performance. This shows that the association between network geographic embeddedness and performance cannot be predicted based on the individual mean value comparison and implies further emphasis on the estimations of Model 1 and Model 2.

Table 19: Summary statistics for eigenvector and local coefficient values
Depiction of selected summary statistics values for the eigenvector and local coefficient values. Selected measures are the mean value and the standard deviation subdivided by sub network level.

Whole Network				
	Eigenvector (EV)		**Local Coefficient (λ)**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
BUYER at time t=0	0.538387	0.251728	2.033403	1.477903
TARGET at time t=0	0.008299	0.0342186	7.420843	8.11434
BUYER at time t=1	0.5590538	0.2422360	2.284365	1.682047
Vertical Sub network				
	Eigenvector (EV)		**Local Coefficient (λ)**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
BUYER at time t=0	0.425006	0.334002	0.797882	0.377625
TARGET at time t=0	0.008299	0.0342186	23.13776	39.91215
BUYER at time t=1	0.4061506	0.325874	22.10622	39.7615
Horizontal Sub network				
	Eigenvector (EV)		**Local Coefficient (λ)**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
BUYER at time t=0	0.012637	0.029095	1.495302	3.746168
TARGET at time t=0	0.002579	0.0037367	4.227708	6.574994
BUYER at time t=1	0.0172343	0.028150	2.381316	3.219966
Shareholder Sub network				
	Eigenvector (EV)		**Local Coefficient (λ)**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
BUYER at time t=0	0.553678	0.286527	7.864812	16.20615

TARGET at time t=0	0.049606	0.1391004	7.135009	8.480757
BUYER at time t=1	0.560025	0.292774	9.107667	22.09535

Internal Sub network				
	Eigenvector (EV)		Local Coefficient (λ)	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
BUYER at time t=0	0.501072	0.348285	7.877831	16.2007
TARGET at time t=0	0.473040	0.0930123	10.20552	9.389758
BUYER at time t=1	0.516535	0.33954	7.978575	16.33394

Board Sub network				
	Eigenvector (EV)		Local Coefficient (λ)	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
BUYER at time t=0	0.094263	0.064002	6.796915	11.51023
TARGET at time t=0	0.020722	0.0297451	11.30051	15.21124
BUYER at time t=1	0.193900	0.262527	3.911756	8.035904

6. Discussion of Findings, Implications for Practitioners and Conclusion

6.1. Discussion of Findings

For the discussion of my findings, it is very important to note that in order to confirm my hypotheses, my empirical model must fulfil the requirements laid out for both Model 1 and Model 2. Therefore, to gain a hypothesis confirmation, my model must work on both model levels. However, limiting my discussion on the hypotheses confirmation outcomes would neglect the highly significant results within Model 1 and Model 2 and explanatory power of my individual findings on a regression-level vis-à-vis current literature would be lost. Thus, I extend my discussion of finding beyond the explanatory power of my hypotheses and onto the significant results on the regression-level or equation-level.

To discuss my findings, I follow the structure of my hypotheses: First in the section 6.1.1., I discuss the findings in relation to the whole network level as portrayed by H1a and H1b. Secondly, I will discuss the different sub-network level regression results in regards to current literature. Subsequently, in section 6.1.2., I present my findings on vertical sub-network embeddedness, horizontal sub-network embeddedness, shareholder sub-network embeddedness, internal sub-network embeddedness, and board sub-network embeddedness. Lastly, I summarize my findings applicable across all sub-networks.

6.1.1. Discussion on Findings for the Whole Network Level

I begin with my findings of the empirical model on the hypothesis level as displayed in Table 18. Table 18 portrays the rational of hypothesis confirmation and an overview of hypotheses confirmations. For the whole network-level or hypotheses H1a and H1b, I find a statistically significant relationship between strategic complementarity of network centrality and M&A performance outcome, as well as for the relationship between strategic complementarity of network geographic embeddedness and M&A outcome. This outcome aligns with the concept of strategic fit by Homburg and Bucerius (2006) and introduces as such two novel concepts. Firstly, it addresses the idea of strategic fit as the combination of mutually supporting differences and subsequently strategic complementarity of resources or capabilities as key determinant of M&A performance (Larsson and Finkelstein, 1999; King et al., 2004; King et al, 2008; Kim and Finkelstein, 2009; Makri et al., 2010). I show that the same rationale of resource complementarity also applies to network resources as resources embedded between linages outside the boundaries of a single firm (Gulati, 1999). To date strategic complementarity has only been applied and confirmed for top management fit (Keishnan et al., 1997) technological fit (Makri et al., 2010), strategic and market fit (Kim and Finkelstein, 2009), and product fit (Wang and Zajac, 2007). At the same time, the applicability of the strategic complementarity concept implies that network resources can be aligned with the M&A strategic management view of resources as a potential for combinational advantages (Singh and Montgomery, 1987; Shelton, 1988; Meyer and Altenborg, 2008). As such, the correct combination of resources, i.e. the strategic fit between them, creates an added-value that would not be achievable in a stand-alone entity (Sirower, 1997). This introduces a novel and extended characterization to the idea of network resources as defined by Gulati (1999). Thus far, network theory has emphasized the similar of network resources to the mechanisms of social capital (Coleman, 1988). My outcomes for H1a and H1b enhance network resources by this behavior mechanism augmenting our understanding of how network resources operate.

