Innovation Dynamics Between Original Equipment Manufacturers (OEMs) and Tier-1 Suppliers in the Automotive Industry

by

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Abstract

Over the past seven decades, the automotive supply chain has been restructured to a tiered system. OEMs and tier-1 suppliers innovate together through joint product development programs: each OEM has multiple suppliers working on different subsystems, and one supplier may offer similar subsystems to multiple OEMs. This work focuses on the relationship between OEM and tier-1 suppliers that focuses on both parties' interests with a balance in the coexistence of competition and collaboration, using objective data sources. Treating the OEM, its tier-1 supplier, and the competitors in the whole product market as a system, a system-level quantitative study on the buyer-supplier relationship is conducted. A system dynamics (SD) model is proposed to describe the dynamics in an OEM-supplier relationship. To validate the model, the author collects non-subjective data and performs empirical studies on two subsystems – passive keyless entry (PKE) and high-speed transmission (HST) between the model years 2004 and 2021. The empirical studies validate the hypothesis that the outcomes of competitive and collaborative behaviors on the whole product competitiveness depend on market competition, which is reproducible by the model: when the market is stable, the more competitive party in a relationship has a better financial outcome; when the market is highly competitive, collaborative behaviors boost the long-term performance of the OEM-supplier ecosystem. The study also shows that the proposed model delivers accurate predictions with non-subjective inputs when heavy dependence is present in an OEM-supplier relationship.

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Chapter 1

Motivation

1.1. Innovation in Automotive Industry

Like many manufacturers, the automotive industry is a capital-intensive industry, highlighted by a high percentage of fixed assets (property, plant, and equipment), which leads to high fixed costs (overheads) compared to variable costs. Therefore, this industry needs a high sales volume to offset the overheads and generate an adequate return on investment (ROI).

With the aspiration toward a higher ROI, the industry turns to economies of scale, hoping that small changes in sales can magnify profits. Innovation played an essential role in the early decades of the automotive industry: Henry Ford invented the moving assembly line, making Ford Motor Company (Ford) leading the industry into the mass-production era. Even today, both customers and manufacturers benefited from this invention: cars become more affordable year after year, and more and more people own cars. As is shown in Figure 1, the price of Ford's Model T was down by 68.4% in 15 years while sales increased by more than 1000 times.

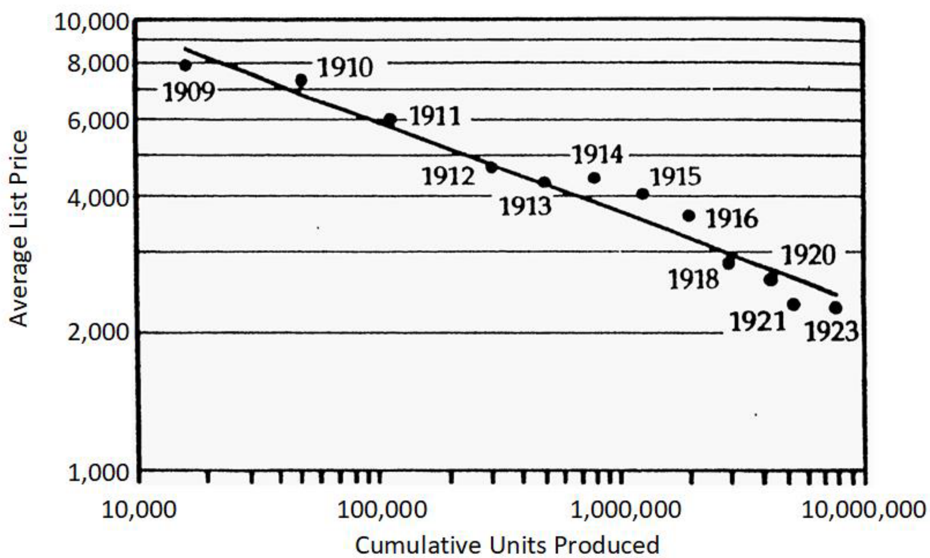

Figure 1 Ford Model T price (constant 1978$) vs. cumulative production, adapted from (Thomas et al., 1998)

Those original equipment manufacturers (OEMs), which fell behind the trend of vertical integration and economics of scale, exited the market. By the late 1920s, only a few OEMs were in the North American market, far less than the peaking 300 in 1910 (Schulze et al., 2015).

As the motor vehicle's architecture grows more complex over time, it becomes harder for a single OEM to keep the whole value chain vertically integrated with adequate investment return (Langlois & Robertson, 1989). The innovative Japanese OEMs have reduced vertical integration since the late 1970s while maintaining system architecture and integration knowledge (Schulze et al., 2015). Suppliers started to capture more added values in the value chain. The collaboration between OEMs and suppliers boosted innovation to create low-cost and high-quality vehicles, which quickly captured the North American market starting from the late 1970s, as shown in Figure 2. With the help of innovative OEMs and suppliers, the world is becoming more and more motorized, as shown in Figure 3. Today, suppliers capture 80% of the added value of a vehicle in the value chain(Nishiguchi, 1987).

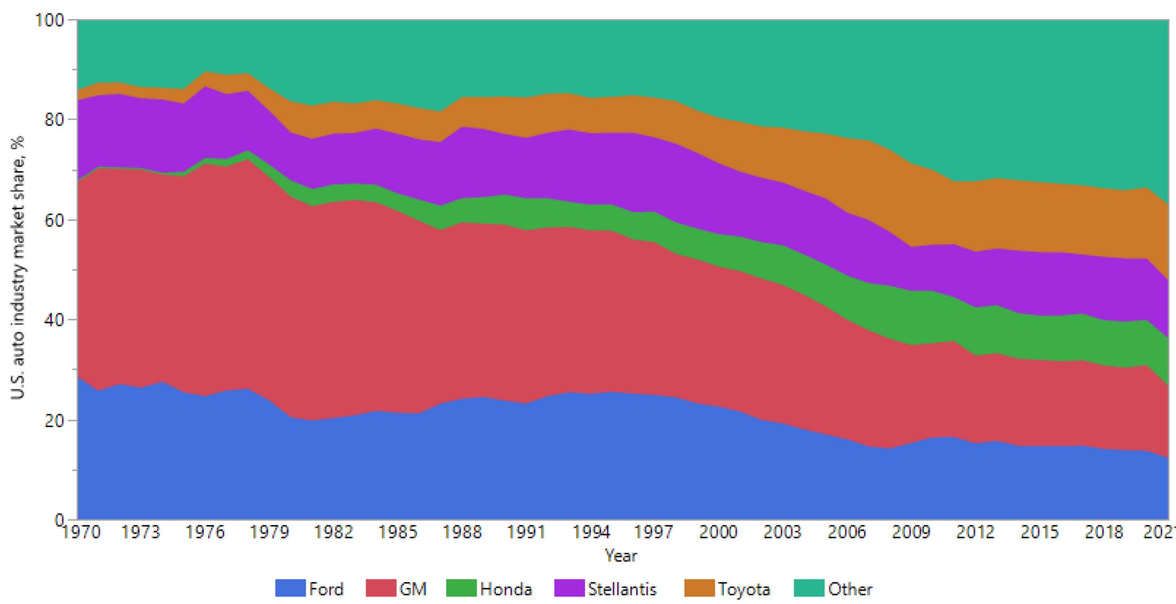

Figure 2 Percent of U.S. auto industry market share by automaker, 1970-2021

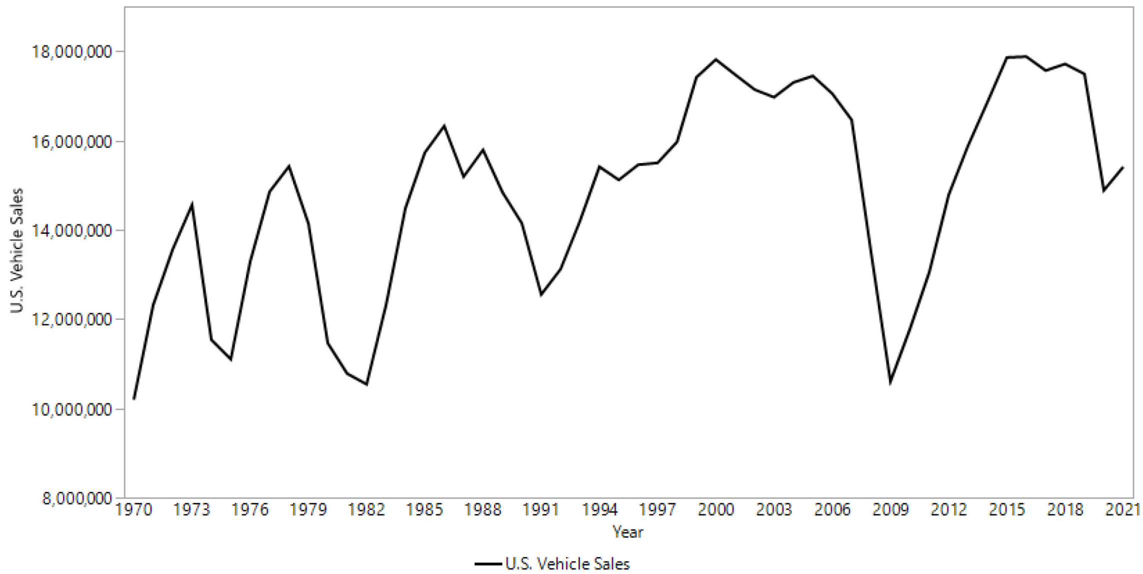

Figure 3 Total U.S. auto industry vehicle sales, 1970-2021

As more profits and product development activities shifted to suppliers, a tiered buyer-supplier network shown in Figure 4 emerged over the past four decades:

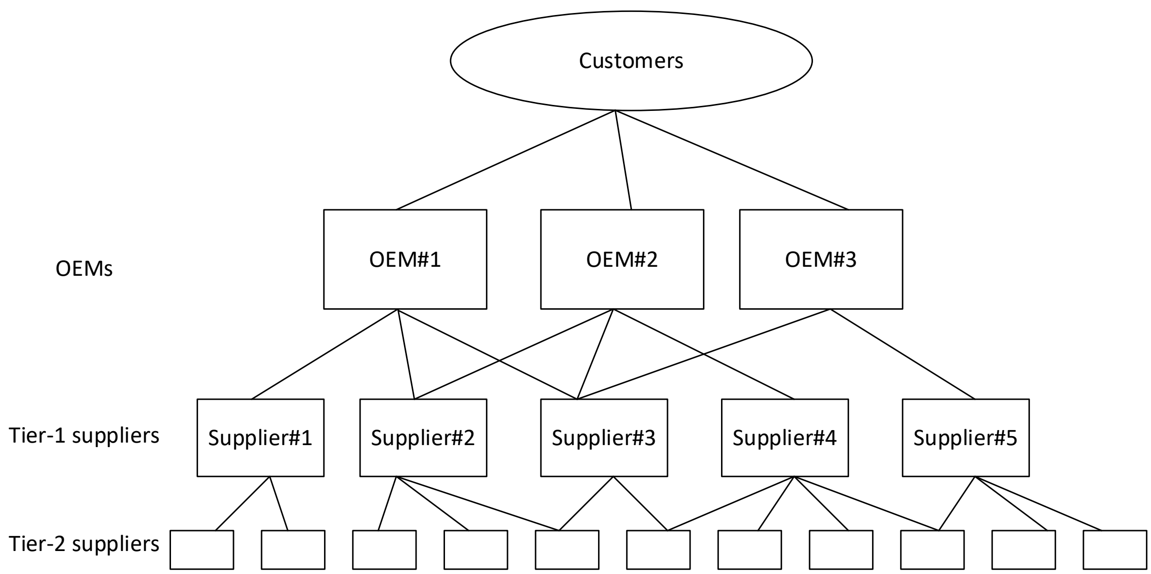

Figure 4 Tiered buyer-supplier network in the auto industry, adapted from (Nishiguchi, 1987)

The term "tiers" was introduced by (Hines, 1994; Nishiguchi, 1987) to describe the levels in the Japanese automotive supply chains. Over the past 3 decades, the North American and European OEMs followed the Japanese supply chain model to restructure the global automotive supply chain base as the tiered model shown in Figure 4.

In this supply chain, buyers in the higher tier consume components manufactured by the lower tier. The customers acquire the final product – motor vehicles from OEMs, and OEMs acquire subsystems (e.g., instrument panels, seats, and transmissions) from tier-1 suppliers for manufacturing. Each OEM has multiple tier-1 suppliers working on different subsystems, and one tier-1 supplier may offer similar subsystems to multiple OEMs. Though the supply chain shares nearly 80% of the added value of one vehicle, suppliers in the higher tier with fewer numbers tend to capture more share in the value chain than the lower tier (Nishiguchi, 1987). In many cases, a business unit from one tier-1 supplier could become a tier-2 supplier to another tier-1 supplier.

The tiered system boosts innovation in the automotive industry in the following ways:

- Division of labor makes suppliers specialized in their domain: Suppliers in the same tier compete to become lean. The tiered system increases product quality and reduces time to market and cost.
- The tiered system simplifies communication during system integration: the buyer only needs to communicate with the direct suppliers (one tier lower in the supply chain) and need not interact with the whole supply chain.
- Long-term relationship boosts collaboration between buyer and suppliers: the relationship stability and years of close partnership encourage deep integration between an OEM and its tier-1 suppliers' product development activities. Combining OEM's knowledge of customer and system integration and supplier's specialty in subsystem design further boosts innovation in the automotive industry. An empirical study from (Atalay et al., 2013) shows that suppliers with more diversified customer portfolios through innovation have a better chance of gaining more orders and broadening their customer base.

The above benefit model works when the automotive market keeps increasing steadily with a certain level of resiliency towards short-term disturbances like the 2008 financial crisis. However, the following recent trends in the automotive industry may disrupt the long-established tiered model:

- Disruption from newcomers – electrical and autonomous vehicles: the trend of more intelligent, safer, and environmentally friendly vehicles introduces outsiders to the automotive industry based on decades of iterations on internal combustion engines (ICEs). Automotive startups like Tesla, Rivian (backed by Ford and Amazon), and Waymo (back by Google) lead the traditional automakers in developing new technologies to capture future customers. These newcomers bring supply chain expertise from other industries, disrupting the existing model (Lee & Berente, 2012).

- Disruption from tier-0.5 suppliers: there is nothing wrong with suppliers in the lower tier who want to level up in the supply chain to pursue a higher profit and a more extensive customer base. As tier-1 suppliers accumulate knowledge and profit while working with OEMs, they are ambitious to harvest larger slices of value-added business by providing major systems in vehicles or even system integration services, competing with OEMs in the supply chain. What's more, tier-0.5 suppliers actively explore new business ideas in the digital and service mobility domain, trying to level themselves up in the supply chain by creating new markets (Beiker & Burgelman, 2020).

The above two trends in the automotive industry's supply chain illustrate the complicated relationship between OEMs and tier-1 suppliers – the symbiosis of competition and collaboration across tiers. The symbiosis attracts the author's interest in studying the dynamics between OEMs and Tier-1 suppliers in this thesis.

1.2. Business Question and General Objectives

Putting oneself into the business owner's shoes, the author has the following essential needs for sustainable innovation:

- As an OEM, I want both myself and suppliers to be lean, so I ship innovative features.
- As a supplier, I want to sell innovative products to more OEMs with more sales and a higher profit margin.

How will the OEM and supplier get there? This question leads to the general objectives of this thesis: a model to describe and predict the innovation dynamics between OEMs and Tier-1 suppliers in the automotive industry.

To be useful for management to make business decisions on innovation, the model shall output the following performance measures for both OEMs and Suppliers over time:

- Financial growth (appear on Form 10-K): the goal of any for-profit organizations
- Competitive positioning: win-win (OEM & supplier grow with more customers), win-lose (one party grows), or lose-lose (both are shrinking)

The following 3 items are more for self-awareness between OEM, supplier, and the market:

- Product attractiveness (to the end customer/ or the entire market): the indicator for future growth
- Innovation diffusion level (to the end customer/ or the entire market): the indicator for success in R&D investment
- Innovation gap between OEM and Supplier: the indicator for OEM/Supplier's self-diagnosis

1.3. Thesis Overview

The thesis is organized as follows:

- Chapter 1 Motivation: presents the research background and author's motivation for this research in the automotive industry.
- Chapter 2 Literature Review: provides an unbiased survey on existing research in the definition of innovation, technology diffusion, buyer-supplier relationship, competition between OEM and suppliers, and socio-technical systems modeling.
- Chapter 3 Research Question: narrows down from business question to research question with treatable hypotheses.
- Chapter 4 Research Method: defines the system problem statement, modeling method, and research processes and highlights constraints on modeling, data collection, and thesis scope.
- Chapter 5 Data Collection: details how different types of empirical data are collected, including market, financial, organizational, innovational, and technological data.
- Chapter 6 Modeling Innovation Dynamics: walks through the modeling and verification of the proposed innovation dynamics model.

- Chapter 7 Model Validation: validates the model with historical data and evaluates the model's ability to reproduce past events.
- Chapter 8 Discussions: concludes hypothesis testing, discusses the management implication offered by the model, presents insights on the modeling and data collection processes, and finally summarizes limitations of this work and possible future works.

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Chapter 2

Literature Review

2.1. Innovation and competitive advantage

The word "Innovation" has been used in many academic, business, social and political areas, and the meaning drifts with the context. It is necessary to limit the scope of the definition in this thesis to focus on product development for for-profit businesses in the automotive industry.

MIT Professor Ed Roberts captured this well with his equation "Innovation = Invention + Commercialization" (Aulet, 2013). The equation provides both definitions in the business context and the corresponding measures. Invention means creating something new inside or outside the organization:

- New forms: technology, patents
- New functions: process
- New form to function mapping: business model, market positioning

The commercialization process mobilizes inventions to generate value in a user context, e.g., creating new revenue streams or saving costs for a for-profit organization.

The literature has long identified product development activities as the source of innovation and competitive advantage. In (Atalay et al., 2013), the authors study the correlation between innovation and firm performance in four dimensions, defined by Organisation for Economic Co-operation and Development (OECD) (OECD & Communities, 2005) at a high level: product, process, marketing, and organizational innovation, and claim that product and process innovation positively and significantly affect firm performance.

Other researchers view the innovation's contribution to a firm's competitive advantage through resource/capabilities in resource dependence theory(RDT), the resource-based view (RBV), or the knowledge-based view (KBV) theories (Nienhüser, 2008). (Kramer et al., 2010) studies location strategies for innovation in multinational enterprises at the meso-level and micro-level in human, organizational and network-level regions' contribution to the firm's innovation processes. (Saranga et al., 2018) examines innovation as resource configuration and interactions that generate innovative capabilities and competitive advantage.

Following the KBV of a firm's competitiveness, mergers and acquisition (M&A) could also gain capability knowledge. Researchers in (Hanelt et al., 2021) find that digital M&A contributes to building a digital knowledge base, which drives digital innovation and improves firm performance.

2.2. Diffusion of Innovation

Similar to the scope of "innovation" in the previous section, "diffusion" is a general term that refers to the spread of something within a social system(Strang & Soule, 1998). In the context of this thesis research, the word "diffusion" describes the process of adaptation of innovation in the market beyond the control of the organization that invents the idea. Authors (Hall & Khan, 2003) define diffusion as results from a series of events by individual decisions to begin using the invention. The decisions are often based on a comparison of the uncertain benefit of the invention with the uncertain cost of adoption. The famous S-shaped curve or ogive distribution could be observed from empirical data(Marimon Viadiu et al., 2006). The epidemic model is widely used in marketing and sociological domains to describe diffusion (Rahmandad & Sterman, 2008).