Furthermore, the confirmation of H1a and H1b further validate the underlying assumption behind the relation of network embeddedness and firm performance. For instance, as H1a confirms a positive statistically significant relationship between strategic complementarity of networks based on network centrality and firm performance, I am able to contribute in the exploration of network centrally and firm performance by adding the dimension of combinational network resource advantages. Thus far, scholars have widely agreed on the positive relationship of network centrality and firm performance but empirically a direct relationship has more often been tested using intermediaries such as access to information and strategic resources (Barney, 1991; Uzzi, 1997; Stuart, 1998, Kratz, 1998; Gulati, 1999; Abuja, 2000; Dyer and Nobeoka, 2000; McEvily and Marcus, 2005) or access to learning and absorption capabilities (Helper, 1991; Cohen and Levinthal, 1990; Powell et al., 1996; Stuart, 1998; Zahler and Bell, 2005). Only a handful of studies empirically test a direct relationship (e.g. Holm et al., 1996; Andersson and Forsgren, 2000; Moody and White, 2003; Dhanaraj, 2007; Johanson and Vahlne, 2009; Awate and Mudambi, 2017; Turkina and Van Assche, 2018). As such, my study enhances the empirical literature surrounding network centrality and firm performance. Furthermore, in order for complementarity to have a positive relationship with M&A outcomes, the direct relationship between network centrality and firm performance must have an inverted quasilinear form. If network centrality and firm performance could be characterized by a fully linear positive function then only similarity would result in an increase in the relationship between network centrality and firm performance. This idea of embeddedness saturation has already been discussed between R&D expenditures and innovation performance (Molina-Morales and Expósito-Langa, 2012; Turkina et al., 2019). In parallel, H1b shows a statistically significant relationship between complementarity of networks based on geographic embeddedness and M&A performance and as such emphasis the inverted U-shaped relationship between geographic embeddedness and firm performance (e.g. Bathelet, 2004).

Additionally, when referring to the regression level of my Models (Table 12a), I emphasize that on a fundamental level network centrality matters not only in the context of firm competitiveness (Uzzi, 1997) or firm innovation (Powell et al., 1996) but also for M&A transaction performance. Similarly, I show that dual embeddedness matters not only on firm capabilities and performance (Giround and Scott-Kennel, 2009; Meyer et al., 2014) but also on M&A transaction performance.

6.1.2. Discussion of Findings on the Sub-Network Level

Next, I discuss my findings on the sub-network level. Here, the pre-regression network visualization as displayed in figures 5a to 5f already emphasized that sub-networks differ in their composition shape mechanisms. My findings emphasize this as I find different results for models built to test for the same concept and for which I find validity on a whole network level. For example, while the similarity of networks based on network centrality has a statistically significant positive relationship with M&A performance on the internal, shareholder and board sub-network level, the statistically significant relationship is negative for the vertical and horizontal networks. As such, my finding emphasizes the view that linkages differ in their resource creation and characteristics (Lavie, 2006). It underlines that network centrality differs in its relationship's direction dependent on sub-network but not in relationship significance (Burt, 1997; Gulati and Westphal, 1999; Podolny and Baron, 1997) similarly, the association of network geographic embeddedness differs by sub-network (Giroud and Scott-Kennel, 2009). For instance, geographic embeddedness can have different effects based on different institutions (Meyer et al., 2011; Khanna and Palepu, 2000; Peng, 2003) constraints or location ownership advantages (Clark and Geppert, 2011; Figueirdo, 2011; Tallman and Chacar, 2011).

Given the need to dissect whole network relationships on the sub-network level, I first begin with my findings on the vertical sub-network. Table 18 shows that I am not able to confirm my H2a stating that there is a positive statistically significant relationship between strategic complementary of networks based on network centrality and M&A performance. Rather, I find that strategic similarity has a statistically significant relationship with M&A performance. This in itself is not contrary to the rationale surrounding H2a as strategic similarity is the natural opposite of strategic complementarity (Homburg and Bucerius, 2006; Larson and Finkelstein, 1999; Kim and Finkelstein, 2009). In addition to not contradicting my rationale in H2a, this finding also emphasizes the underlining inverted quasi linear relationship between network centrality and firm performance as positive relationship between strategic similarity and firm performance would imply a linear relationship between network centrality and firm performance. Similarly, H2b is not confirmed as I find a statistically significant negative relationship between strategic similarity of networks based on geographic embeddedness and M&A performance. As is the case with H2a, this does not contradict the exception in H2b and in itself serves as strong indicator in favor of the underlining rational. Furthermore, the negative relationship of strategic similarity also argues in favor of an inverted U-shape relationship between geographic embeddedness and firm performance, implying a trade-off between local embeddedness and global embeddedness advantages (Bathelet, 2004; Vora, 2007). On a regression-level, I find that network centrality has a statistically significant negative relationship with firm performance across buyer pre-transaction, buyer post-transaction and target pre-transaction regressions (Table 13a). This lies in contrast to my literature's depiction of the positive relationship between network centrality and firm performance as a positive (Holm et al., 1996; Andersson & Forsgren, 2000; Moody and White, 2003; Dhanaraj, 2007; Johanson and Vahlne, 2009; Molina-Morales and Expósito-Langa, 2012; Awate and Mudambi, 2017; Turkina and Van Assche, 2018). However, this could be explained by automotive industry specific factors. Sturgeon et al. (2008) highlight the emergence of global suppliers that are heavily embedded with individual OEMs and that build expansive infrastructure to support individual OEMs globally. Furthermore, OEMs act as "lead firms" within the industry and as such have strong relational ties with suppliers (Gereffi et al, 2005; Kano, 2018; Mudambi, 2008). This translates into "lead firms" sharing product technologies, quality control systems, and assisting in the acquisition of new technologies (Crespo and Fontoura, 2007; Javorcik and Spatareanu, 2008). Additionally, studies show that close vertical relationships help supplier firms move up the value chain (Alcácer and Oxley, 2014; Pietrobelli and Rabellotti, 2011). This shows that OEMs tend to keep a limited number of vertical linkages while binding existing suppliers into an oligopolistic relationship ships in which OEMs have strong market power over suppliers. This would help explain, why I find network centrality to have a negative relationship on firm performance on a vertical sub-network level. In contrast to this, I find that geographic embeddedness to have a statistically significant positive relationship on firm performance. This finding aligns with current literature as it emphasizes the localization advantages of vertical linkages vis-à-vis global embeddedness advantages (e.g. Meyer et al., 2014).

Secondly, I turn to my findings for the horizontal network level. For the horizontal sub-network, I am not able to confirm my hypotheses H3a. However, this does not contradict my overall rationale. In the contrary, I find no increase in M&A performance while also finding that buyer and target pre-transaction networks are not similar in terms of network centrality. As described above, this underlines my theoretical conception in two ways. First, network similarity and no increase in M&A performance are conceptually the opposite of network complementarity and an increasing M&A performance. Hence, this result can in fact be seen in alignment to my theoretical rational. Second, my finding supports the underlying mechanisms between network centrality and firm performance on the horizontal sub-network level (Holm et al., 1996; Andersson and Forsgren, 2000; Moody and White, 2003; Dhanaraj, 2007; Johanson and Vahlne, 2009; Molina-Morales and Expósito-Langa, 2012; Awate and Mudambi, 2017; Turkina and Van Assche, 2018). It follows that the relationship between network centrality and firm performance on the horizontal sub-network level is found to be curvilinear. If this relationship were in contrast a linear relationship, similarity of networks based on network centrality should conceptually yield an increase on M&A performance. As to hypothesis H3b, I find confirmation in my empirical analysis that there is a positive statistically significant relationship between strategic complementarity and M&A performance on the horizontal sub-network level. This aligns with my findings on the whole network level and shows support of strategic complementarity (Larsson and Finkelstein, 1999; King et al., 2004; King et al, 2008; Kim and Finkelstein, 2009; Makri et al., 2010) by extending it to another type of "fit" (Homburg and Bucerius, 2006). This finding is novel on the level of horizontal subnetworks and enhancing the thought of how network resource on a horizontal partnership level function. Collaborative networks have long been the focus of IB research but to date, the description of network relationship have not included combinational network advantages when merging two networks. Moreover, my findings both from H3a and H3b show that horizontal network structures matter in M&A transactions. Next, I dive into the regression level results of my estimations on the horizontal network level. There, I find a statistically significant negative relationship between network centrality and firm performance. This finding is parallel to network centrally based findings for the vertical sub-network. However, this does not per se clash with current literature on network centrality. Despite an overwhelming literature on the positive effects of network centrality (Holm et al., 1996; Andersson and Forsgren, 2000; Moody and White, 2003; Dhanaraj, 2007; Johanson and Vahlne, 2009; Awate and Mudambi, 2017; Turkina and Van Assche, 2018), other authors have suggested that network embeddedness benefits, I.e. network centrality benefits have saturation points (Molina-Morales and Expósito-Langa, 2012; Hutzschenreuter et al., 2012; Turkina et al., 2019). The negative relationship between centrality and firm performance on the horizontal level could be interpreted in support of this saturation stream. However it is undisputed that the network centrality mechanism are not yet fully understood and my findings enhance that fact by adding a combinational resource dimension to network centrality on the horizontal sub-network level. In contrast to my findings on network centrality on the horizontal sub-network level, I find a statistically significant relationship between network geographic embeddedness and firm performance. This finding is in tune with current academic literature in favor of the dual embeddedness paradigm as described by Bathelet et al. (2004) and supports it on the level of horizontal linkages.

Thirdly, I turn to the shareholder sub-network or commonly referred to as the "corporate control" network (Vitali et al., 2011). There, I find similar results to the board sub-network as I cannot confirm both H4a, hypothesizing a statistically significant positive relationship between strategic network complementarity in terms of network centrality and M&A performance as well as H4b, hypothesizing a statistically significant positive relationship between strategic network complementarity in terms of network geographical embeddedness and M&A performance. Also in similarity to the horizontal and vertical sub-network level, I cannot confirm a positive relationship between strategic network complementarity in terms of network centrality and M&A performance as I find the opposite scenario in that there is a statistically significant negative relationship between strategic similarity and M&A performance at a 0% significance level. As described above, this does not contradict the rational of strategic complementarity but as the perfect opposite supports the concept (Homburg and Bucerius, 2006; Larsson and Finkelstein, 1999; Kim and Finkelstein, 2009) on the shareholder network level. More critical to my theoretical approach are the findings for H4b in which strategic complementarity appears to have a negative association with M&A transaction performance. Despite this counterintuitive approach, this does underline the impact of the strategic fit parameter, although further research will be needed to precisely decode this element. Next, I discuss these findings for shareholder networks. Across the buyer pre-and post-transaction and target pre-transaction networks, I find a negative statistically significant relationship between network centrality and firm performance. This relationship is similar to the association on the vertical, horizontal and shareholder sub-network levels and isn't surprising. However, it does stand in contrast to prevalent network embeddedness literature (Holm et al., 1996; Andersson and Forsgren, 2000; Moody and White, 2003; Dhanaraj, 2007; Johanson and Vahlne, 2009; Awate and Mudambi, 2017; Turkina and Van Assche, 2018). This negative, counterintuitive relationship could be explained by a higher impact of shareholder disadvantages and I initially anticipated. These disadvantages can include higher scrutiny for return from well-connected shareholders as well as high political cost when shareholders attempt to leverage their ownership networks for policy changes (Easely, 2004; Faccio, 2006). Either way, my findings highlight that network centrality on the shareholder level are not as simple as a "the more, the merry" relationship and thus requires further precise empirical analysis. Moreover, these results nonetheless contribute to the existing stream of literature by applying it to the shareholder sub-network, which to date has not been done within and outside of IB research.