According to (Hall & Khan, 2003), diffusion is affected by demand (industry capacity, customer base, network effects), supply (improvements of the invention, improvements of the baseline, complementary inputs for the invention), and environmental factors (market and firm, government, and regulation).

Early pioneers like (Premkumar, Ramamurthy et al. 1994) and (Ahire and Ravichandran 2001) perform empirical studies on the diffusion of new technologies inside a company to validate diffusion factors. At the meso-level, (Premkumar et al., 2015) find technical compatibility, relative advantage, and cost leads to better diffusion internally in the organization. Technical compatibility and time are important factors to boost diffusion external to the organization. Organizational compatibility is more relevant to the success of implementation. (Ahire & Ravichandran, 2001) dive deeper into micro-level factors that boost diffusion inside a company, including top management leadership, employee management, supplier management, customer focus, and cooperation. At the macro-level, (Thomas et al., 1998) models the diffusion of fuel cell vehicle technology by considering vehicle technology, fuel, vehicle markets, and government actions to study the impact of government actions (Regulations, education, mandates, incentives, etc.) on diffusion.

2.3. Innovation Dynamics in a buyer-supplier relationship

As mentioned in Section 1.1, OEMs and suppliers innovate together through joint product development programs. Though few works of literature offer detailed studies in the automotive industry, studies from other industries in a buyer-supplier relationship during product development would inspire this thesis research.

In (Johnsen, 2009), the authors summarize the benefit (or the measure) of supplier involvement in the product development processes as follows:

- Shorten time to market
- Improve product quality
- Reduce development and product cost

From the literature, general factors affecting buyer-supplier joint innovation include:

- Buyer-supplier relationship development:
    - Shared training/learning/supplier development program (Jean et al., 2012; Johnsen, 2009; Petroni & Panciroli, 2002; Pulles et al., 2014)
    - Technical uncertainty and risk-sharing (Bensaou, 1997; Jean et al., 2012; Jean et al., 2014; Johnsen, 2009)
    - Mutual trust(Jean et al., 2014; Johnsen, 2009)
    - Mutual performance measure and commitment(Bensaou, 1997; Ellis et al., 2012; Johnsen, 2009; Petroni & Panciroli, 2002)
    - Level of integration between development teams, codesign (Ellis et al., 2012; Jean et al., 2014; Johnsen, 2009; Petroni & Panciroli, 2002)

    - Power status, preferred customer, stability of relationship (Bensaou, 1997; Ellis et al., 2012; Jean et al., 2012; Jean et al., 2014; Petroni & Panciroli, 2002; Pulles et al., 2014)
    - Switching cost (Bensaou, 1997)
- Supplier internal capability:
    - Innovative capability and complementarity (Jean et al., 2012; Johnsen, 2009; Pulles et al., 2014; Wynstra et al., 2010)
    - Downstream Position(Wynstra et al., 2010)
    - Professionalism, collaborative attitude, protectionism (Jean et al., 2012; Jean et al., 2014; Pulles et al., 2014)
- Buyer internal capability:
    - Top management commitment(Johnsen, 2009; Wynstra et al., 2010)
    - Internal coordination, legal and institutional hostility (Jean et al., 2014; Johnsen, 2009)
    - Early supplier involvement (Ellis et al., 2012; Johnsen, 2009)

Apart from the qualitative view of the above works, researchers turn to RBV, RDT, and network theory to understand the buyer-supplier dynamics at the system level. (Jean et al., 2012) explores power dependence and innovation in interfirm relationships. According to the authors, innovative capabilities could ultimately increase the bargaining power in the relationship. In (Yan et al., 2017), the authors propose a network-based theory to predict supplier contributions to buyer innovation using buyer-supplier structural similarity in a dual-ego network, where the two parties are the two egos with ties to their customers and suppliers.

2.4. Competition and Collaboration between Tier-1 suppliers and OEMs in the Automotive Industry

If the automotive industry is in a fast-growing stage, suppliers and OEMs tend to collaborate to make the "pie" bigger to gain more profit from this market upwind. However, when the market stagnates or starts to go down (the "pie" grows slower), both OEMs and suppliers want a more significant share of the "pie" to prosper or survive.

(Henke Jr & Zhang, 2010) point out the three factors leading to competitiveness between OEMs and suppliers in the automotive industry and suggests the parties minimize competitive activities to achieve win-win situations:

- Conflicting objectives across functional areas
- Excessive or late engineering and specification challenges
- Price reduction pressure on both sides

Research (Talay & Townsend, 2015) is inspired by "Red Queen" dynamics in evolutionary biology. This type of ecological dynamics was used to interpret organizational evolution proposed by (Barnett & Hansen, 1996), describing the iterative process of the competitive strength of one organization triggering learning in its rivals. In (Derfus et al., 2008; Talay & Townsend, 2015), the authors regard innovations as means to counteract and outperform competitors to survive and propose the following four major factors affecting the survival:

- "Lag load" measures how a model falls behind its competition.
- Reputation
- Competitive history
- Market share/market position

2.5. Modeling innovation dynamics as behaviors in a socio-technical system

There are many ways to model socio-technical behaviors at different organizational levels (Zacharias et al., 2008):

- Micro-level models study human cognitive, emotional behaviors, and human expertise. These models are built for basic research and applied purposes, focusing on human information processing and decision-making as an individual.
- Macro-level models represent a group or organizational behaviors. System dynamics modeling (Forrester, 1968; Sterman, 2018) views the organization as a complex system and models the underlying structure to explain the dynamics within and between the subject system. The other major category of macro-level modeling is organization modeling (Scott & Davis, 2015). This modeling method views organizations as individuals working together on an overall task and individuals are

linked by organizational structures.

- Meso-level models are between micro-level and macro-level models: they describe decision-making processes balancing group aggregation and individual details. Theories are based on different assumptions of behavior aggregation from individuals in an organization. This group of diversified modeling methods includes social decision(Satterthwaite, 1975) (Ostrom, 2008), social network(Council, 2003; Freeman, 2004), and agent-based modeling (Axelrod, 1997).

Unlike the modeling methods used in previous work, System Dynamics (SD) and Agent-based Modeling (ABM) are suitable for the thesis topic due to their ability to both underlying model structures of organizational behaviors and simulate the changes over time at organizational scales. The rest of the section zooms into SD and ABM's application on innovation dynamics from various industries and their modeling limitations.

2.5.1. Innovation dynamics modeled by System Dynamics

An SD model breaks a complex system (e.g., interactions between organizations) into smaller interconnected subsystems. This modeling method focuses on the dynamic behavior over time and feedback between different subsystems.

Each subsystem has internal states, and the "flow rate" changing the states described by differential equations represents the "dynamics" between subsystems. Depending on the depth of the model, each subsystem could be expanded into more detailed models close to a micro-level model. An SD model is described in causal loop diagrams and stock and flow maps.

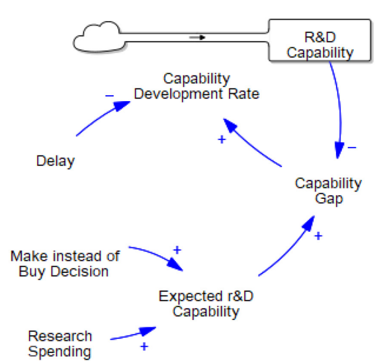

Figure 5 Stock-flow and causal loop diagram for an SD model about a firm's innovation through R&D, adopted from (Moser et al., 2021; Sterman, 2000)

In Figure 5's example about the dynamics of a firm's internal R&D, the top stock and flow map shows how the capability development rate contributes to a firm's R&D capability over time. The causal loops in the rest of the figure show how different "subsystems" influence the development rate and the resulted capability.

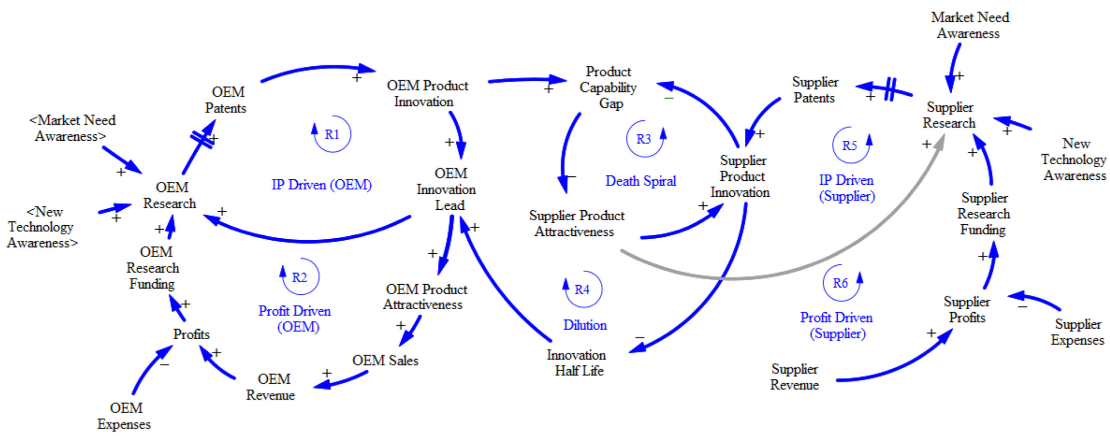

Figure 6 Causal loop diagram depicting OEM vs. Tier-1 supplier innovation model from (Moser et al., 2021)

SD modeling can be applied to various social behaviors, from epidemiology (Rahmandad et al., 2021), project management (Lyneis & Ford, 2007), and technology diffusion (Intrapairot & Quaddus, 1999) to policy design(Liu & Xiao, 2018). Figure 6 demonstrates a research work that inspired this thesis topic. In (Moser et al., 2021), the authors present the competing innovation between the Tier-1 supplier and the OEM and its effect on the dilution of innovation.

Limitations of the SD modeling approach include:

- Difficulties translating organizational dynamics into numbers and equations (Zacharias et al., 2008)
- Models need rigorous verification and validation since an SD model makes assumptions on both structure and parameters (Senge & Forrester, 1980)

2.5.2. Innovation dynamics modeled by Agent-based Modeling

Unlike the SD modeling approach using a structure of feedback loops to describe the source of emergence, ABM methods focus on individual decision-making of each heterogeneous "subsystem" to explore emergences of the system that cannot be deduced by averaging individual "subsystems."

In an ABM model, each "subsystem" is an autonomous agent. Each agent in the system has different states and mechanisms responding to external influences across the system or from outside the system boundary, generating emergence from the bottom up.

ABM models systems at the meso-level to generate emergence at the macro-level, while SD starts at the macro-level with the ability to zoom in to the meso-level structures. Both modeling methods have overlapping applications. Many socio-technical systems between the meso- and macro-level can be modeled by both SD and ABM. For example, ABM can be used to model technology innovation and diffusion among customers (Kiesling et al., 2012; Ma & Nakamori, 2005).

According to (Bonabeau, 2002; Garcia, 2005), ABM is most useful when both agent's behavior, decision-making process, and inter-agent interactions are nonlinear, discontinuous, and complex. However, the flexibility and generalization become the limitations of ABM's application: lack of domain specifications requires the modeler spend more time on tradeoffs between model depth and generalization(Zacharias et al., 2008), qualitative and quantitative data(Bonabeau, 2002), and computational complexity with a large number of agents (Rahmandad & Sterman, 2008).

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Chapter 3

Research Question

3.1. Gaps in literature

The literature review in the previous chapter surveys existing research from innovation to competitive advantage, both at the firm-level and paired buyer-supplier level. However, a few gaps in the literature could be identified when viewing innovation dynamics between buyers and suppliers as a system in the automotive industry.

3.1.1. The balance between collaboration and competition in the Buyer-supplier relationship

As pointed out by (MacDuffie & Helper, 1997), the OEMs prefer suppliers to be "lean" in the long run, minimizing the mutual dependence in this lifelong relationship. Suppliers are expected to become self-sufficient so both parties in the relationship can learn from each other to boost innovation.

To illustrate the benefit of this relationship, the author builds the stakeholder network focusing on one OEM-supplier system and its relationship with competitors, as shown in Figure 7. Within one OEM-supplier system, two firms share common financial and innovational needs, such as profit, customer satisfaction, and product learning. By working together to fulfill the aligned needs, the system gets access to capital from shareholders, gains innovation from universities and startups, gets approval from regulators, and earns profits through product sales to end customers. As shown in Figure 7 (right bottom corner), market competitors also learn through research on end customer behaviors to strengthen their product attractiveness. The OEM works with its lean suppliers to compete with other OEM-supplier systems to win more market shares and invest in external entities to access disruptive innovation. Diffusion of innovations with market approvals results from competition between OEM-supplier systems.

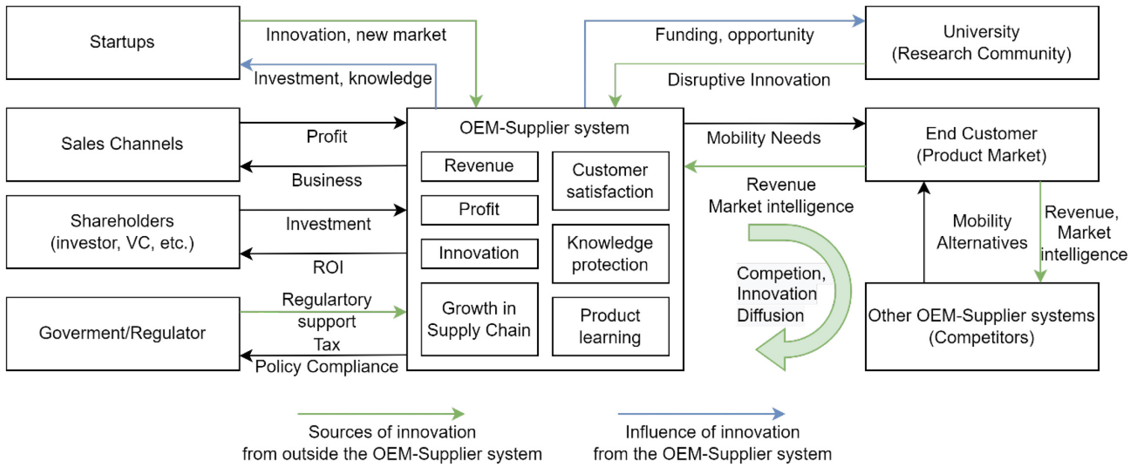

Figure 7 Stakeholder network centering OEM-supplier system, inspired by (Moser et al., 2021)

The lifelong relationship between buyers and suppliers in the automotive industry (the pyramid-shaped tiered supply chain) and the natural conflict between buyer-supplier profit-sharing causes a mixture of competition and collaboration between OEMs and their suppliers:

- **Competition**: inside the realm between OEM and supplier, there is a race toward a larger share of profit in the automotive value chain. (Talay & Townsend, 2015) describes the competition between them as "Red Queen" dynamics reviewed in Section 2.4 as both parties competing for the relatively superior position.
- **Collaboration**: viewing from the greater product system, the higher-level "Red Queen" dynamics in the automotive product market (competition between OEM-supplier ecosystems to win over end customers) demand collaboration from the OEM-supplier relationship. Modern motor vehicles are highly complex systems so that a single company is hard to manage the design effectively with 100% vertical integration. The OEM must work with suppliers to share subsystem-level knowledge to remain innovative. Collaboration in the relationship translates innovation into a competitive advantage over other vehicles and OEM-supplier relationships.

To better understand the co-existence of competition and collaboration within an OEM-supplier relationship, the author creates a Design Structure Matrix (DSM) on stakeholder needs in Table 1.

Table 1 The stakeholder needs network within an OEM-supplier system, with DSM representation

Compatibility DSM Collab: collaborate Comp: compete		Supplier						
		R	P	G	I	C	L	K
OEM	Revenue (R)	Collab	Collab		Collab		Collab	
	Profit (P)	Collab	Comp	Comp				Comp
	Growth in Supply Chain (G)		Comp	Collab	Collab			Comp
	Innovation (I)	Collab		Collab	Collab	Collab		
	Customer Satisfaction (C)				Collab	Collab	Collab	
	Product Learning (L)	Collab				Collab	Collab	Comp
	Knowledge Protection (K)		Comp	Comp			Comp	Comp

In Table 1's symmetrical matrix, cells with green color indicate the two parties' corresponding needs align with each other, which boosts collaboration. For example, a higher OEM revenue leads to more orders (revenue) from the supplier, so both parties collaborate to achieve a higher whole product market share. On the other hand, some needs conflict with each other, which serves as the source of competitive behaviors. The profit margin could be an example. As the supplier gains more orders from other competing OEMs, the growing negotiating power of the supplier leaves the OEM with a lower profit margin. The OEM may resort to knowledge protection to limit the supplier's product learning to regain negotiating power.

In literature, researchers notice the coexistence of competition and collaboration but emphasize either the competition side or the collaboration/innovation side. Few works study how competition and collaboration interact with each other. A balanced study between competition and collaboration could fill this gap by relating previous studies on competition and collaboration sides.

3.1.2. System-level quantitative studies on the Buyer-supplier relationship in the Automotive Industry

The previous chapter reviews quantitative studies on general buyer-supplier relationships. Most of the studies put themselves into buyer's shoes, focusing on supplier's contribution to buyer's product innovation (Ellis et al., 2012; Jean et al., 2014; Johnsen, 2009) and supplier selection and performance evaluation (Petroni & Panciroli, 2002; Pulles et al., 2014).

Fewer studies focus on the supplier side's performance and relationship in other industries (Jean et al., 2012), which may not apply to the automotive industry as the buyer-supplier relationship is much less volatile.

One study (Henke Jr & Zhang, 2010) discussed collaboration and competition in the automotive industry but was not a quantitative study.

Previous works focus on one party and dive deep when approaching a quantitative study on the buyer-supplier relationship. While many studies mentioned the system-level dynamics between buyers and suppliers, very few perform quantitative studies on both buyer and supplier sides, particularly in the automotive industry with fewer lean tier-1 suppliers and a lifelong relationship with OEMs. This gap in the literature demands more quantitative studies viewing buyers and suppliers in a system.

3.1.3. System thinking in Buyer-supplier relationship modeling

Most quantitative studies in the literature look for a causal relationship between a firm's behavior in a buyer-supplier relationship. And statistical methods like linear regression are widely used in these studies to indicate the strength of causal relationships.

However, these input factors (firm's behavior indicator) may reinforce or balance each other, or their performances may affect the innovation outcome. A few studies (Pulles et al., 2014; Wynstra et al., 2010) try to add reinforcement or feedback loops to statistical methods to capture these dynamics but only at a small scale. Other researchers try to fill this modeling gap in dynamics by proposing new modeling theories (Yan et al., 2017).

As reviewed in the previous chapter, many other modeling methods featuring "system thinking" could better capture the system-level dynamics between OEM and tier-1 suppliers. The above two gaps in the previous subsection may also be filled with new modeling methods focusing on dynamics, not just causality.

3.2. The Research Motivation

Relating to the business questions in the previous chapter and treating companies as beneficiaries of research work, the sum of current literature provides a sound theory to illustrate dynamics between buyers and suppliers in the automotive industry both qualitatively and quantitatively.

However, the fragments of the sound theory are distributed between different research works with different emphasis on the part of the buyer-supplier system. The fragmented theory base makes it harder to extract and consistently apply managerial implications at the system level. The gaps analyzed in the previous subsection inspire the research question of this thesis in the following ways:

- Research works are often interpreted as qualitative. Many previous works are based on data from surveys, which contain levels of subjectivity due to self-reporting on surveys. The subjectivity makes the model and the underlying theory hard to apply to corporate settings. Managers rely on timely objective data sources such as financial or operational data to guide managerial decisions instead of time-consuming subjective data collection and processing.
- Analysis methods in the literature lead to snapshot models instead the dynamic modeling needed to guide business decisions. The more helpful model will present a system view between competition and collaboration and enable managers to learn from the past, present the current, and predict the future.

Gaps in the literature and the unmet needs of business lead to the research question of this thesis:

Would a model of the relationship between OEM and tier-1 suppliers be better able to explain innovation in the automotive industry if it includes dynamic interactions of competition and collaboration?
Can this model be grounded and validated in objective data sources?

The research question in business needs leads to a modeling method that incorporates the following characteristics:

- Rely on objective data, ideally from non-proprietary sources. Managers can fine-tune the model with the company's internal operational or financial data.
- System view of the dynamics, treating the OEM, its supplier, and competitors in the whole product market as a system, balancing OEM and supplier, and competition and collaboration at the system level. The system view captures more emergences inside the OEM-supplier ecosystem, enhancing model fidelity.
- Generate a "movie" instead of a static picture of the situation. Dynamics over time enable scenario studies and learning from past events, and the model prediction offers a longer time horizon, encouraging managers to pursue long-term wins.

3.3. The Research Hypothesis

The needs in the previous section led to a set of hypotheses (H1 to H4) in this thesis:

- **H1**: A model using non-subjective data including financial (e.g., profit, expense, P/E ratio), strategic (e.g., annual report, alliance, joint venture), supply chain (e.g., shipment, supplier list), and product (e.g., feature diffusion, product lifecycle) data could more accurately predict the dynamics of buyer-supplier relationship compared to previous work.
- **H2**: A model focusing on system-level interactions in a buyer-supplier relationship generates more applicable managerial implications and accurate firm performance predictions than previous works for both OEMs and suppliers.
- **H3**: Competitive and collaborative outcomes in the buyer-supplier relationship have different impacts on firms depending on the competitive environment in the whole product market:
    - **H3.1:** The more competitive firm has a better relative long-term performance in one buyer-supplier relationship when the whole product market is stable.
    - **H3.2**: The OEM and supplier improve firm performance through more collaborative behaviors in a highly competitive whole product market.

- **H4**: Competition inside one buyer-supplier relationship without collaboration negatively impacts the buyer-supplier system's long-term performance in the whole product market.

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Chapter 4

Research Method

4.1. System problem statement

The gap analysis and hypothesis extraction begin this chapter with the system problem statement for this thesis topic:

To explain and predict innovation dynamics between OEMs and suppliers,
By modeling competition and collaboration, treating the OEM, its supplier, and competitors in the whole product market as a system,
Using macro- and meso-level modeling methods with non-proprietary and objective data.

The model in this thesis that addresses the problem described in the above system problem statement, if demonstrated as valid, may deliver the following benefits to stakeholders (shown in Figure 8):

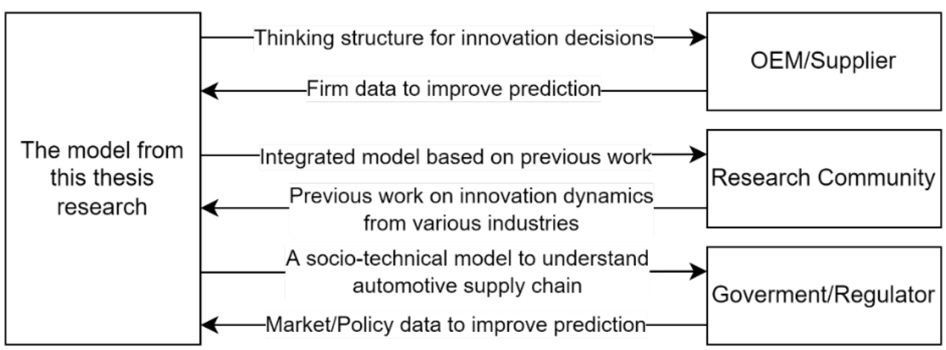

Figure 8 Stakeholder network between this thesis and the beneficial stakeholders

- For OEMs and suppliers, this model provides a thinking structure for managers to interact with their customers/clients and make innovation and supply chain decisions that lead to a "win-win" outcome in a buyer-supplier relationship.
- For researchers, this thesis integrates fragments explaining innovation dynamics in a buyer-supplier relationship from previous works at the system level, delivering a balanced model that covers both sides in a relationship and collaboration and competition.
- For governments and regulatory agencies that oversee the automotive industry, this

model helps them understand and boosts system thinking that generates long-term benefits to the end customers when regulating the automotive supply chain.

4.2. Constraints on modeling, data collection, and thesis scope

The limited timeline and funding support for this thesis research impose the following constraints:

- No existing commercial or academic database contains all data needed for model building. Input data requires the author to synthesize multiple data sources, which imposes a tradeoff between timeline and data coverage in the automotive industry.
- Limited funding support from the institution and the author cannot access proprietary or business confidential information in the industry. The funding constraints limit modeling efforts with data inputs from public, non-proprietary sources.

The above two constraints limit the scope of this thesis in the following ways:

- Horizontally in the automotive market: the thesis focuses on innovation dynamics between North American OEMs and their tier-1 suppliers. The intention is to develop a high-fidelity model with high-quality data to verify the hypothesis and validate the model.
- Vertically within each OEM-supplier system: the thesis focuses on dynamics at the meso-level (cross-business unit collaboration) and above because direct measures at the micro-level of a company are inaccessible without proprietary or confidential data sources.

The limited scope suggests a set of social-technical modeling methods describing the meso- and macro-level dynamics in the OEM-supplier relationship and between OEM-customer relationships. The literature review in Section 2.5 shows that System Dynamics (SD) and Agent-based Modeling (ABM) are two candidates to model the research question. System dynamics at the macro-level can be used to model interactions between OEM and supplier within an OEM-supplier system and interaction between the system and other OEM-supplier systems and the automotive market. Agent-based modeling at the meso-level can model interactions within organizations and generate intermediate data inputs feeding to the macro-level model.

Both SD and ABM require empirical data to validate the underlying structure and theory operationalization. The constraints from timeline and funding support and the research hypothesis in Section 3.3 lead to a data collection method based on publicly or academically available research and commercial databases and credible news sources, as illustrated in the next chapter.

4.3. Modeling method

System Dynamics (SD) is the primary modeling method in this thesis.

As mentioned in the previous subsection and Section 2.5, both SD and ABM are suitable for modeling the research question at the meso- or macro-level. The major difference between the two is ABM's ability to capture the heterogeneity across a large number (100+) of agents or business entities. Since the automotive market has a relatively small number of players, and the focus of this thesis is a one-to-one relationship between an OEM and its supplier, SD's capability is good enough for the needs of this topic. Moreover, SD's relatively mature graphical modeling tools and the more readable causal loop diagrams make it easier to win over buy-ins from managers in the industry.

However, when future research studies the relationship between multiple OEMs and multiple suppliers, ABM can be a better choice over SD due to its scalability.

4.4. Research Process

The overall research steps are presented in Figure 9. There are seven steps towards a useful model with applicable managerial implications.

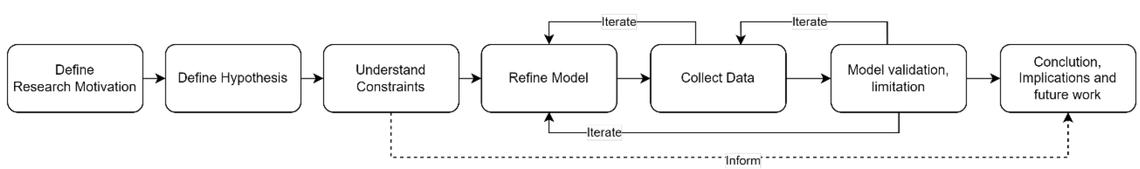

Figure 9 Research steps

As highlighted with arrows in Figure 9, the process is highly iterative between "Refine model", "collect data", and "model validation." There are a few iterations between steps before a valid model is built.

4.4.1. Define research motivation

This step is the start of this process. The research motivation and the extracted requirements (or expectations) help frame the overall goals for this thesis. Though most of this work is around modeling and validation, alignment with research motivation drives the modeling process to stay consistent and focused on the research question.

4.4.2. Define Hypothesis:

Hypothesis/models should align with research motivation and requirements. This step develops a set of falsifiable hypotheses as research questions. The rest of this thesis designs an experiment to validate the hypotheses, answering the research questions.

4.4.3. Understand constraints

The thesis research is in an academic setting. The constraints influence available methods of modeling and data collection. The constraints also inform both limitations and future works of the modeling approach and the resulted managerial implications. Factors imposing constraints include thesis timeline, research funding, research data access, proprietary data access, market region, and customer segmentation.

4.4.4. Refine Model:

This step derives the research model from the requirements and hypothesis, bounded by the constraints.

Though the final modeling method in this thesis, defined by the system problem statement, seems to be decided by a one-off effort like a traditional waterfall development process, the actual process of modeling method selection went through multiple iterations between modeling-data collection-model validation.

4.4.5. Collect data

This step collects data from various sources to support modeling and model validation. Constraints bound data collection methods. As mentioned in the previous section, data collection helps refine the modeling and validation approaches.

In addition, data collection methods inform managerial implications and limitations of methods used in this thesis.

4.4.6. Model verification and validation

This step puts data and models together to verify and validate the hypothesis on the technical side: to which extent the set of research questions are answered. The modeling methods used in this thesis make assumptions both on parameters and the underlying structure. Apart from validation on replication of historical behavior, robustness under extreme conditions and sensitivity analysis are employed to assess uncertainty in assumption, both parametric and structural (Sterman, 2000). This step summarizes information from previous steps and details the limitations of the modeling and data collection methods.

4.4.7. Conclusion

The final step concludes this thesis study with managerial implications (insights for policy design, what-if effects of policies, and interaction of policies) and this research's limitations and future works.

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Chapter 5

Data Collection Methods

This thesis combines different data collection methods to gather automotive market, financial, organizational, and technological data to support modeling. This chapter explains the detailed data collection method for each data category. Appendix A through E show the original data covering 8 major OEMs serving the mass-produced market and 14 tier-1 suppliers mentioned in this chapter.

5.1. Market data

The market data include disaggregated sales (shipment per year) data for each OEM and the North American mass-produced light vehicle market model. Once the data is acquired at the vehicle model level, aggregated market information such as market share and product attractiveness at the model, brand, and OEM levels could be inferred. A visualization of the collected market share data is shown in Figure 10. Over the past two decades, the U.S auto market has become more diversified, with an average market share of 15% for major OEMs.

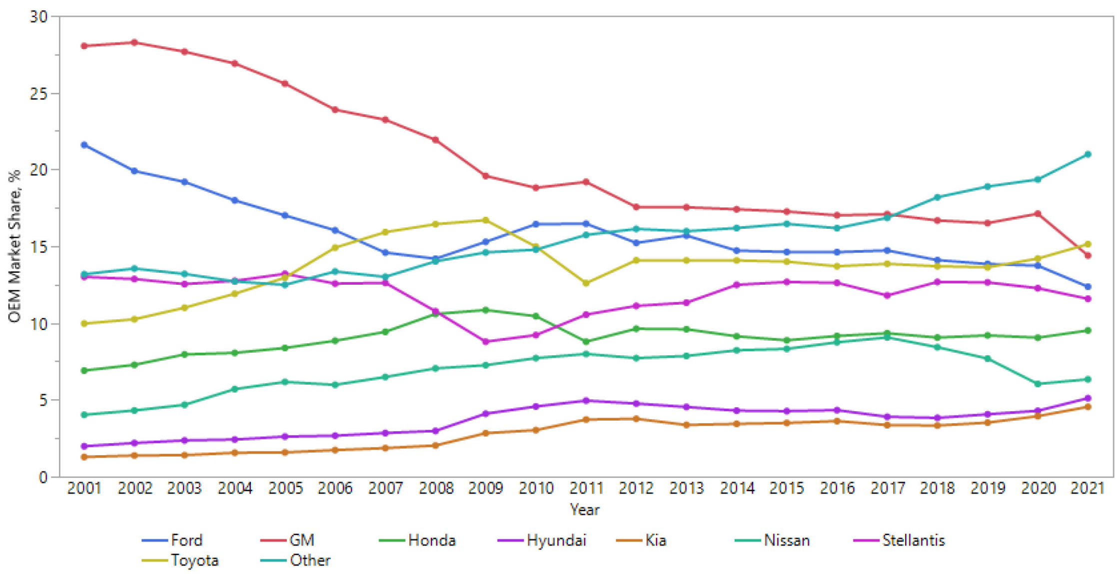

Figure 10 OEM light-vehicle market share in the U.S., 2001-2021

The disaggregated market data also include vehicle specification data, which will facilitate the measurement of feature innovation diffusion in the diffusion data collection. Though OEMs publish their sales data on their online newsroom monthly (E.g., Ford has a Media Center at https://media.ford.com/) as part of the standard financial reporting process, other public and commercial databases offer all historical sales data in a consistent format. Therefore, the following two databases serve as the primary data source for market information:

- Wards Intelligence (https://wardsintelligence.informa.com/), a commercial database in automotive research.
- Car sales database (https://carsalesbase.com/), a public database for global automotive sales data.

The OEMs' news releases serve as the secondary data source in case of incomplete data from commercial databases.

5.2. Financial data

Financial data related to return of investment (or corporate social responsibility) is the goal of the for-profit OEMs and suppliers under this thesis topic. The established financial reporting process and financial databases provide clean and structured data to evaluate a firm's performance at the macro level.

Financial data include revenue, profit margin, CAPEX, R&D expenditure, human capital, price-to-earnings (P/E) ratio, etc. The primary data sources are the following two well-known financial data service providers:

- FactSet (https://www.factset.com)
- Bloomberg Terminal (https://bba.bloomberg.net/)

The company's 10-K release (if listed in the US market) and annual reports serve as the secondary data source in case of incomplete data from commercial sources.

Figure 11 shows the major OEMs' R&D expense (as % of revenue). The industry average has been 4.5% in the past two decades.

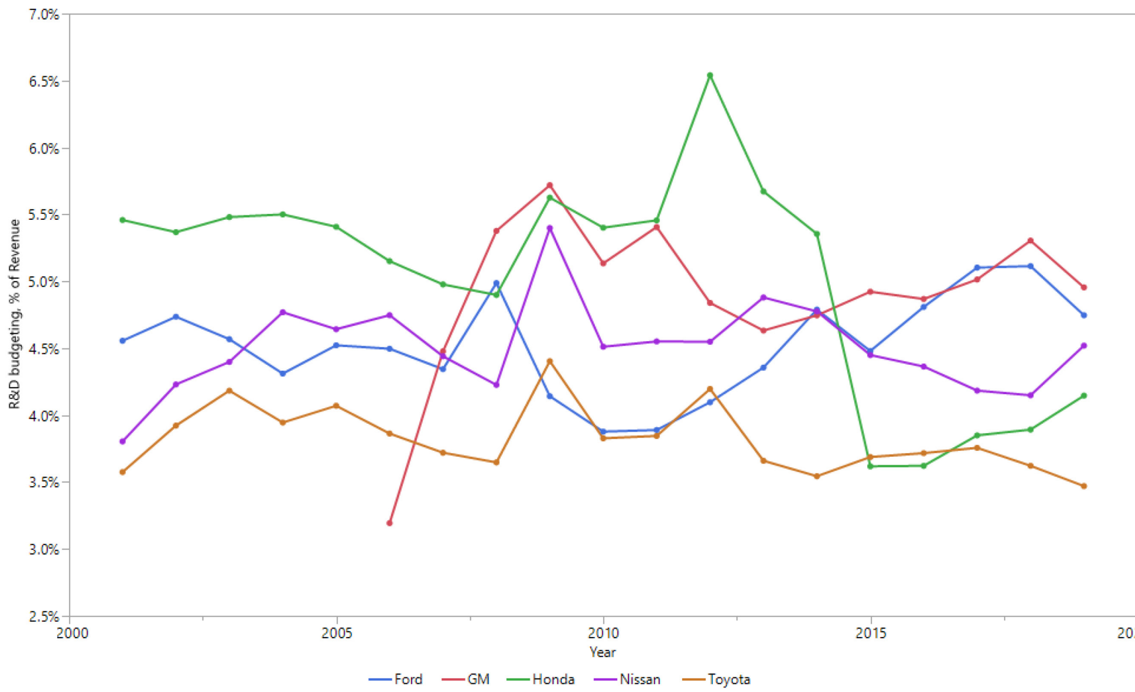

Figure 11 R&D budgeting of selected OEMs, 2001-2021

5.3. Organizational data

Organizational data provide a leading factor in a firm's performance perspective. These data include strategic, cultural, and partnership-level information. The original form for most of the data in this category is qualitative. The conversion from the qualitative natural language representation of the information to the quantitative inputs as expected by the modeling processes is subject to the author's interpretations and assumptions.

5.3.1. Strategic intents

A firm's innovation strategy affects innovation outcome and resource allocation. The author collects an OEM or a supplier's innovation strategy from their annual reports or Form 10-K if the company is listed in the US. The company newsroom is the secondary source for this data.

5.3.2. Corporate entrepreneurship programs

These programs execution and commercialization of innovation processes, including:

- Crowdsourcing

- New venture incubator
- Internal accelerator
- Technology licensing
- Corporate Venture Capital (CVC)
- Merger & Acquisition (M&A)
- Partnerships, including joint ventures and university research labs.

Some of the information in the above list are company confidential. The author gets the information from indirect sources (public, commercial, and academic research databases). The company newsroom is the primary source of this data. Also, automotive market research platforms serve as the primary data source, including:

- Wards Intelligence (https://wardsintelligence.informa.com/)
- HIS Markit (https://ihsmarkit.com/)
- S&P Capital IQ (https://www.capitaliq.com)
- Fitch Connect (https://www.fitchsolutions.com/)
- Frost & Sullivan (https://www.frost.com)

5.3.3. Entrepreneurial culture

Like the corporate entrepreneurship programs, entrepreneurial culture is a catalyst for innovation outcomes. To quantify an innovation-driven company's cultural factor, the author follows the idea of (Zheng et al., 2010) by linking cultural measures to a firm's valuation.

The P/E ratio collected from financial data in section 5.2 is a well-known accounting ratio to measure a company's valuation against its peers. The author uses the company's P/E ratio (relative to the industry) to measure the entrepreneurial culture.

5.3.4. Trading between OEM and suppliers

Trade between an OEM and its suppliers is an essential indicator of a buyer-supplier relationship. However, detailed supply chain trading data between an OEM and its suppliers is typically a "top secret" in the business world.