Fourthly, I next refer to the internal sub-network and based on my results I again am not able to confirm my hypothesis H5a based on network centrality. However, in contrast to the vertical, horizontal and shareholder sub-network, where I do not find a limitation to my rational of strategic complementarity, I find a statistically significant positive relationship between network strategic similarities based on network centrality, which at first thought stands in contrast to the findings on the whole network level. Nonetheless, it allows for support of two key findings. First, a positive relationship of M&A performance and of both strategic complementarity and similarity is in support of the applicability of the strategic fit concept (Homburg and Bucerius, 2006) onto the field of network resources. Secondly, a presence of the strategic fit concept for network resources implies that there are combinational advantages of network resources when merging two networks. This has important extensions for the characterization of network resources based on Gulati (1999) in that network resources can combinational behave similar to "traditional" inner-firm resources. Theses finding is consistent across H1a, in which I have a full confirmation on a whole network level, H2a through H4a, in which I have a non-confirmation due to an opposite relationship but not due to contradictory relationship and the internal sub-network, in which I have a non-confirmation based on contradictory relationship to my hypothesis H5a. However, in addition to these positive findings, the positive relationship between strategic similarity and M&A performance also has implications for the relationship between network centrality and firm performance. It implies that the relationship is linear without starvation point. This alternately could be explained by either that the starvation point has not yet been reached for my internal data set sample. Yet given the sample size of my internal sub-network at 4,090 observations this seems unlikely. More probable seems the explanation that the interplay of horizontal and vertical internal linkages, i.e. the interplay of HQ-subsidiary and inter-subsidiary ties has an interaction relationship which impacts the application of strategic fit onto the internal sub-network level. This aligns with the vast body of literature on MNE subsidiary roles, in which inner MNE ties are differentiate given their difference in effect (e.g. Barlett, 1998; Ghosal and Barlett, 1990; Rugman et al., 2011; Figuiredo, 2011). However, internal vertical and horizontal linkages cannot be confused with external vertical and horizontal linkages (Turkina and Van Assche, 2018). Furthermore, given the impracticality of the non-public nature of these relationships a conceptualization as one linkage type is favorable. Yet, my findings clearly show that the internal subnetwork needs more study as it behaves in contrast to my findings on the whole network associations. Nonetheless, the internal sub-network findings do not contradict the validity of my findings on the whole network level. It merely emphasizes the complex interplay of mechanisms on different sub-network levels that lead to an association with the whole network level. In contrast to these findings on strategic fit of network centrality, I find a statistically significant positive relationship between strategic complementarity of network geographic embeddedness and M&A performance. As such, I am able to extend not only the strategic fit concept (Homburg and Buccerieus, 2006) on network geographic embeddedness as for H2a through H5a but also the concept of strategic complementarity onto the internal sub-network level. This finding also shows that strategic fit can differ between network characteristics such as network centrality and network geographical embeddedness. As applying the strategic fit concept onto network resources is novel in itself, the separation of strategic fit by network characteristic enhance the strategic fit concept. Lastly on the internal sub-network level, I turn to the regression level results and find clear statistically significant relationships between network centrality and firm performance on the internal sub-network level. This is in tune with academic literature on network centrality (Holm et al., 1996; Andersson and Forsgren, 2000; Moody and White, 2003; Dhanaraj, 2007; Johanson and Vahlne, 2009; Awate and Mudambi, 2017; Turkina and Van Assche, 2018). For geographic embeddedness, my regression-level results find that network geographic embeddedness is positively associated with firm performance on the internal sub-network level. This is also in tune with current academic literature on dual geographic embeddedness and shows that location matters (Bathelet et al., 2004; Vora, 2007).

Lastly, I turn to the board sub-network. In parallel to the findings on the internal sub-network, my board network level results show a statistically significant positive association with network similarity as defined by network centrality and M&A performance. As for internal linkages, this goes in contrary to the strategic complementarity concept found on the whole network level and not contradicted on the vertical, horizontal and shareholder network level. However, it does underline the overall validate of strategic fit rational on network resources as well as it enhances the view of network resources by an additional characteristic. Despite the similarities in the findings implications for network and M&A research, the interpretation differs as to why strategic similarity is positively associated with M&A performance as opposed to strategic complementarity. Although, sample size could play more of a misconstruing association than for the internal sub-network as my data set has a total of 95 linkages, I do not think the outcome is thereby explainable. Board networks resource are on the beneficial side associated with increased access to information for risk mitigation (Gompers and Xuan, 2008; Cai and Sevilir, 2012), reputation-based positive behavior control as a negative firm performance is associated with a loss of future financial and reputation gains through less board appointments (e.g. Kaplan and Reishus, 1990) while on the cost of board subnetwork embeddedness falls an increase risk to “familiarity bias” (Ishii and Xuan, 2014) and reputation-based risks as board members are more likely commit fraud in the fear of reputation-based backlash of the network (Khanna et al., 2015). As such, the fit of strategic similarity can be explained by the benefits of board networks outweighing its limitations with increasing network centrality to the extent that the relationship between board network centrality and firm performance is positive. Similarly to the findings relating to H6a, H6b findings are misaligned with whole network level finds in I am not able to statistically significantly confirm the positive relationship between strategic complementary of networks based on geographical embeddedness and M&A performance on the board sub-network. This emphasizes underlines the applicability of the strategic fit concept for dual geographic embeddedness beyond organization-based linkages onto individual-based linkages. On a regression level, I find that network centrality has similarly to the vertical, horizontal and shareholder sub-network, a negative association with firm performance. This enhances my interpretation of the H6a findings in that centrality has a different marginal relationship based on network structures.