The author gets the trade data through the following two indirect data sources:

- Annual report or Form 10-K (if US-listed): a public listed company enumerates its biggest customers/suppliers and share of revenue streams in the annual report. This practice helps investors understand potential risks in the supply chain.
- Supply chain insights platform - Panjiva (https://panjiva.com): this commercial database contains import and export details on commercial shipments worldwide.

5.4. Innovation data

Apart from the indirect indicators of innovation outcome in financial and organizational data, the direct outcome of innovation – yearly patent grants data- is gathered from the Espacenet patent database (https://worldwide.espacenet.com/patent). The secondary source for patent grants is the company newsroom and annual reports or Form 10-K (if US-listed).

Figure 12 shows the relationship between R&D expenditures and issued U.S. patents each year in the last decade for both OEMs and major tier-1 suppliers. Though the R&D efficiency (converting investment to patents) varies, the relationship is largely linear.

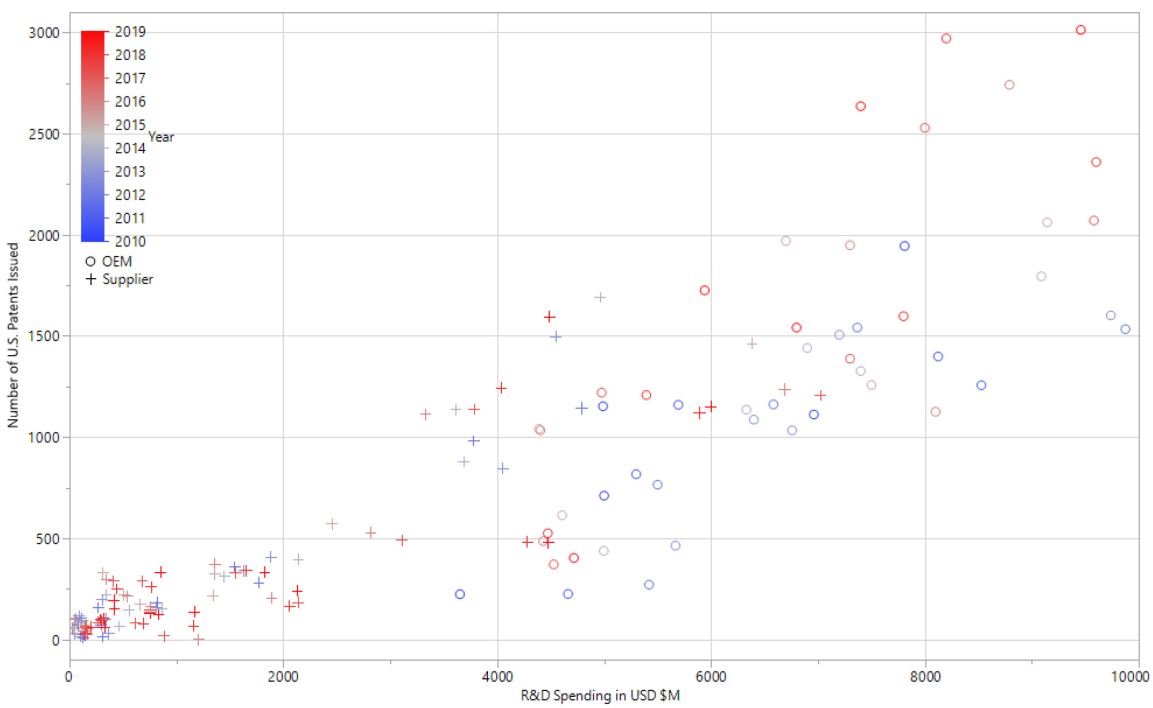

Figure 12 Annual R&D spending vs. Number of U.S patents issued, selected OEMs, and tier-1 suppliers, 2010-2019

5.5. Diffusion data

Diffusion data provides insights into how innovative features are invented and adopted by the whole product market. Since no academic or commercial database is dedicated to feature-diffusion in the automotive industry, the author develops a research process to gather empirical data. A similar process contributed to the research by (Moser et al., 2021), which is

The process aims to first downselect a few past or ongoing innovation diffusion processes on vehicle features and then collect the empirical data based on the sample subsystem and feature. Figure 13 shows the research process for technology diffusion data:

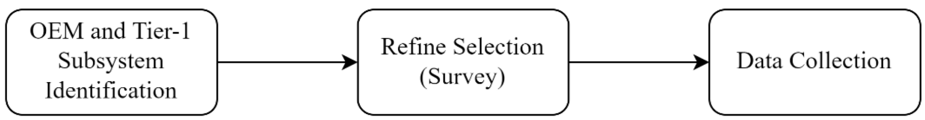

Figure 13 Data collection process for technology diffusion

The process begins with subsystem identification. This step collects and summarizes all innovative features in a lightweight vehicle. Given the limited resources and research scope, the second step is to narrow down from various subsystems to a few most "interesting "candidates. The last step is to design and execute a data collection process for each candidate.

5.5.1. Subsystem Identification

The process begins with the functional decomposition of a typical lightweight vehicle and identifies 17 subsystems with innovation cycles over the last three decades (1990 to 2019). As is shown in Figure 14, the subsystems include Powertrain, Chassis, Interior & Comfort, Infotainment & Telematics, and Advanced Driver Assistance Systems (ADAS).

The decomposition synthesizes market intelligence reports from automotive research sources in section 5.3.2, notably Frost & Sullivan's strategic analysis reports. The decomposition focuses on major subsystems supplied by tier-1 suppliers. Therefore, this decomposition does not include smaller systems or systems managed by tier-2 suppliers and below. These excluded systems include valvetrain and exhaust after-treatment systems.

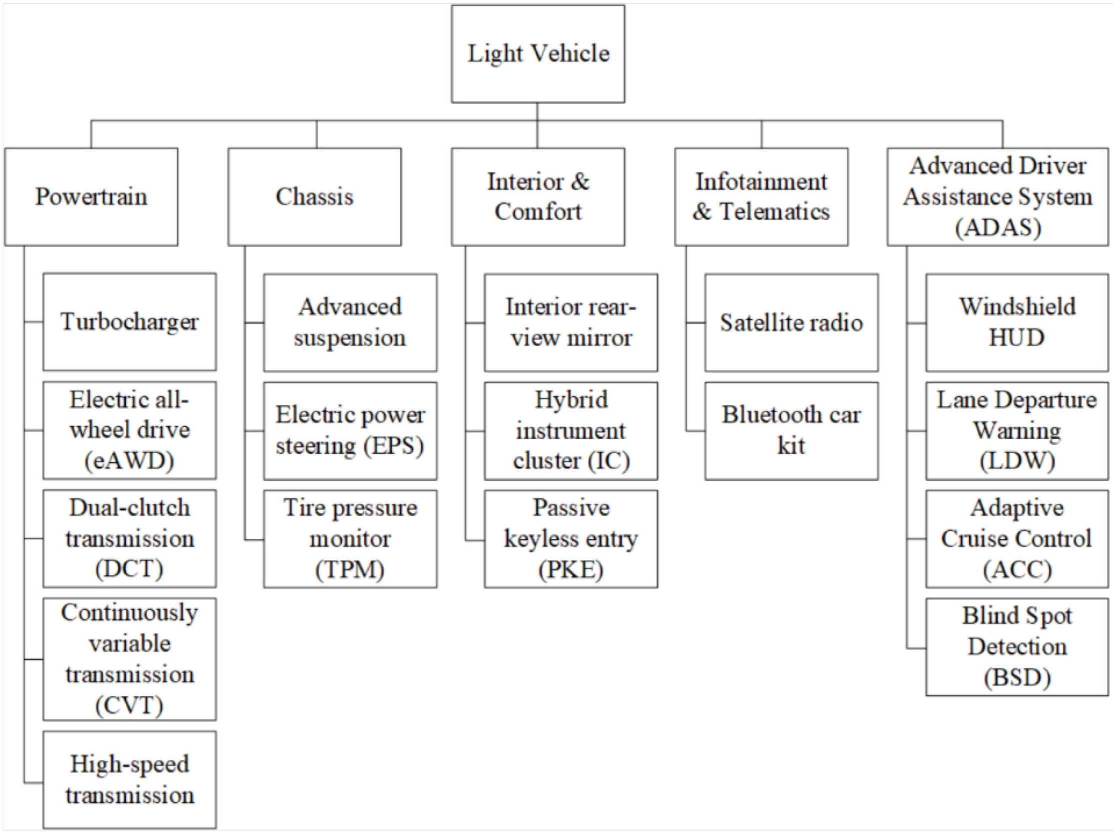

Figure 14 Light Vehicle product system decomposition used for evaluation and selection of product subsystems for the empirical study, from (Moser et al., 2021)

Note that the innovation drivers for each subsystem are different other than cost reduction. For example:

- For Powertrain (engine and drivetrain), the primary drivers are carbon emission reduction, better fuel consumption, and a smoother driving experience.
- For Chassis, the drivers are ride/handling quality and safety.
- For Interior & Comfort, Infotainment & Telematics, and ADAS, the drivers are safety, convenience, and communication.

The differences in the driving factors of innovation in the subsystems call for a formal method to downselect and prioritize data collection.

5.5.2. Refining subsystem selection with a survey

To prioritize and further down-select from the 17 subsystems, a survey was conducted with mid-career product development professionals in the automotive industry.

The survey evaluated the subsystems in Figure 14 based on the following 5 factors:

- **The pace of market adoption**: A measure of the strength (as speed and ease) of the market's adoption of the innovative feature of the subsystem. Fast adoption of a new feature could benefit the first movers (both OEMs and Tier-1 suppliers). A subsystem with a high market adoption pace may reach a significant and sustainable presence in its market just a few years since its introduction.
- **The breadth of technology diffusion**: A measure for the spread of adoption across the whole market (regardless of timing). Low breadth: application of a new feature may be limited to a few OEMs in the premium market instead of appearing on mass-produced vehicles. A subsystem with high technology diffusion is widely adopted by both premium and mass-produced markets.
- **Level of technical defensibility**: A measure of difficulty for others to develop and provide the innovation. Technology barriers help the supplier maintain a competitive advantage over OEMs or other Tier-1 suppliers. A subsystem with a higher score is more difficult to develop: it takes a longer time and more capital and requires more talents and experience.
- **Value to the total system performance**: A measure of the contribution of the subsystem feature innovation to the total vehicle performance. Innovation may seem significant at the subsystem level but have a negligible influence on overall vehicle performance. Innovation with high value boosts its subsystem and improves the overall performance of a vehicle.
- **Degree of potential achieved**: A measure of achievement of this innovation in its lifecycle. Was the technology or innovation exploited to its full potential? It could be determined from the market landscape, including market segmentation, technology maturity, subsystem features changes, and supplier market position changes. A subsystem with a high score usually has matured technology and has few to no remaining improvements in features and changes in market position, a later stage in its innovation cycle.

The survey participants score each subsystem with the above 5 factors on a scale of 1-5 (1: "lowest" to 5: "highest"), based on the state of the subsystem in the calendar year 2021.

The survey identified the Passive Keyless Entry (PKE) and High-Speed Transmission (HST) as the most "interesting" subsystems which represent technology diffusion in the North American lightweight vehicle market for data collection.

5.5.3. Data collection for selected subsystems

As shown in Figure 14, PKE and HST are from different functional groups of vehicles with different drivers for innovation and benefits for the customer and market. Therefore, it is necessary to design separate data collection processes for each subsystem.

5.5.3.1. Passive Keyless Entry (PKE)

PKE offers drivers the convenience of hands-free entry to a vehicle and ignition-start (i.e., push-button-start), with the key fob remaining in the driver's pocket. The technology was invented by Siemens VDO and introduced to the market by Mercedes-Benz in the late 1990s. PKE has reached an installation rate of around 20% in 2018.

Since PKE has a low share of the added value of the whole vehicle and the innovation is driven by convenience, the research coverage of PKE is low in commercial/academic databases. Therefore, the author designs the following process in Figure 15 to collect empirical data:

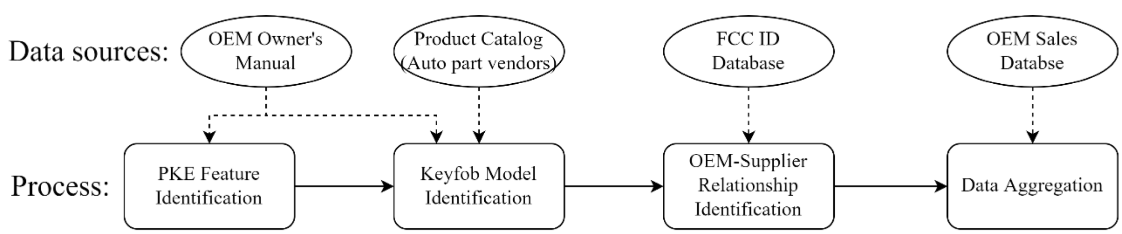

Figure 15 Process and data sources for PKE diffusion data collection

The first step is to confirm the detailed list of vehicle models with the PKE feature as standard or optional. The author scouts OEM's official website for owner's manual for all lightweight vehicle models in the research period (2000-2018) to generate the list.

The OEM markets subsystem parts manufactured by the tier-1 suppliers as "genuine OEM parts." There is no direct way to trace back the OEM-supplier business relationship without access to the automotive supply chain management systems. Therefore, the author turns to online OEM key fob retailers for the supplier information. The online retailers have vehicle compatibility information for key fob listing. Cross-validation between online listing and owner's manual is needed to distinguish aftermarket and OEM parts.

The key fob and PKE systems are regulated by the Federal Communications Commission (FCC) in the US market. Each registered key fob product has a unique ID issued by FCC, with the manufacturer's information available to the public via the FCC ID database (https://fccid.io/). The FCC ID information for each key fob is also listed on the retailer's listing pages. Therefore, the author uses the FCC ID database and information from retailers to identify the "who supplies whom" information for vehicle models with the PKE option.

Finally, the OEM-supplier relationship data is joined with OEM sales data from section 5.1 to generate diffusion data. Note that the sales mix of standard and optional configurations for vehicle models is not available. The author assumes a 50-50 split between standard and optional features in the data processing.

The collected aggregated empirical data in Appendix D and visualized in Figure 16 and Figure 17 show that the PKE system is considered to be at a mature state as of the model year 2020, with the empirical data covering the whole diffusion process. Diffusion of PKE follows the adoption s-curve: an initial period of slow growth between 2004-2009, followed by a fast adoption period between 2010-2018, and culminated with a plateau around 2020-2021. The automotive models of two major North American OEMs - General Motors (GM) and Ford Motor Company (Ford), are included, representing 30-40% of the US light-vehicle market, with 99 current and discontinued models from brands including Ford, Lincoln, and Mercury from Ford, and Cadillac, Buick, Chevrolet, and GMC from GM. The number of models and sales data for a few light-truck models (i.e., F-series from Ford and Silverado from GM) are aggregated to align with OEM's sales release. By the end of the model year 2020, 95% of models manufactured by GM and Ford offered PKE either as a standard or optional configuration, with an estimated 67% of new vehicles equipped with PKE.

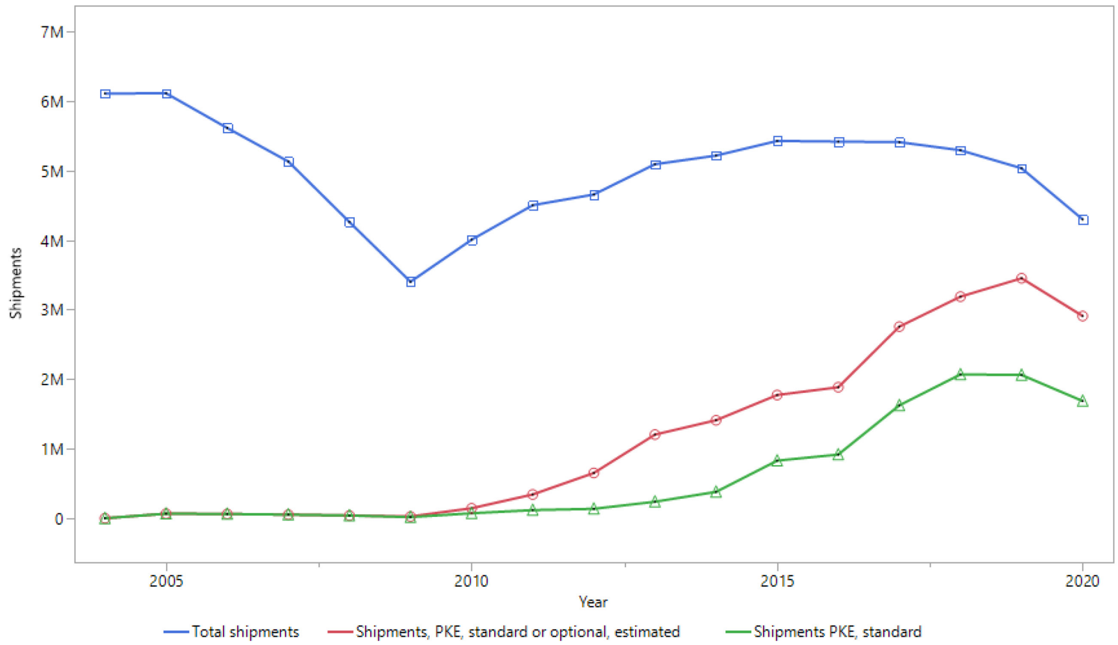

Figure 16 PKE Adoption by shipment in N.A. market, Ford and GM together, 2004-2020

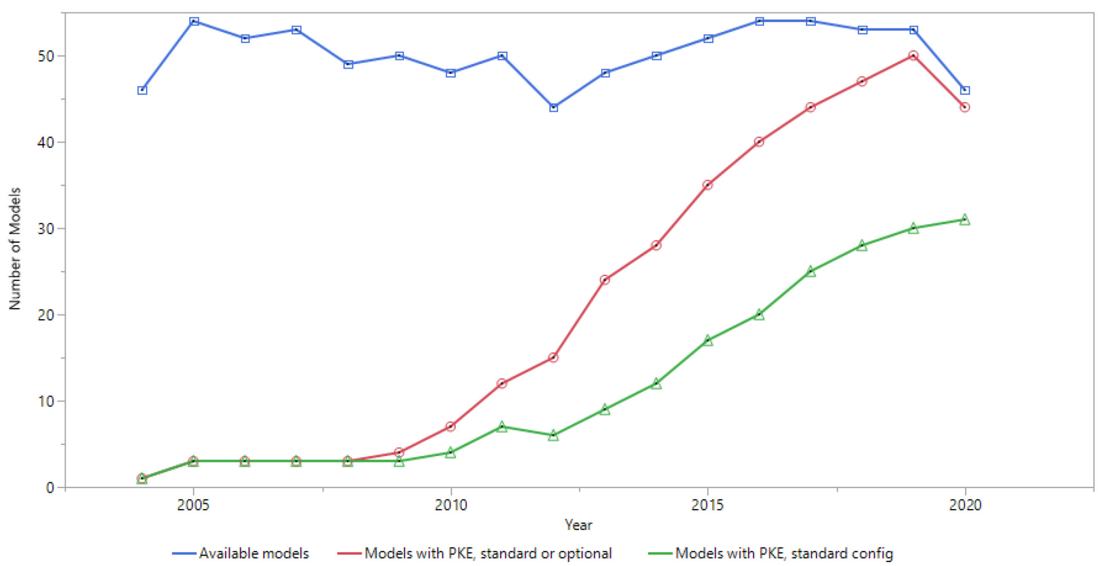

Figure 17 PKE Adoption by model in N.A. market, Ford and GM together, 2004-2020

The shipment and model adoption data only show the market's response to PKE diffusion. One could draw more insights from the similar adoption curves for each OEM. Figure 18 shows the adoption of PKE by model across Ford and GM. As shown in the figure, compared to Ford, which started to introduce PKE in the late 2010s, GM introduced PKE to its customer in 2005 on Cadillac vehicles. However, Ford later led GM in the pace of PKE diffusion across all models. The factors affecting technology introduction and the decision-making processes on diffusion are interesting dynamics to model, though not covered by this thesis.

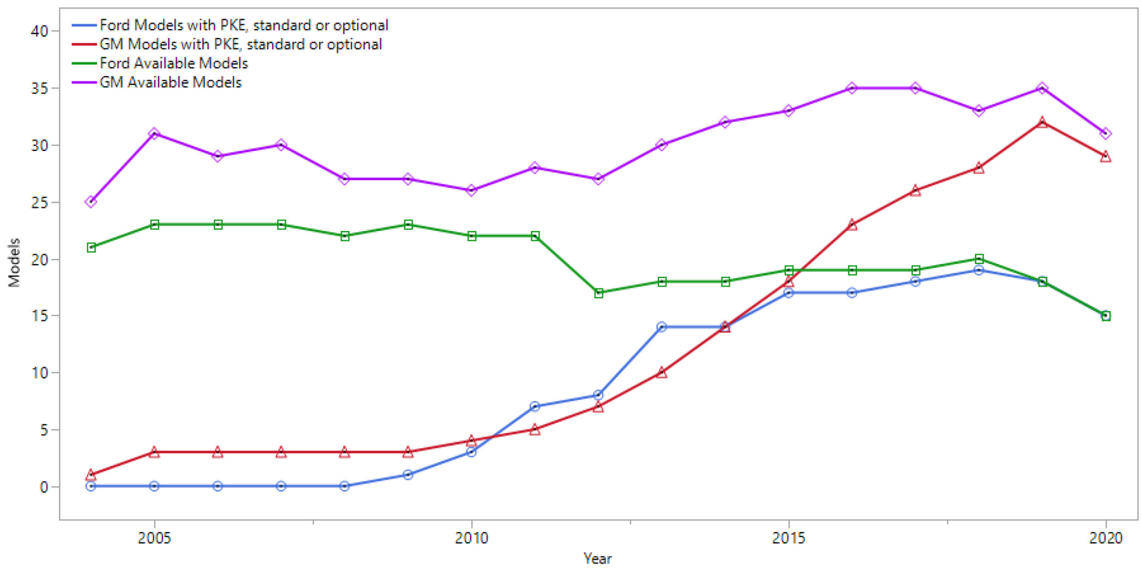

Figure 18 Adoption of PKE by model across Ford and GM, 2004-2020

5.5.3.2. High-Speed Transmission (HST)

The transmission (gearbox) adapts the engine's output to the drive wheels. The process reduces engine speed to the slower wheel speed, increasing torque. HST is a category of stepped automatic transmission with 8 or above gears, including Automated Manual Transmission (AMT), Automatic Transmission (AT), and Dual Clutch Transmission (DCT). The primary innovation driver is the smooth driving experience and reduced fuel consumption. Note that the Continuously Variable Transmission (CVT), which is preferred by Japanese OEMs (Nissan and Toyota), is an AT changing gear ratio seamlessly and is not in this HST category. Premium OEMs (i.e., BMW) offered HST before 2010. The mass-produced OEMs started the feature introduced to the market around 2012. Early adopters include Fiat-Chrysler Automotive and Honda in 2012, with Tier-1 suppliers ZF, Magna, and Aisin.

Since HST is the connector between driver and engine, this high-profile subsystem is considered to be part of OEM's system integration domain, with a high barrier of entry for tier-1 suppliers. Compared to PKE, fewer tier-1 suppliers offer HST, and many OEMs (Hyundai, Ford, and GM) prefer in-house engineering over outsourcing to tier-1 suppliers.

Thanks to the importance of the transmission subsystem, commercial research databases contain vehicle specification data that identifies HST features with structured data entries, which simplifies the data collection process compared to PKE, as shown in Figure 19.

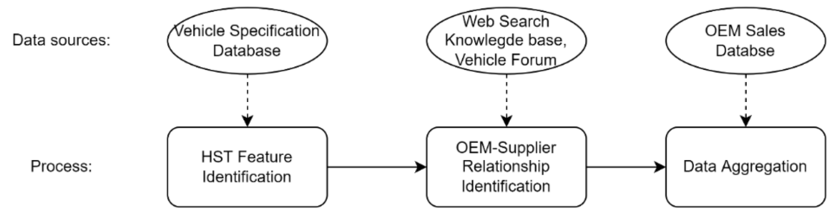

Figure 19 Process and data sources for HST diffusion data collection

In the OEM-Supplier relationship identification step, the author searches for various data sources to cross-validate the manufacturer data, including online vehicle knowledge bases, vehicle owner's online forums, and automotive market research providers listed in 5.3.2. HST shares a similar data aggregation process with PKE.

The collected aggregated empirical data in Appendix E and Figure 20, and Figure 21 show that the HST diffusion is at a steady pace as of 2021, with the empirical data covering the diffusion process in the mass-produced market. Like PKE, HST's market diffusion follows a similar s-curve, with the growth rate slowing down. The data include most OEMs in the North American market, except for OEMs serving premium markets such as BMW, Audi, Mercedes-Benz, etc. The empirical data cover 71% of the car and 79% of the light truck market in the US, with 8 OEMs and 248 current and discontinued models as of the model year 2021.

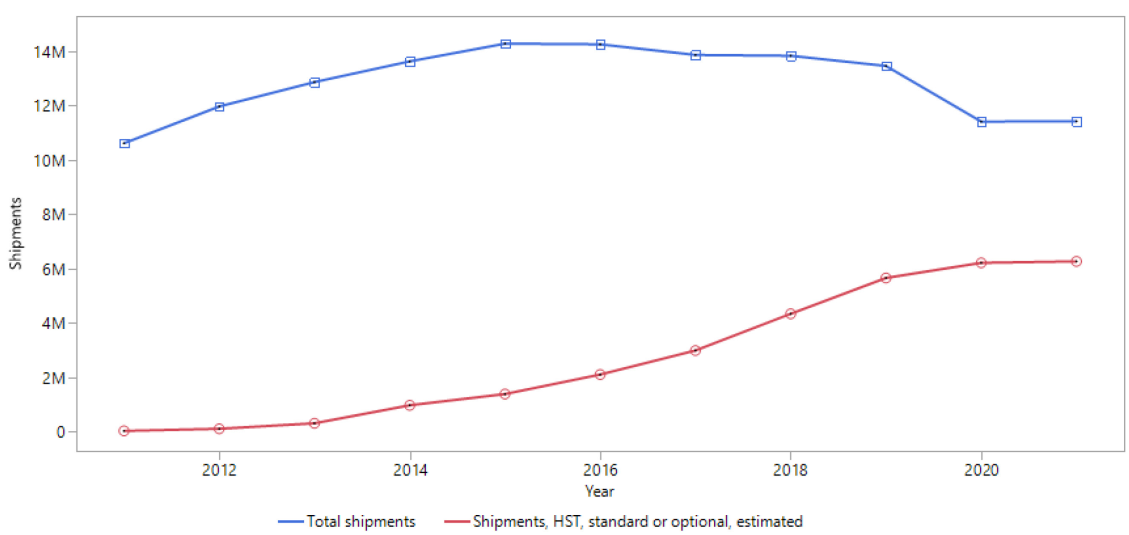

Figure 20 HST Adoption by model in the U.S market, 8 OEMs, 2011-2021

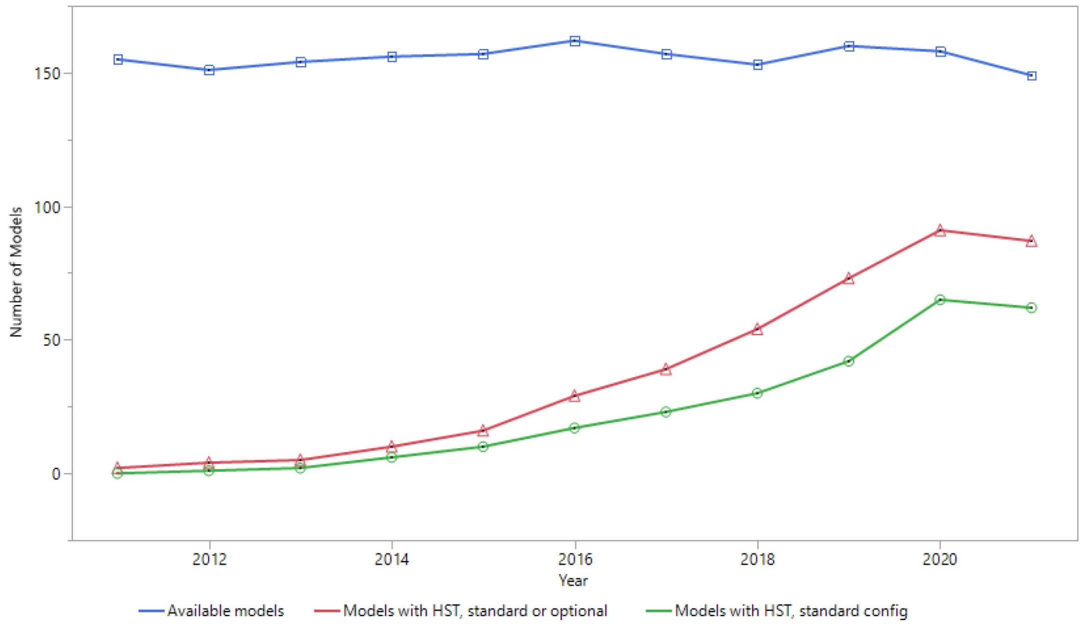

Figure 21 HST Adoption by shipment in the U.S market, 8 OEMs, 2004-2020

Figure 22 shows the adoption of PKE by model across Ford, GM, and Stellantis in the U.S. market. Stellantis (formerly Fiat Chrysler Automobiles before 2020) first introduced 8-speed AT in its Chrysler brand around 2011 in the mass-produced market, leading GM and Ford in HST diffusion. GM started HST introduction in 2014 Cadillac models and led Ford's F-series light trucks by 3 years in HST diffusion.

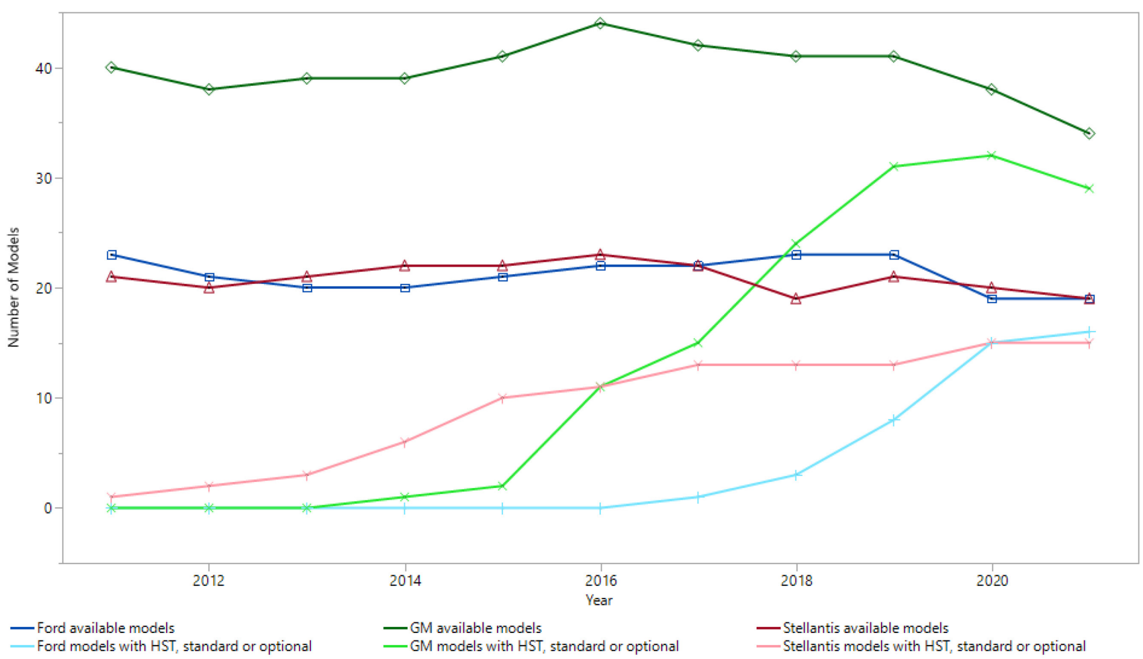

Figure 22 Adoption of PKE by model across Ford, GM, and Stellantis, 2011-2021

Unlike PKE in the convenience group, HST is a high-profile feature coupled with the powertrain performance. Both OEMs and tier-1 suppliers are incentivized to develop technical know-how in HST to capture more negotiation power in an OEM-supplier relationship and profit in the whole product market. Factors like sourcing strategy, technology maturity, company's R&D efficiency all influence the rate of adoption across OEM products.

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Chapter 6

Modeling Innovation Dynamics

Inspired by the previous work (Moser et al., 2021), this section proposes an innovation dynamics model to answer the research question from Chapter 3. As stated in Chapter 3, the modeling effort in this chapter balances both OEM and supplier's interests and offers a holistic view of competition and collaboration between OEM and its supplier.

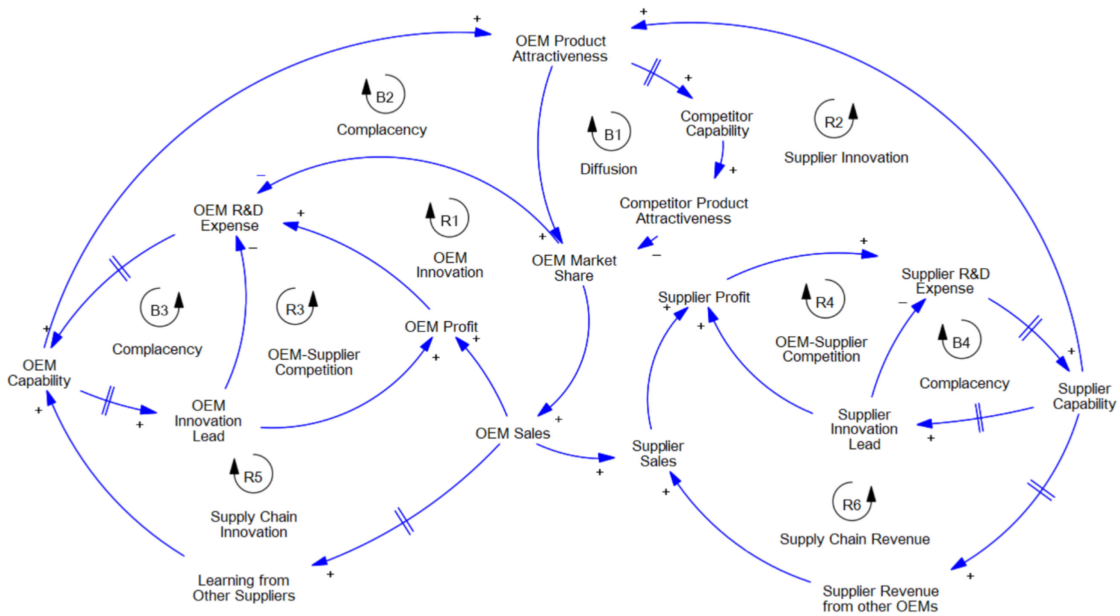


Figure 23 Overview of the innovation dynamics model

Figure 23 shows the top-level view of the proposed model with 6 reinforcement loops and 4 balancing loops. The top-view can be further decomposed into three submodules:

- Innovation-driven growth for both OEM and supplier.
- Competition in the OEM-Supplier relationship.
- Competition in the whole product market through technology diffusion between the OEM-Supplier ecosystem and the competitor ecosystems.

One can argue that some business elements are missing from the model in Figure 23. However, according to (Sterman, 2000), this model aims to solve the research question about innovation dynamics between OEM and its supplier, not to model the system.

Therefore, only the endogenous factors related to the research question are represented in the model. The model boundary chart is shown in Table 2, which lists important variables that are endogenous, exogenous, and excluded from the model.

Table 2 Model boundary chart

Endogenous	Exogenous	Excluded
Innovation strategy, culture R&D expense, patents, innovation vehicles Business development with other OEM/Suppliers Sales, Profit, Patents Innovation lead, capability, lifetime Product attractiveness	Market size Policy	Diffusion through marketing, advertisement, word of mouth International trade Revenue through financing Operational excellence and cost structure

This chapter is organized as follows:

- Section 6.1: Loops on the left (OEM: R1, R5, B2, B3) and right (Supplier: R2, R6, B4) sides of Figure 23 relate to innovation-driven growth.
- Section 6.2: OEM-Supplier competition-related loops (R3, R4).
- Section 6.3: Diffusion (B1) caused competition between OEMs.
- The remaining sections: Model verification with empirical data collected from Chapter 5.

6.1. Innovation-driven growth of market share and profit

This section describes how an OEM and its supplier increase market share/sales and profit through collaborative innovation. The collaboration echoes a key hypothesis in Chapter 3: collaborative innovation between the OEM and its supplier drives a higher market share, which leads to higher profit and sales. Complacency and its balancing effect are also discussed on both OEM and supplier sides.

6.1.1. Innovation from R&D

6.1.1.1. OEM Innovation model

The OEM innovation model is shown in Figure 24. This model presents how a firm's innovation (R1, R2 in Figure 23) boosts product market share, sales, and profits.

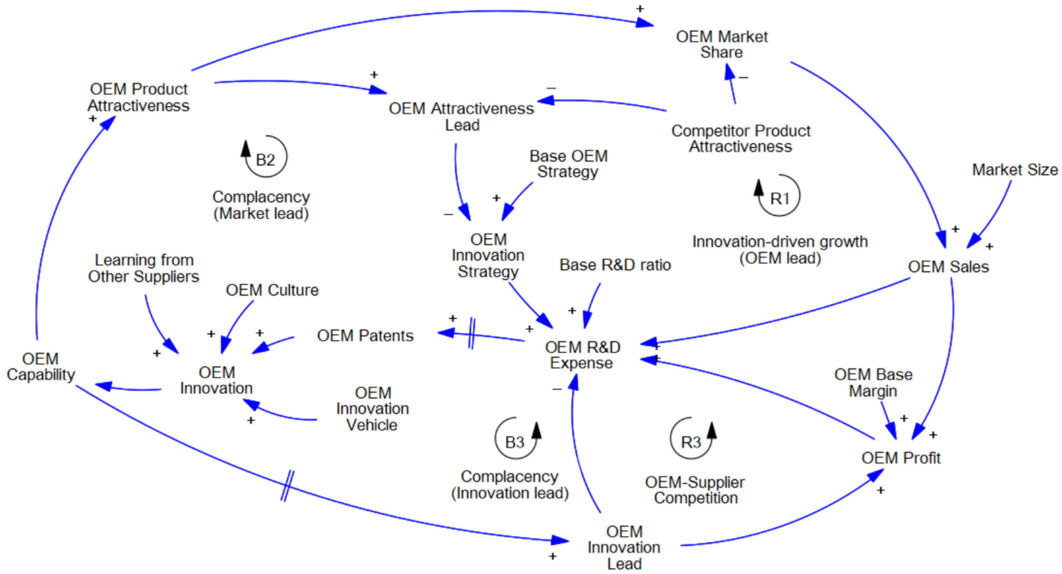


Figure 24 OEM innovation model

The reinforcing loop R1 illustrates the classic view from Chapter 2 on how innovation drives the OEM's sales and profit. The increased attractiveness of OEM products leads to an increasing market share, with a greater sales volume. The increased sales bring more budget for R&D activities that strengthen the OEM innovation and capability. Higher OEM capability leads to more attractive products, which helps the OEM win over more market share from its competitors, forming an innovation-driven flying wheel.