In conclusion of my findings, I find that I am able to confirm the application of the strategic fit concept (Homburg and Buccerieus, 2006) through the different sub-rework levels. In addition, I am able to deduct that strategic fit applies differently depending on the different dimensions of networks, such as network centrality and network embeddedness. Furthermore, I am able to confirm that there are combinational advantages of network resources and subsequently can extend Gulati (1999)’s interpretation of network resources to that extend. Lastly, I find heterogeneous results that differ by sub-network category which underlines the necessity of distinguishing networks by linkage types and underlining the different mechanisms in different sub-network (Lavie, 2006; Turkina and Van Assche, 2018). In terms of strategic complementary, I find more robust positive relationship between network geographic embeddedness strategic complementary and M&A performance than for network centrality strategic complementary and M&A performance despite validation of both relationships on the whole network level.

6.2. Limitations

After discussing my findings, I next turn to the limitations of my study. First and foremost, while it increases the industrial validity, the global validity of my theoretical model is open for criticism as I limited myself to the automotive Industry in North America. An application to other regions and industry would sure advance my theoretical explorations but this work may not be transferable on every transaction.

Secondly, as aforementioned my model is limited by my two stepped approach. Despite best efforts in the model construction, my model does not conclusively and solely contribute network strategic complementarity as the sole factor for the increase in the association of network centrality and network geographic embeddedness on firm performance as I treat M&A performance not as causality of strategic complementary but as a correlated event. As such I am able to link both occurrences together and derive strategic complementarity as an antecedent of M&A success. I am not able to derive causality of complementary on M&A performance.

6.3. Implications for Practitioners

Lastly, I explore the implications of my findings for future research as well as for practitioners in the M&A environment. The idea of strategic complementary of network resources is despite this work still in its early stages and requires more voluminous research. As defined in limitations, my study is limited by the observation heterogeneity of my linkages as I am limited in the data collection. Future could focus on one specific network resource to provide a more thorough depiction of the underlining mechanism of which I am only able to scrap the surface. Additionally, future research could focus on analyzing combinational network benefits within the M&A integration process. As a key determinant of M&A success, network integration has high potential of having an impact on M&A performances.

Furthermore, the pending merger of the American/Italian automaker Fiat Chrysler Automotive (FCA) with French PSA provides an excellent testing ground for network resources if completed. The main limitation of my data collection is the firm size of target transactions. A transition of this magnitude would allow a deeper and more significant look onto the combinational benefits of network resources. Additional, both FCA and PSA have in light of current automotive market trends engaged in numerous partnerships both vertical and horizontal which would allow a deeper look on knowledge exchanges on linkage level which are otherwise hard to observe.

Lastly, I outline the implications of my research for practitioners. With practitioners, I reserve to professions who participate in M&A transaction in an active manner, e.g. MNEs, M&A Consultants, Investment Banks, Investment Funds, and Industrials with inorganic growth strategies. My work underlines the importance of abandoning a "one-size fits all approach. Despite push, particularly from M&A consultants, to focus on case-by-case models, M&A transaction cannot be seen as a universal checklist that guarantees success. Network resource impact are another dimension of M&A transactions that underlines the complexity of M&A transaction and importance of pre-transaction due diligence.

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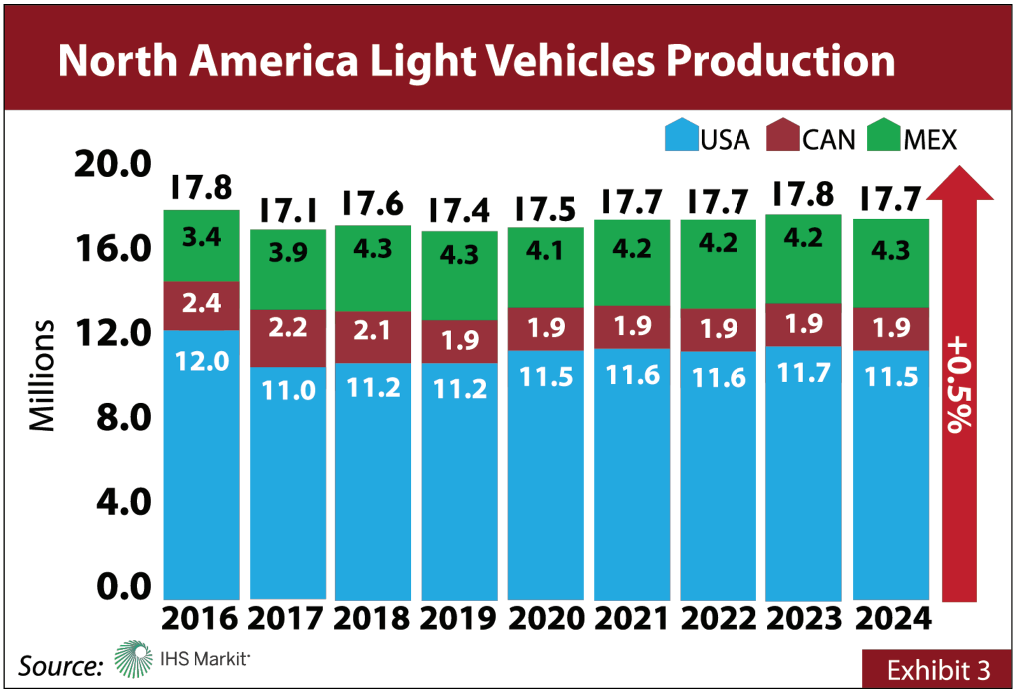
8. Appendix

Appendix A: Overview of FCA's US Suppliers of the Year (Source: FCA, 2018)