Apart from R&D expenses from annual budgeting practices aligned with revenue, profit could also affect R&D expenses through competition with the supplier, as illustrated by reinforcing loop R3 in Figure 24. With all other factors equal, including operational excellence, the OEM and its supplier share the profit with an upper limit proportional to sales. Therefore, pursuing a higher profit is represented by competition on how to split the "pie" of shared profit. In the R3 loop, the "innovation lead" perceived by both parties dictates the power of each party when negotiating the profit split. A more innovative OEM could harvest higher profit in an OEM-supplier relationship. A better profit further drives higher investment in R&D.

Two complacency-related balancing loops (B2, B3) counter the reinforcing effects from R1 and R3 endogenously inside the OEM innovation model. On the OEM innovation side

(B2), reaching the desired attractiveness lead in the market will offset the aggressive innovation strategy, reducing R&D spending to boost profit margin. On the OEM-supplier competition side (B3), similar goal-seeking behavior of innovation lead in an OEM-supplier relationship produces a similar effect compared to B2.

As mentioned in Table 2 about model boundary, the effect of marketing dynamics (e.g., advertising, word of mouth, etc.) are excluded and treated as equal strength for all OEMs, so the model. Therefore, the change in market share could be represented as competition in product attractiveness:

$$OEM\ Market\ Share = OEM\ base\ Market\ Share \times \frac{OEM\ Product\ Attractiveness}{Competitor\ Product\ Attractiveness} \quad (1)$$

Sales (Revenue) could be represented as:

$$OEM\ Sales = OEM\ Market\ Share \times\ Market\ Size \quad (2)$$

The profit could be calculated as proportional to sales plus a premium from the competition:

$$OEM\ Profit = OEM\ Sales \times (OEM\ base\ Margin + OEM\ Innovation\ Lead \times Scaling\ Factor) \quad (3)$$

,where the competition-related factor OEM Innovation Lead will be detailed in section 6.2.

The R&D Expense could be modeled as the sum of proportions of sales and profit:

$$OEM\ R\&D\ Expense =\ OEM\ Innovation\ Strategy\ \times\ (OEM\ Sales * Base\ R\&D\ Ratio + OEM\ Profit \times Base\ Profit\ to\ R\&D\ Ratio) \quad (4)$$

Two measures are introduced to convert R&D investments to OEM innovation: patents and innovation vehicles. As mentioned in Section 2.1, innovation is the combined effort of invention and commercialization. Therefore, the author uses patent filing as a measure for invention and innovation vehicles (e.g., partnership, CVC, incubators, etc.) for commercialization. The conversion from R&D expense to OEM innovation is as follows:

$$OEM\ Patents = SMOOTH(OEM\ R\&D\ Expense\ \times R\&D\ to\ Patent\ ratio, Innovation\ Delay) \quad (5)$$

$$OEM\ Innovation = OEM\ Culture\ \times OEM\ Innovation\ Vehicle \times (OEM\ Patents + Learning\ from\ Other\ Suppliers)$$

(6)

,where the function SMOOTH() in Eq.(5) introduces first-order delays indicated by Innovation Delay in years. Note that "Learning from Other Suppliers" in Eq.(6) will be detailed in the following sub-section. The OEM capability is integral to OEM innovation and other factors detailed in section 6.2.

As for the balancing loops, complacency in OEM-supplier competition (B3) is captured in Eq.(3). The complacency in market leadership, which affects innovation strategy, can be represented as follows:

$$OEM\ Attractiveness\ Lead = \frac{OEM\ Product\ Attractiveness - Competitor\ Product\ Attractiveness}{OEM\ Product\ Attractiveness + Competitor\ Product\ Attractiveness} \quad (7)$$

$$OEM\ Innovation\ Strategy = Base\ OEM\ strategy - OEM\ Attractiveness\ Lead \quad (8)$$

6.1.1.2. Supplier innovation model

Since both OEM and the supplier are in the same industry with growth driven by innovation, the supplier innovation model is similar to the OEM's case. Figure 25 presents the supplier innovation model.

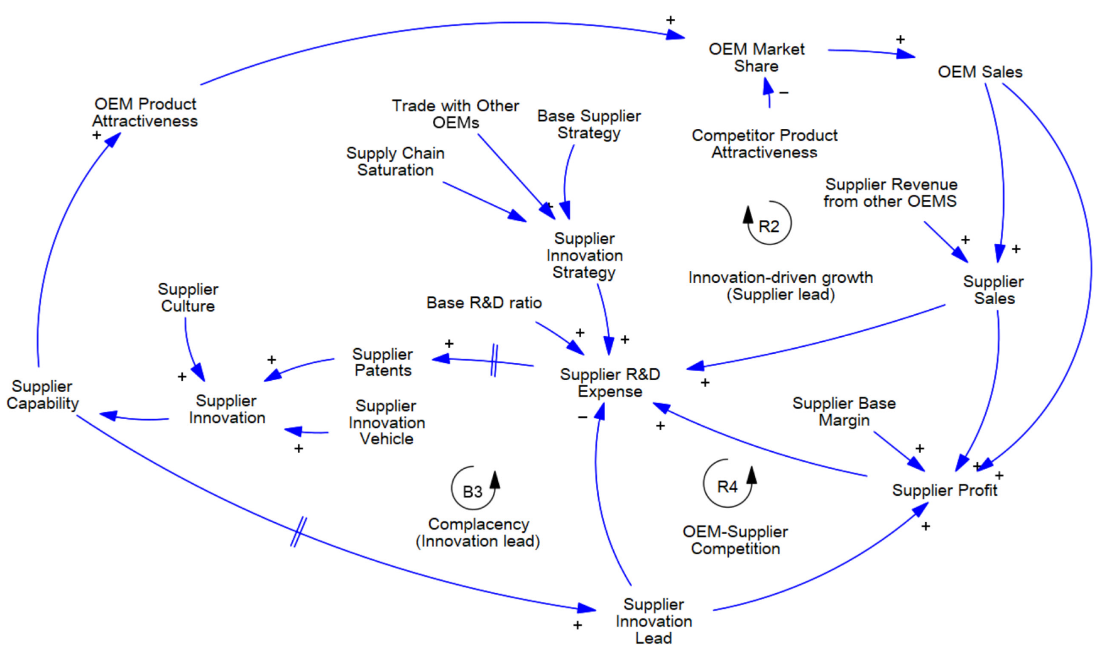


Figure 25 Supplier innovation model

Similar to the OEM's case, the supplier innovation and capability contribute to the OEM product attractiveness, increasing OEM market share, as represented by R2 in Figure 25. The supplier gains higher sales through more shipments of the OEM products. Higher sales drive higher profit, resulting in higher investment in R&D. However, a supplier may work with multiple OEMs to generate revenue (detailed in the following sub-section). The resulted supplier sales can be represented by:

$$Supplier\ Sales = OEM\ Sales\ \times OEM\ Revenue\ mix + Supplier\ Revenue\ mix + Revenue\ from\ other\ OEMs \tag{9}$$

,where "OEM Revenue mix" scales OEM sales down to the supplier, and "Supplier Revenue mix" defines the portion of total supplier revenue from the OEM. Similar to the OEM-supplier profit-sharing described in Eq.(3), the "zero-sum" game distributes the profit "pie" through R4 as:

$$Supplier\ Profit = Supplier\ Sales\ \times Base\ Supplier\ Margin + OEM\ Sales \times Supplier\ Innovation\ Lead \tag{10}$$

$$Supplier\ Innovation\ Lead = -OEM\ Innovation\ Lead \tag{11}$$

The supplier R&D expense can be calculated as:

$$Supplier\ R\&D\ Expense = Supplier\ Innovation\ Strategy\ * \ (Supplier\ Sales * Supplier\ base\ R\&D\ Ratio + \ Supplier\ Profit * \ Base\ profit\ R\&D\ ratio) \tag{12}$$

The supplier innovation strategy includes complacency in an OEM-supplier relationship as a balancing loop(B3), as well as the strategic intent to build relationships with other OEMs in the market (detailed in the following sub-section):

$$Supplier\ Innovation\ Strategy = Base\ Supplier\ strategy - Supplier\ Innovation\ Lead - \frac{Trade\ with\ Other\ OEMs}{Supply\ Chain\ Saturation} \tag{13}$$

Similar to Eq.(5) to (7), measures for supplier innovation can be represented by:

$$Supplier\ Patents = SMOOTH(Supplier\ R\&D\ Expense \times R\&D\ to\ Patent\ ratio, Innovation\ Delay) \tag{14}$$

$$Supplier\ Innovation = Supplier\ Culture \times Supplier\ Innovation\ Vehicle \times Supplier\ Patents \tag{15}$$

, where the function SMOOTH() in Eq.(14) introduces first-order delays indicated by Innovation Delay and Vehicle Delay in years. Unlike Eq.(7), working with other OEMs (competitors) does not directly contribute to supplier innovation to the OEM's product capability as this subsystem is built for an OEM-supplier relationship.

6.1.2. Other sources of innovation

Section 6.1.1 focuses on capability development through internal R&D and innovation vehicles. However, both OEMs and suppliers also learn from their business partners, i.e., other OEMs and tier-1 suppliers. This section models business partners as alternative sources (R5, R6 in Figure 23).

6.1.2.1. OEM: other sources of innovation

As shown in Figure 26, the higher OEM sales demand more suppliers through OEM's business development efforts, and more suppliers will further increase OEM product capability.

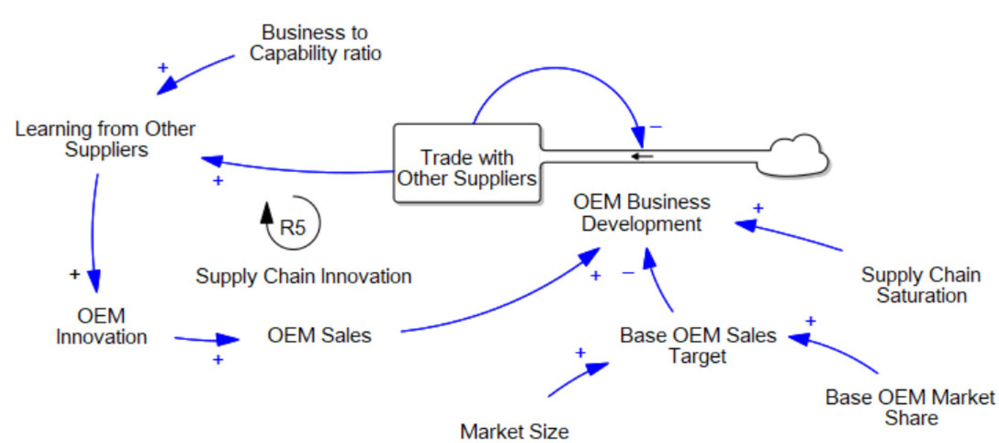


Figure 26 OEM's alternative sources of innovation

To capture the learning from supplier trading, learning from other suppliers could be represented as:

$$Learning\ from\ Other\ suppliers = Business\ to\ Capability\ Ratio \times Trade\ with\ other\ Suppliers \tag{16}$$

$$Trade\ with\ other\ Suppliers = INTEG(OEM\ Business\ Development) \tag{17}$$

,where "Trade with other Suppliers" indicates the number of tier-1 suppliers in the OEM's supply chain, "Business to Capability Ratio" is a scaling factor converting from the number of companies to capability contribution, and INTEG() in Eq.(17) shows the delay as integral between business development and capability development.

However, the marginal benefit of learning from other suppliers will quickly diminish when OEMs work with all available suppliers, reaching supply chain saturation. Supplier development will slow down when the OEM misses the sales target. These two dynamics can be captured as:

$$OEM\ Business\ Development = \frac{OEM\ Sales}{Base\ OEM\ sales\ target} \times \left(1 - \frac{Trade\ with\ other\ Suppliers}{Supply\ Chain\ Saturation}\right) \tag{18}$$

6.1.2.2. Supplier: other sources of revenue

Different from OEM's case (sales-driven business development), the supplier's leading capability wins more OEM clients. Figure 27 presents the supplier's alternative sources of innovation.

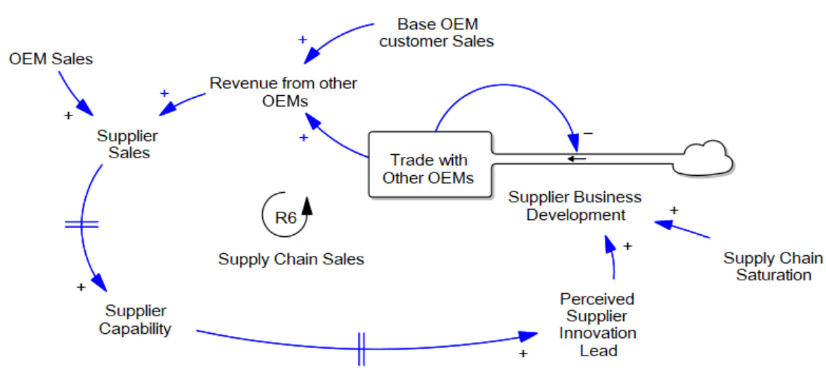


Figure 27 Supplier's alternative sources of innovation

A supplier can get more sales and R&D expenses and increased capability with more clients. Connecting to Eq.(10), the revenue from other OEMs can be calculated as:

$$Revenue\ from\ other\ OEMs = Base\ OEM\ customer\ Sales \times INTEG(Supplier\ Buinsess\ Development) \tag{19}$$

Similar to the case in OEM working with other suppliers, the marginal benefit of this reinforcement loop (R6) will quickly diminish when the supplier works with all available OEMs in the market. The diminishing benefit could be captured through supply chain saturation on the supplier side and tuned by a time factor, as:

$$Supplier\ Business\ Development = (1 + Supplier\ Innovation\ lead\ ) \times \left(1 - \frac{Trade\ with\ other\ OEMs}{Supplier\ market\ saturation}\right) \times Time\ Factor \tag{20}$$

6.2. Competition between the OEM and Supplier

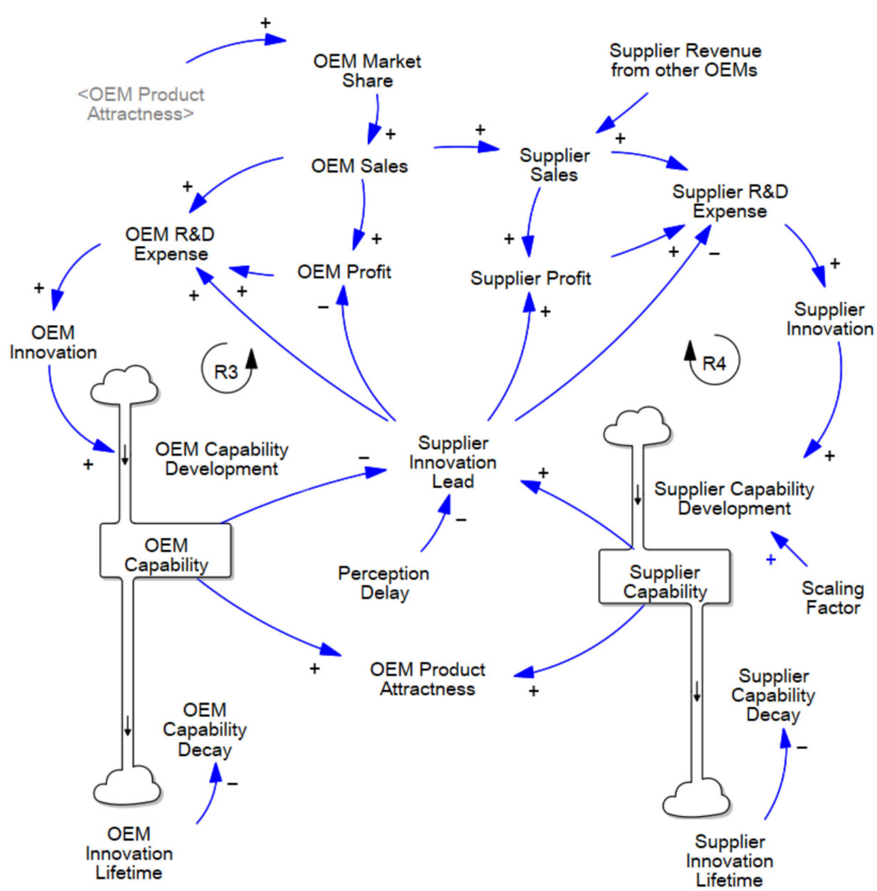


Figure 28 Competition model in an OEM-supplier relationship

This section details capability building and competition (R3, R4 from Figure 23) between OEM and supplier through profit sharing and innovation lead. Figure 28 shows the competition sub-model in an OEM-supplier relationship, focusing on reinforcing loops R3 and R4.

As mentioned in the previous section, the competition inside an OEM-supplier relationship is modeled by sharing the whole product profit (splitting the "pie"). The sharing ratio is determined by capability contribution to the OEM product. This section starts with capability development using stock-flow representation, then details the profit sharing.

6.2.1. Capability Development

In this model, the product attractiveness is defined by the sum of capability from both the OEM and supplier:

$$OEM\ Product\ Attractiveness = \ OEM\ Capability + Supplier\ Capability \tag{21}$$

As shown in Appendix B, OEMs are usually several times bigger than an average tier-1 supplier in terms of sales, R&D expense, and patent filings. Yet the OEM and its tier-1 supplier collaborate to ensure the successful delivery of one subsystem. Therefore, it is reasonable to assume both parties contribute equally to product capability and negotiation power in an average buyer-supplier relationship. The Scaling Factor in Eq.(24) captures this assumption:

$$OEM\ Capability\ Development = OEM\ Innovation \tag{22}$$

$$Supplier\ Capability\ Development = \ Supplier\ Innovation\ \times Scaling\ Factor \tag{23}$$

Innovation activities like R&D and learning from partners increase the product capability, and other factors such as technology iteration, employee turnover, and macroeconomic factors would reduce the capability over time. The model assumes a linear capability decay over the innovation lifetime, as:

$$OEM\ Capacity\ Decay = \frac{OEM\ Capability}{Innovation\ Lifetime} \tag{24}$$

$$OEM\ Capability = INTEG(OEM\ Capability\ Development - OEM\ Capacity\ Decay) \tag{25}$$

$$Supplier\ Capacity\ Decay = \frac{Supplier\ Capability}{Innovation\ Lifetime} \tag{26}$$

$$Supplier\ Capability = INTEG(Supplier\ Capability\ Development - Supplier\ Capacity\ Decay) \quad (27)$$

,where the function INTEG() captures the delay between the increase of a firm's innovation and capability. With the capacity increase and decay through Eq.(21) to (27), the product attractiveness and the resulted market share will reach equilibrium if all other factors remain unchanged.

6.2.2. Profit-Sharing

The goal for a higher profit creates competition in one OEM-supplier relationship. As mentioned in 6.1.1, the leading innovator in the relationship harvests a more significant share of profit from the OEM product profit pool, as described in Eq.(3) and (10). The "winner's" fractional profit margin over OEM sales can be represented by supplier innovation lead as:

$$\begin{aligned} &Supplier\ Innovation\ Lead \\ &= SMOOTH\left(\frac{Supplier\ capability\ -\ OEM\ capability}{OEM\ capability + Supplier\ capability}, Perception\ Delay\right) \\ &= \ -OEM\ Innovation\ Lead \end{aligned} \quad (28)$$

In Eq.(28), a first-order delay function SMOOTH() is employed to represent a perception delay in profit sharing between the two parties.

6.3. Diffusion and competition in the whole product market

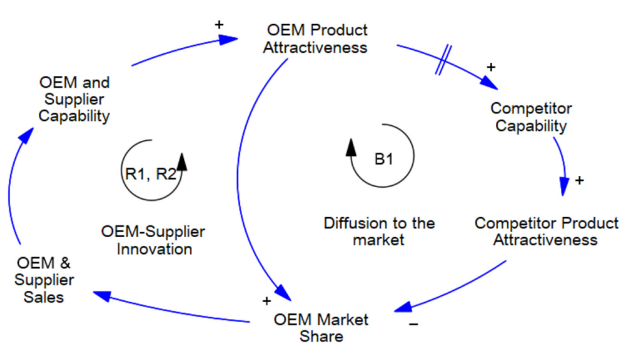


Figure 29 Top-view of competition between OEM-supplier ecosystems

Competition does not only exist within the OEM-supplier relationship. Zooming out from the OEM-supplier system, the OEMs compete in the whole product system for a more significant market share and customer base. This higher-level competition is described as a balancing loop (B1) in Figure 29. At the whole product market level, an OEM and the supplier collaborate to enhance their capability through R1, and R2 to compete with similar ecosystems of competitors.

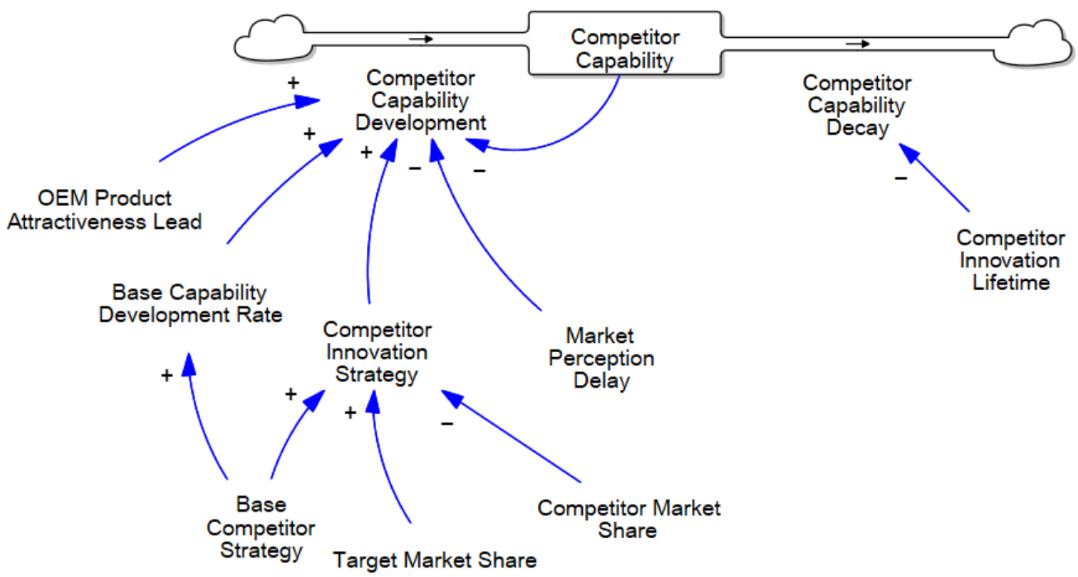


Figure 30 Technology diffusion model between OEMs

Since the model focuses on dynamics within one OEM-supplier system and excludes marketing and consumer dynamics, as stated in Table 2, it is reasonable to lump all other competitor ecosystems into one homogeneous diffusion model shown in Figure 30. This model is based on the classic Bass diffusion model (Bass, 1969), describing how innovations diffuse from one OEM to competitors, represented by capability and product attractiveness

Competitor's product attractiveness and capability follow the formulation from OEM/Supplier's case in Figure 28:

$$\begin{aligned} Competitor\ Product\ Attractiveness &= Competitor\ Capability \\ &= INTEG(Competitor\ Capability\ Development \\ &- Competitor\ Capacity\ Decay) \end{aligned} \tag{29}$$

The integral function INTEG() reflects the delay between capability development through R&D activities and product attractiveness. Similar assumptions on linear decay of the learned capability apply to the competitor's case:

$$Competitor\ Capacity\ Decay = \frac{Competitor\ Capability}{Competitor\ Innovation\ Lifetime} \tag{30}$$

The competitors build capability through R&D activities based on their base innovation strategy, investment, and OEM's innovation lead, as:

$$\begin{aligned} &Competitor\ Capability\ Development \\ &\qquad = Base\ Capability\ Development\ Rate \\ &\qquad + SMOOTH(Competitor\ Innovation\ Strategy \\ &\qquad \times OEM\ Attractiveness\ Lead \\ &\qquad \times Competitor\ Capability, Market\ Perception\ Delay) \end{aligned} \tag{31}$$

When the market reaches equilibrium, the competitors maintain a stable strategy and base capability development rate with a fixed market share. The OEM attractiveness lead will incentivize competitors to catch up through diffusion after a perception delay when an OEM-supplier ecosystem builds a more attractive product.

Finally, the competitor innovation strategy is based on the base strategy and market share to represent a goal-seeking behavior:

$$\begin{aligned} &Competitor\ Innovation\ Strategy \\ &\qquad = Base\ Competitor\ Strategy \times \frac{Target\ Market\ Share}{Competitor\ Market\ Share} \end{aligned} \tag{32}$$

6.4. Parameter Assessment for the baseline model

This section describes how model variables are defined in the baseline model using empirical data. Though OEMs and suppliers are different in scale, product, culture, and strategy, a baseline model attempts to capture homogeneous behaviors across the industry. Once configured with a base set of parameters, the baseline model serves as a starting point for customization for each OEM-supplier relationship to accurately capture the heterogeneous dynamics.

This section first illustrates how to estimate the values of parameters with statistical estimation with empirical data. The second half of this section discusses judgmental estimations with soft variables.

6.4.1. Numerical variables

Numerical variables have real-life meanings and tangible units. For example, "Market Size" relates to the market capitalization of the whole light vehicle market. With empirical data, statistical methods generate accurate estimations to reproduce historical events. This thesis uses the following two basic statistical methods for estimation:

6.4.1.1. Average and weighted-average historical values

It is reasonable to regard the baseline model's historical average or weighted-average data for relatively stable variables over time. These variables include financial data (sales, sales mix, market share) and financial ratios (P/E ratio, R&D spending, profit margin). The following Table 3 shows the estimations for variables in this category for the baseline model, using data from Appendix B:

Table 3 Variables using average or weighted average historical values

Variable Name	Estimated Value	Method
Market size	1.41 trillion \$/Year	Historical average on aggregated sales data from major OEMs
Base OEM Market Share	10%	Historical average market share data from 10 major OEMs
Base OEM R&D ratio	4.4%	Historical weighted-average (on sales) R&D spending data from 10 major OEMs' financial reporting
Base OEM profit margin	15%	
Base Supplier Sales	26 billion \$/Year	Historical average on aggregated sales data from 20 major tier-1 suppliers
Supplier Sales Mix	15%	Historical weighted-average (on sales) number of customers data from 20 major tier-1 suppliers. Assuming sales distribute evenly across OEMs.
Base Supplier R&D ratio	5.2%	Historical weighted-average (on sales) R&D spending data from 20 major tier-1 suppliers financial reporting
Base Supplier profit margin	10%	

6.4.1.2. Regression-based estimation

Regressors could be used to estimate conversion ratios between variables that have different units but with solid causality. This thesis applies the ordinary least squares (OLS) method to the conversion ratio between R&D expense and patent issuance. The results are presented in Figure 31 and Figure 32, with a linear relationship between spending and patent grant, as is shown in the following Table 4.

Table 4 Variables with regression-based estimation

Variable Name	Estimated Value	Method
OEM R&D to Patent ratio	0.32 patents/Million $/Year	Linear regression with OLS on historical yearly R&D spending and US patent issuance from major OEMs
Supplier R&D to Patent ratio	0.21 patents/Million $/Year	Linear regression with OLS on historical yearly R&D spending and US patent issuance from major tier-1 suppliers

Though different companies have different R&D efficiency, it is reasonable to use the regressor to gain an average model - a linear relationship between R&D spending and issued patents as a baseline, and then introduce strategic, cultural factors and feedback from competitors in the market to adjust the efficiency curve.

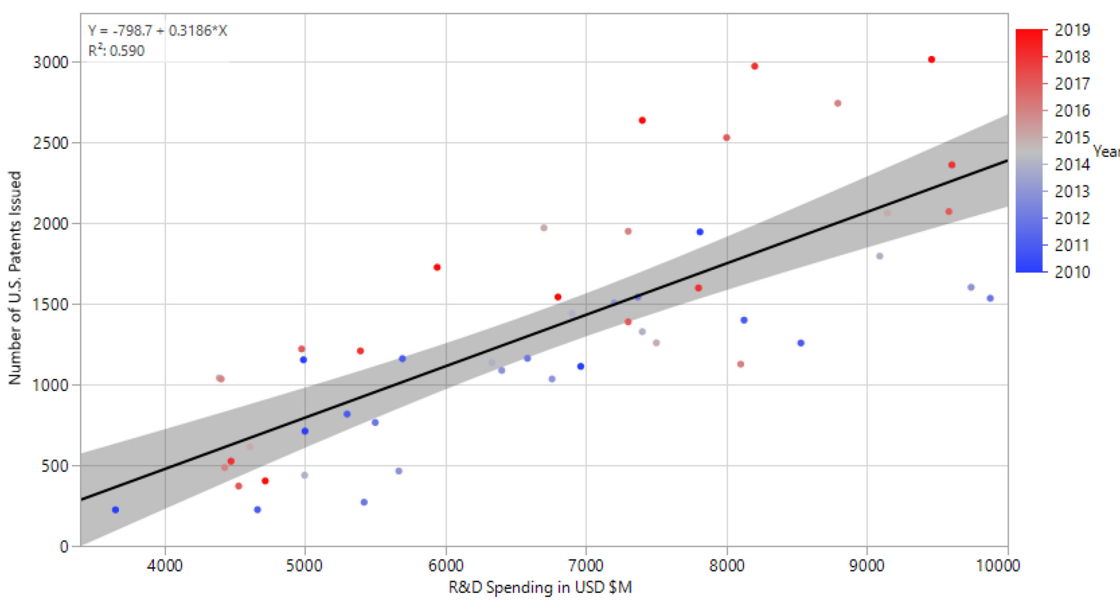


Figure 31 OEM baseline R&D efficiency estimation using linear regression with R^2=0.590

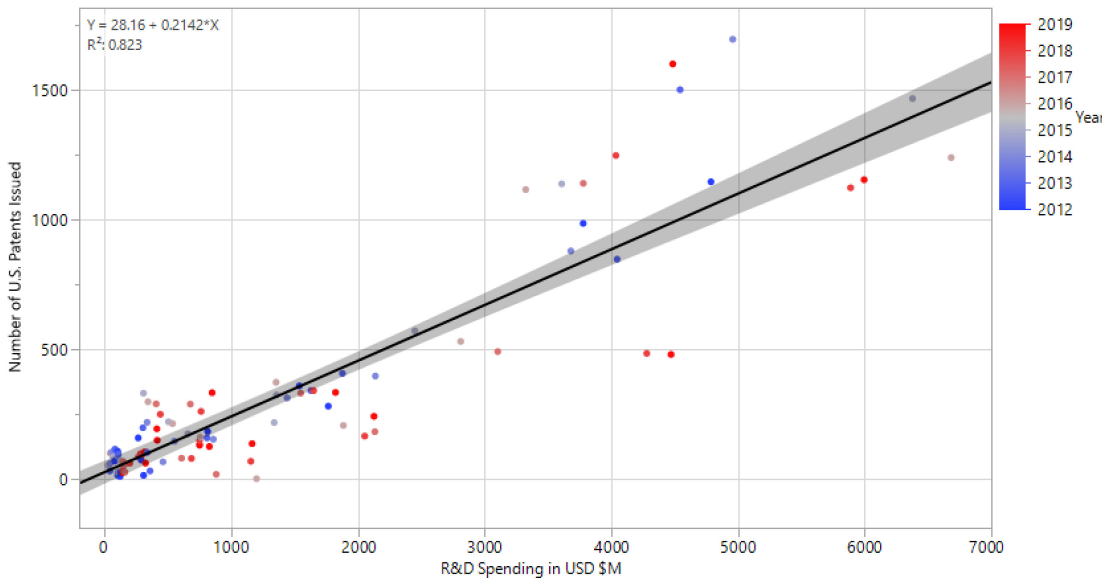


Figure 32 Tier-1 supplier baseline R&D efficiency estimation using linear regression with R^2=0.823

6.4.2. Soft Variables

Soft variables are hard to measure, including qualitative factors such as culture, strategy, and various time delays. However, the computational nature of SD requires the quantification of these qualitative factors. Numerical estimation methods work best if data is available and is directly related to the parameter. However, data availability limitations make it impossible to estimate all parameters numerically. For example, in this thesis, cultural and strategic factors are usually treated as trade secretes with limited and ambiguous disclosure. This thesis combines empirical/archival data with indirect causality and judgment calls to accomplish this "mission impossible".

6.4.2.1. Statistical methods with indirect empirical data

Estimation of market perception delay in section 6.3's diffusion sub-model is one of the soft variables that aggregate lower-level dynamics at the macro-level. The detailed dynamics of meso-and micro-level factors impacting diffusion could be another topic outside the model boundary. To get a good estimation, the author applies a diffusion model (mentioned in Section 6.3) to the two empirical data from Appendix D and E about the diffusion of PKE and HST in the US light vehicle market. Figure 33 compares the estimated parameter and the historical data with R^2>0.96 for PKE and HST market diffusion. All empirical data is aligned to year 0 as the starting year of market diffusion. The simulated curve matches the observation from 5.5.3 that PKE leads HST in market diffusion, and both of them have passed the "mid-point" with the rate of diffusion starting to slow down. The numerical method of "curve-fitting" is similar to the previous subsection on regression modeling, but the empirical data only has an indirect causal relationship to the soft variables.

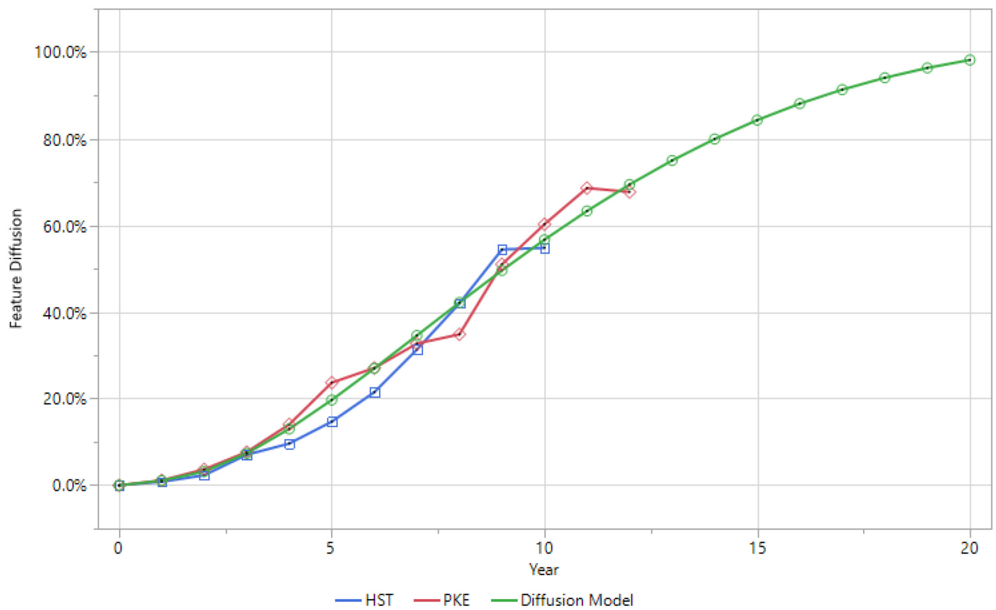


Figure 33 Parameter estimation for diffusion model using curve-fitting, R^2>0.96 for both PKE and HST cases, with competitor innovation strategy = 0.39, market perception delay=20 and competitor innovation lifetime=5

6.4.2.2. Judgment calls with limited archival data

The author exercises judgment calls with inputs from annual reports, financial reports, credible news sources, and patent co-filing data for soft variables with only limited archival data. Other sources of judgment calls not used in this thesis research include expert interviews, workshops, and direct experiences.

This thesis's soft variables with judgment calls are all "catalysts" for innovation and appear in the computational models as multipliers. The default value "1" indexes the variables as a per-unit number representing a base quantity across the industry. The direction of change in these indexed numbers through mathematical relationships with other factors leads to qualitative managerial implications. The variables with judgment calls are summarized in Table 5.

Table 5 Variables with judgment calls

Variable Name	Archival data
OEM/Supplier innovation strategy	Annual report; Form 10-K (if US-listed)
OEM/Supplier culture	Relative change of P/E ratio compared to the industry average
OEM/Supplier innovation vehicles	Company newsroom, announcements, and patent search

6.5. Model verification

This section follows the suggested model verification steps (Sterman 2000), including testing on structural assumptions and model parameters.

Section 6.5.1 and 6.5.2 are about structural verifications, trying to capture key reflective points during the "verification - model refinement" iterations to reveal structural limitations of the current model. The remaining sub-sections are about verifying the baseline model parameters, dynamics, and hypothesis testing.

6.5.1. Boundary Adequacy

This test assesses the adequacy of the model boundary to serve its purpose. A well-designed model should include all important endogenous feedback to the model. The purpose is to reduce reliance on exogenous variables. The summary of the model boundary is in Table 2 at the beginning of this chapter. The model is considered to have an adequate boundary in the following ways:

6.5.1.1. Purpose and boundary of the model

The model investigates innovation dynamics between an OEM and its tier-1 supplier, including collaboration and red-queen dynamics – competition within an OEM-supplier relationship and between the OEM and other OEMs in the market.

The endogenous factors for collaboration include capability development through R&D investment from both the OEM and its supplier, learning from other OEM and suppliers influenced by culture and innovation strategy. The competition within an OEM-supplier relationship is represented by the whole product profit sharing based on relative capability leadership between two parties. Competition between one OEM-supplier ecosystem with other competitors in the whole product market is represented by competing for superior product capabilities.