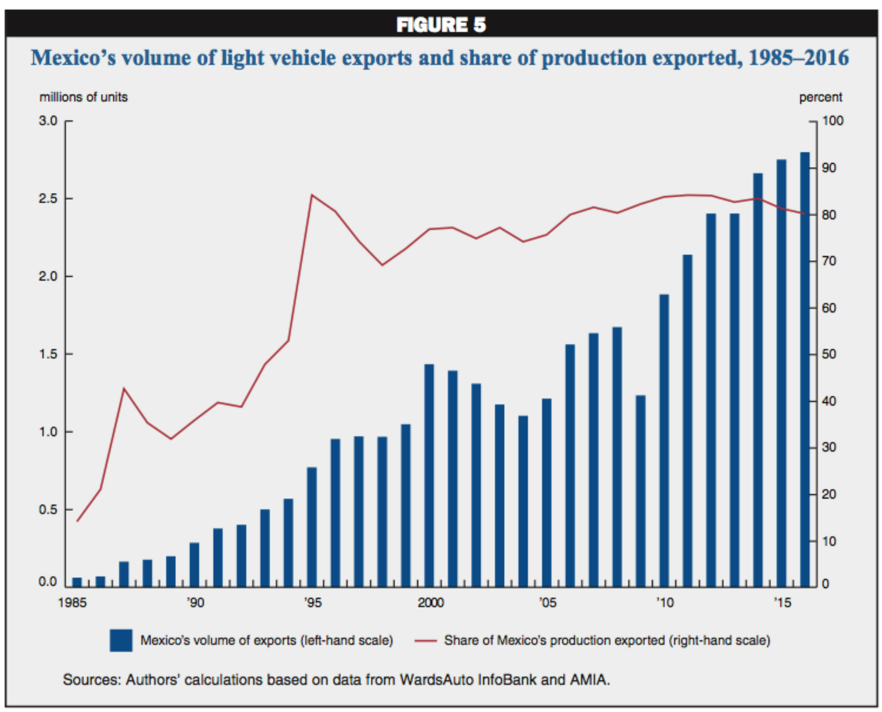
The 2017 FCA US Suppliers of the Year are:

- Body Supplier of the Year – Gentex Corporation
- Capital Equipment Supplier of the Year – International Industrial Contracting Corporation
- Chassis Supplier of the Year – ILJIN USA Corporation
- Diversity Supplier of the Year – Henkel Corporation
- Electrical Supplier of the Year – N.S. International Ltd.
- Engine Systems Supplier of the Year – Avon Automotive – MGI Coutier
- Foundational Principles Supplier of the Year – Quaker Chemical Corporation
- Innovation Supplier of the Year – Webasto Convertibles USA Inc.
- Interior Supplier of the Year – US Farathane
- Mopar Supplier of the Year – North American Assembly LLC
- Powertrain Supplier of the Year – Hitchiner Manufacturing Co. Inc.
- Raw Material Supplier of the Year – Steel Technologies LLC
- Services Supplier of the Year – Corrigan Oil Company Inc.
- Supply Chain Management Supplier of the Year – DTR Corporation
- Sustainability Supplier of the Year – PPG
- Value Optimization Supplier of the Year – Prime Wheel Corporation

Appendix B: The North American Light Vehicle Production by Region from 2016 to 2024 (Source: MexicoNow, 2018)



Appendix C: Mexico's volume of light vehicle exports and share of production exported 1985 -2016 (Source Klier and Rubenstein, 2017)



Appendix D: The nested geographic and organizational Structure of the automotive industry (Source: Sturgeon, 2008)

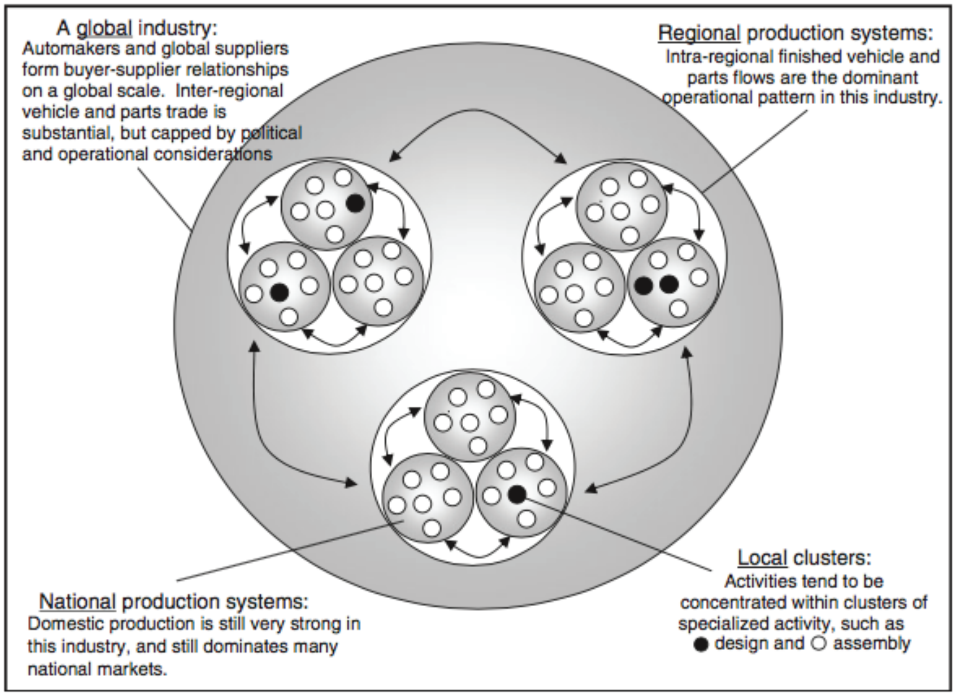
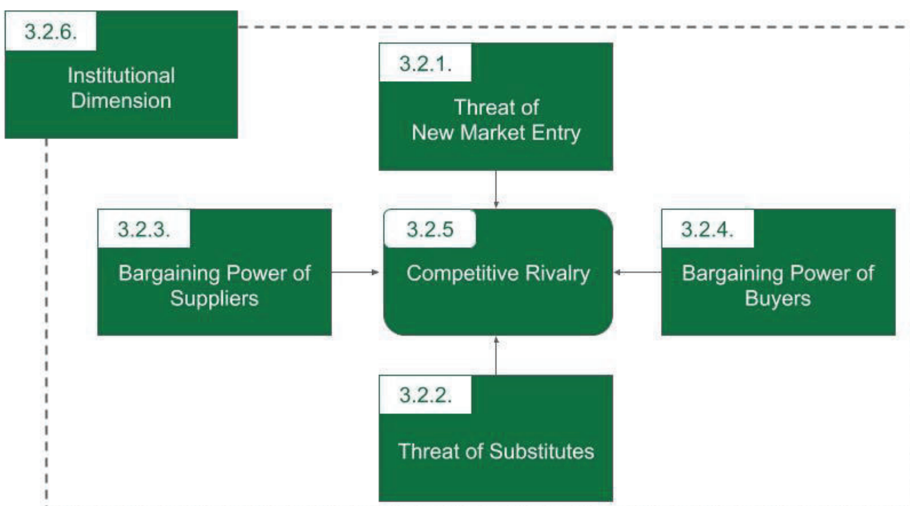
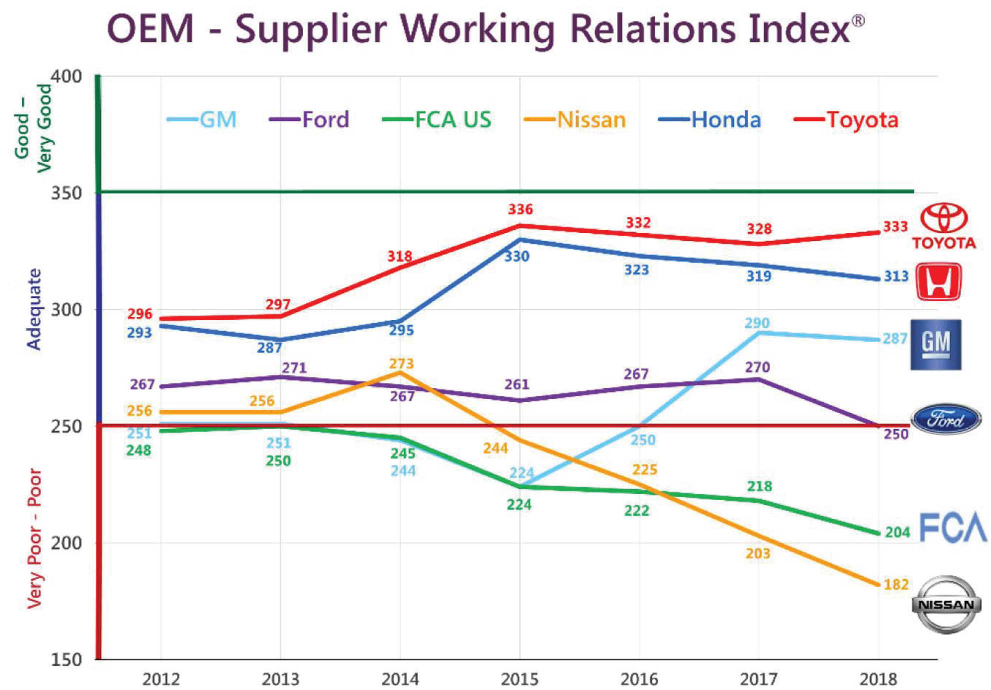


Figure 1. The nested geographic and organizational structure of the automotive industry.

Appendix E: Overview of Porter's Five Forces with the addition of the Institutional Dimension (Source: Porter, 1980)



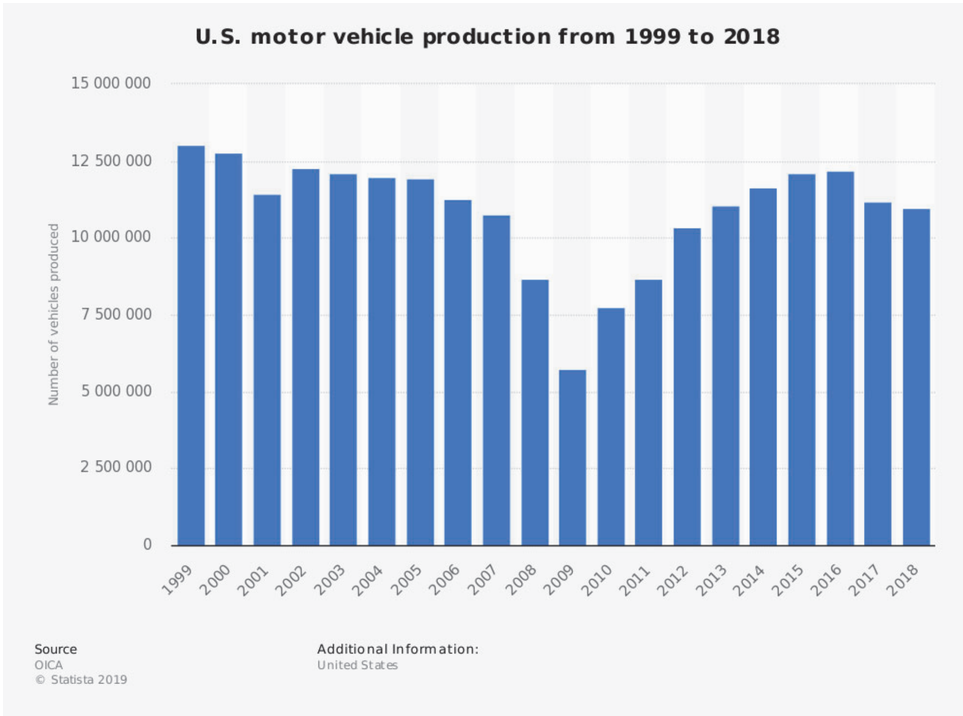
Appendix F: OEM-Supplier Working Relationship Index 2012 to 2018 (Source: Planning Perspectives, 2018)



2018 Grade
B
B-
C
D
F
F

Appendix G: US Motor Vehicle Production from 1999 to 2018

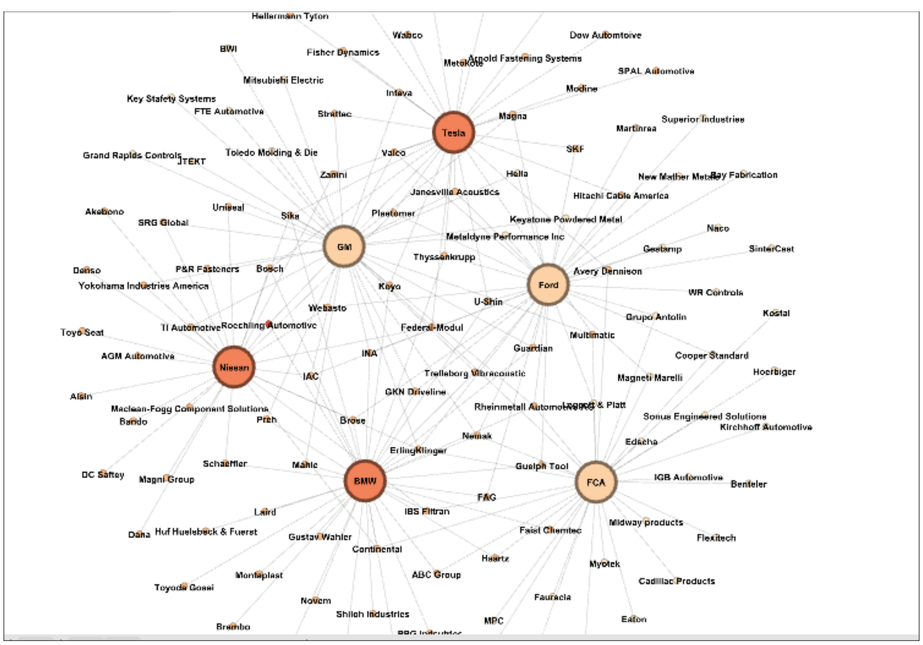
(Source: Statista, 2019)



Appendix H: Visualization of the Network Analysis of the Supply Chain

Selected 6 vehicles specified in Appendix I

(Source: Automotive News, 2014; 2015a; 2015b; 2016a; 2016b; 2017)



Appendix I: Vehicles analyzed in the Network Analysis by Final Location

(Source: Automotive News, 2014; 2015a; 2015b; 2016a; 2016b; 2017)

OEM	Nissan	FCA	GM	Ford	Tesla	BMW
Vehicle	2017 Versa	2018 Jeep Wrangler	2017 GMC Canyon	2015 Ford Edge	2016 Model X	2015 X6
Country	Mexico	USA	USA	Canada	USA	USA
Region	Cuernavaca	Toledo, OH	Wentzville, MS	Oaksville, ON	Fremont, CA	Spartanburg, SC

Appendix J: Overview of Data Collection Logic and ZYPHER / ORBIS characteristics

Data Sample Progression with search step parameters

	1. Step: Transaction-level (ZYPHER)	2. Step: Firm-level (ORBIS)	3. Step: Linkage Research

Search Parameters	- Buyer-based:
	    - Within Automotive Industry (NAICS 33611, 336211, 3363)
	    - From North America (CA, US, MX)
	    - Publicly listed entities
	- Target-based:
	  - US/NA based
	- Deal-based
	  - Completed
	  - Completion post-2000
	  - Deal type: 100% Acquisition
		Based on BvD ID from 1.Step	Search basis:
			- Annual Reports from year prior to year of completion
			- Firm Official Websites
			- Media Reports (Appendix A.I.)
			-

Variables	- Deal ID
	- Buyer Information
	  - Name, BvD, ID, State, Country, Ticker, Industry
	- Vendor
	  - Name, BvD ID, State, Country, Ticker, Industry
	- Target
	  - Name, BvD ID, State, Country, Ticker, Industry
	- Completion Date
	- Deal Size in kUSD
	- Deal Type
		- Name, BvD ID
		- Location (City, State, ISO Country Code)
		- Size (Turnover in kUSD, Cashflow in kUSD, Total Assets in kUSD, Number of Employees)
		- Fiscal Year of Size information
		- NAICS 2017 Industry Classification
		- Linkages:
		  - Internal
		  - Shareholder
			Used Medias:
			- Annual Reports of

Appendix K: Overview of Transactions

Target name	Buyer name	Year
GUILFORD MILLS INC.	LEAR CORPORATION	2012
TRANSLOC INC.	FORD MOTOR COMPANY	2018
SEVCON INC.	BORGWARNER INC.	2017
STROBE INC.	GENERAL MOTORS COMPANY	2017
XEVO INC.	LEAR CORPORATION	2019
SOLARCITY CORPORATION	TESLA MOTORS INC.	2016
CRUISE AUTOMATION INC.	GENERAL MOTORS COMPANY	2014
SGL AUTOMOTIVE SE	BAYERISCHE MOTOREN WERKE AG	2009
ZENUITY AB	AUTOLIV INC.	2017
MOZAIQ OPERATIONS GMBH	ROBERT BOSCH GMBH	2015
METALDYNE PERFORMANCE GROUP INC.	AMERICAN AXLE & MANUFACTURING HOLDINGS INC.	2017

Appendix L: Abnormal Returns:

Comparison actual return and expected return over τ=[-5,+60]