The model boundary includes financial, market, and organizational factors at the macro-level that influence innovation's sources, catalysts, and outcomes.

6.5.1.2. Important variables that are exogenous or excluded

Ideally, there should be zero reliance on important variables that are exogenous or excluded. The model includes one important exogenous variable and two potentially important factors excluded, revealing the limitations of this model.

Policy and macroeconomic factors are important exogenous variables that the automotive industry is not fully controlled. Macroeconomic data such as inflation, consumer price, and GDP growth are indicators of the market size of automotive products. For example, the 2008-2009 financial crisis caused negative global sales growth in automobile shipments (Oh, 2014). Though the market quickly caught up after the crisis with strong growth, the resulting low innovation investment had a long-term effect on the industry. The policy impact on electric vehicles, including government subsidies, has similar effects (Keith et al., 2017). Luckily, this exogenous factor is usually recorded and forecasted by various financial service providers, research groups, and government agencies. The model inputs this factor as input from credible sources.

The first excluded variable that may be potentially important is the impact of marketing and consumer dynamics on innovation diffusion. The model assumes the effect of customer dynamics like word of mouth and marking dynamics like advertising are stable and equal and chooses to focus on innovation-driven market adoption. This assumption works well in the established major OEMs with large marketing groups and customer bases. However, modeling innovations in marketing from newcomers to the market demand should revise this assumption. Therefore, the current model has enough boundary adequacy on market dynamics when modeling established major OEM ecosystems but is inadequate for newcomers with disruptive innovations in marketing.

The second excluded variable that may be potentially important is the impact of cost structure on profit margin. The model assumes a traditional financial ratio conversion between sales, sales mix, profit, and R&D expenses, implying operational excellence does not change regardless of sales. This method works well when OEMs and suppliers are in a relatively stable financial market. However, when the system is disturbed by strong political or economic factors, a detailed cost structure with COGS, SG&A, income tax, and a qualitative human decision model should be included to represent the dynamics under fundamental disturbances. Therefore, the current model has enough boundary adequacy on endogenous financial factors with relatively stable exogenous variables but is inadequate with non-linear decision-making in a turbulent financial market.

6.5.2. Structure Assessment

This test assesses the model's structural consistency with the operation of the real system. This section first reviews the model's conformation to realities on key assumptions and then verifies the model's level of aggregation to capture the total costs and benefits of actions.

6.5.2.1. Conformation to realities

Since pursuing financial gains drives innovation, conservation laws applied in financial equations ensure "no free lunch". The boundary adequacy test in the previous sub-section also helps confirm the model does not generate financial and capability gains without a cost by monitoring important exogenous factors. The model uses first-order delays with SMOOTH() function and accumulative effects in innovation activities from stock-flow charts with INTEG() to capture dynamics combining human decision making, innovation development, and diffusion across OEMs at the macro-level.

Innovation culture is a known factor affecting a firm's innovation capabilities. Though the literature does not suggest a direct quantitative measurement of culture, its impact could be modeled by its outcome – a firm's valuation. The thesis uses the P/E ratio, a factor that represents the investor's confidence in the innovation-driven growth of a firm, as an objective indicator of cultural measurement.

6.5.2.2. Level of Aggregation

This thesis builds a model at the macro-level, and the following dynamics at the meso- and micro-level are aggregated to simply the model.

The behavior of "other" suppliers and OEMs in one OEM-supplier relationship are lumped into single entities "other suppliers" and "other OEMs". While the heterogeneous nature between different suppliers and OEMs is worth investigating in a separate study on the multi-to-multi relationship between OEMs and suppliers, it is reasonable to aggregate the homogenous behaviors among the companies in a one-to-one OEM-supplier relationship studied by this thesis. Similar rationalities apply to the lumped competitors in market diffusion.

The meso- and micro-level factors affecting competition between an OEM and its supplier are modeled by profit-sharing based on innovation capability. The aggregated factors affecting competition include switching costs, making-buy decision-making, and team dynamics. Though these lower-level factors affect contract negotiation at the individual subsystem level, at the corporate level managing the whole product line, financial benefits and strategic intents dominate. Therefore, it is reasonable to model competition between OEMs and suppliers through profit sharing and innovation capability at the macro-level, assuming enough transparency between companies with negligible information arbitrage.

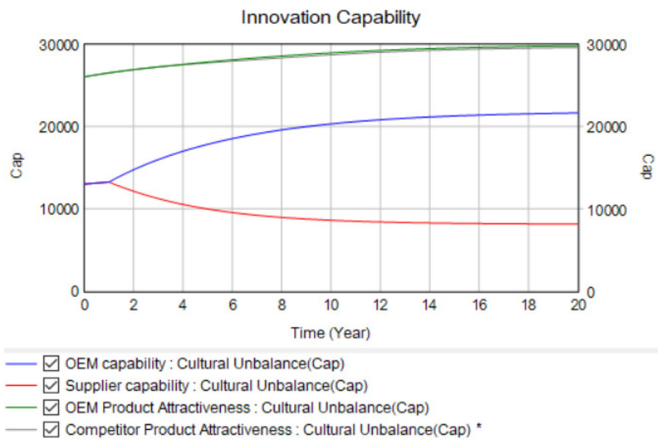
6.5.3. Extreme Conditions

The model should remain realistic no matter how extreme the inputs can be. This test assesses how robust the model is under extreme conditions. In this section, the author focuses on extreme conditions to the indexed variables described in section 6.4.2, which are soft variables configured with the modeler's judgment.

6.5.3.1. Cultural and strategical Unbalance

The cultural and strategical soft variables are multipliers in capability building in an OEM-supplier relationship and are not supposed to deviate more than 50% from the unity value "1". Therefore, the test conditions for these indexed variables are set at 0.5 (lower bound) and 1.5 (upper bound).

Figure 34 shows the model's dynamic response of profit and capability under extreme cultural unbalance between OEM(blue) and its supplier(red). The simulation begins with the baseline model in an equilibrium. In year 1, OEM's cultural variable changes from default 1 to 1.5, and the supplier's cultural variable changes from 1 to 0.5. Since "culture" is modeled as a catalyst to innovation, under this extreme contrast in an OEM-supplier relationship, the supplier starts to lose innovation capability over time while the OEM earns a bigger share in the whole product capability development shown in Figure 34(a). Figure 34(b) and (c) show that the OEM's innovation leadership translates to profit sharing. Since the OEM's revenue scale is several times bigger than the supplier, winning the competition over the supplier leads to only a slight increase in both profit and profit margin on the OEM side. The "innovate or die" effect is more significant than on the OEM. The system returns to equilibrium 10 years after the extreme disturbance.



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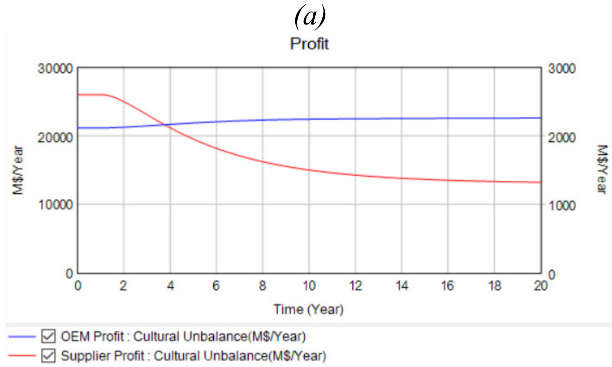

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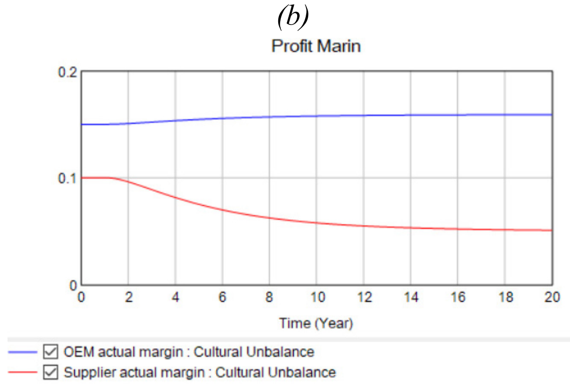
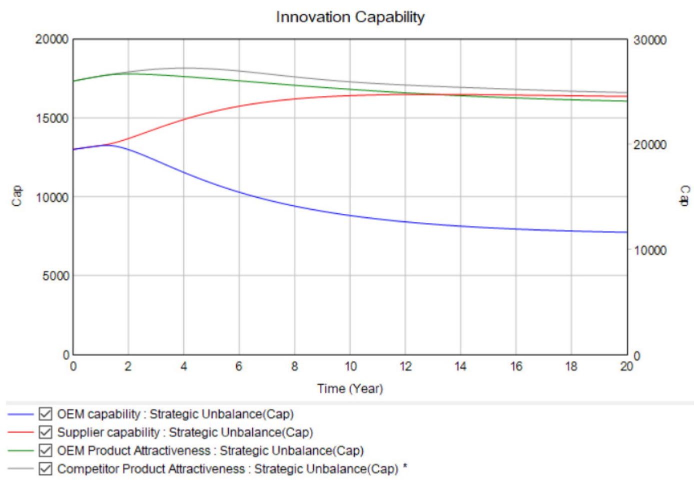


(c)

Figure 34 Extreme conditions for cultural unbalance in an OEM-supplier relationship

Strategic unbalance has a similar effect, as is shown in Figure 35. In year 1, OEM's base strategy variable changes from default 1 to 0.5, and the supplier's base strategy changes from 1 to 1.5. Unlike cultural factors, strategy has a stronger impact on innovation capability building as it directs research spending. However, the unbalanced innovation strategy follows a similar behavior to cultural unbalance in Figure 34.



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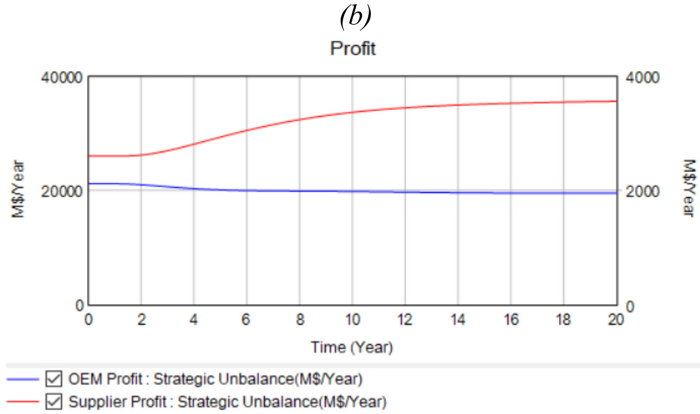


(c)

Figure 35 Extreme conditions for strategic unbalance in an OEM-supplier relationship

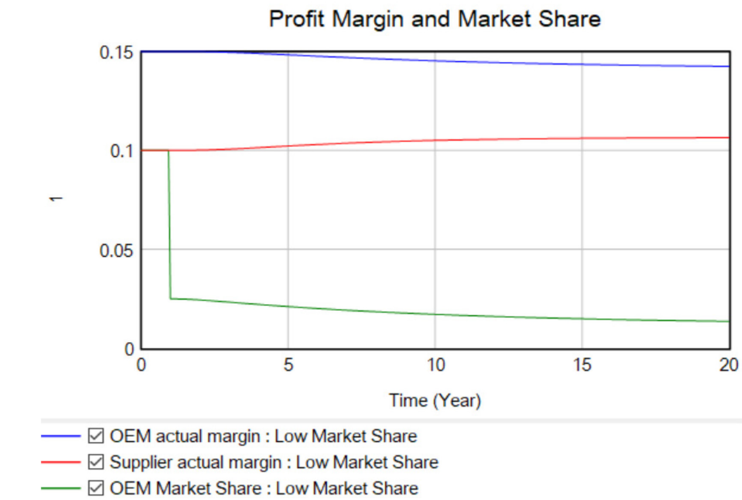
As the OEM switches to a highly passive innovation strategy, it loses the innovation leadership in an OEM-supplier relationship. At the same time, the supplier picks up the lead with an aggressive strategy, as is shown in Figure 35(a). However, the unbalance causes the OEM whole product attractiveness to lag the competitors in the market (grey in Figure 35(a)). This leads to the OEM-supplier ecosystem with a lower market share, as shown in Figure 35(b). The low market share hurts the OEM more than the supplier, as the supplier has a diversified revenue stream from other OEMs. The supplier's extremely aggressive innovation is rewarding. It wins more negotiation power in profit sharing with the OEM and thus ends up with a much higher profit margin and profit, as is shown in Figure 35(c).

6.5.3.2. Very low market share

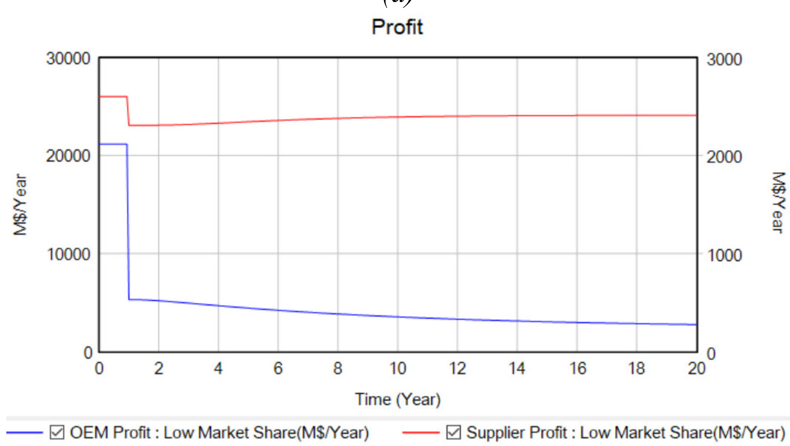
One interesting test case for the extreme condition is the system's behavior under very low market share. As mentioned in 6.5.1, the model's fidelity decreases because the fixed costs are not modeled in the cost structure. Capital-intensive firms can scale down operations linearly with sales only within certain limits. Though the model fidelity degradation is a known limitation, the model should remain stable and generate meaningful results. Another reason why the case is interesting is that the model treats market share as an important interface between the OEM-supplier ecosystem and other competitors in the whole product market.

Figure 36 shows the model's dynamic response of profit and capability under a very low market share. In year 1, a step-change in OEM market share is introduced, reducing OEM market share from 10% to less than 3%, as shown in Figure 36(a). This disturbance is implemented by a step-up change in a competitor's product attractiveness.

Due to the enormous market share loss, both the OEM and supplier have less profit, as shown in Figure 36(b). However, the supplier has less dip in profit because it has other OEM customers as profit streams. The reduced revenue and profit lead to less R&D budget, slowing down the capability development rate. Since the rate cannot catch up with innovation decay, the OEM product loses attractiveness in the market, reducing the market share further. The sudden change in the market share causes the OEM-supplier ecosystem to be trapped in a death spiral: lower market share reduces innovation capability, and the reduced product attractiveness lowers the market share.



(a)



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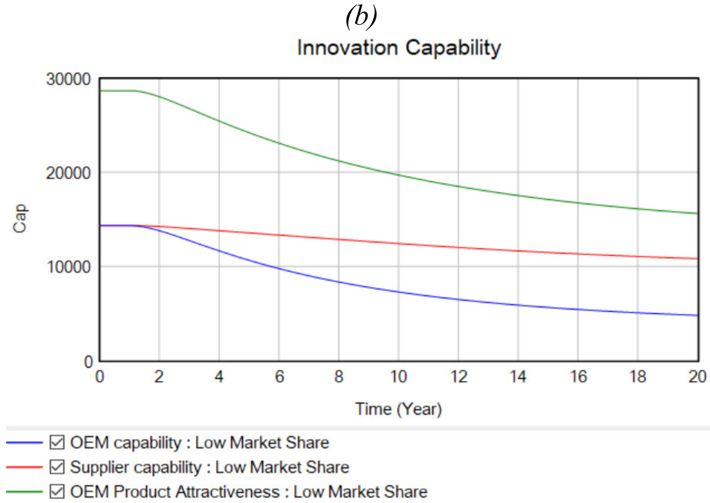


(c)

Figure 36 Extreme conditions for very low market share in an OEM-supplier relationship

Since the OEM suffers from a greater impact than the supplier, the unbalanced impact propagates competition in profit sharing between the OEM and its supplier. The supplier builds resilience from business relationships with other OEMs. The resilience supports the supplier with innovation lead over the OEM during this market share downturn. This shift in power makes the OEM "loses" the competition with an even lower profit margin. In contrast, the supplier's profit gains a slow recovery, though still lower than before the disturbance, as shown in Figure 36(b).

6.5.4. Sensitivity Analysis

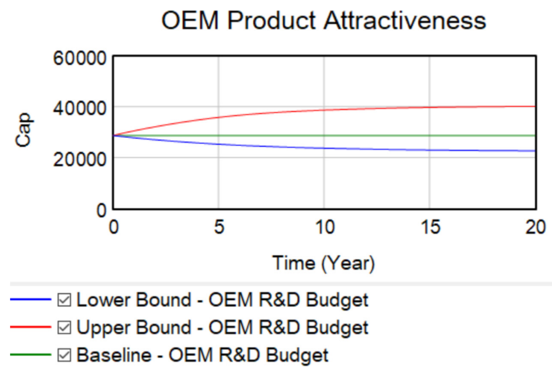
Sensitivity analysis tests the robustness of the model on uncertainty in the assumptions. This section assesses both numerical and behavior mode sensitivity. Numerical sensitivity impacts the variances of numerical values in model output. Behavior mode sensitivity is complementary to the structural assessments in section 6.5.2, numerically verifying the changes of behavior modes when assumptions are changed.

The analysis in this section focuses on conversion ratios such as revenue-to-R&D-budget ratio, profit margin, and product importance ratio and delays like perception delay for innovation leadership. These ratios and delays are interfaces between different reinforcing/balancing loops inside the OEM-supplier relationship, and their changes directly impact numerical outcomes and behavior modes.

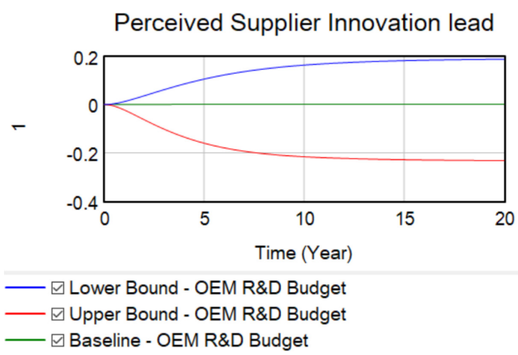
Since the model does not use high-order (3^{rd} and above) differential equations to represent the dynamics, a "best and worst case" sensitivity analysis is good enough to assess uncertainties of assumptions in key conversion ratios. All sensitivity tests share the same baseline model with parameters configured in Section 6.4.

6.5.4.1. R&D Budget

The sensitivity analysis of the R&D budget explores how a change in the revenue-to-R&D-budget ratio affects profit and innovation leadership in an OEM-supplier relationship. The baseline model has an R&D budget of 4.4% (the industry average from section 5.2). The best- and worst-case scenario ratios are 9% and 2%. The sensitivity analysis on R&D budgeting's impact on product attractiveness, an innovation lead, and supplier profit is shown in Figure 37.



(a)



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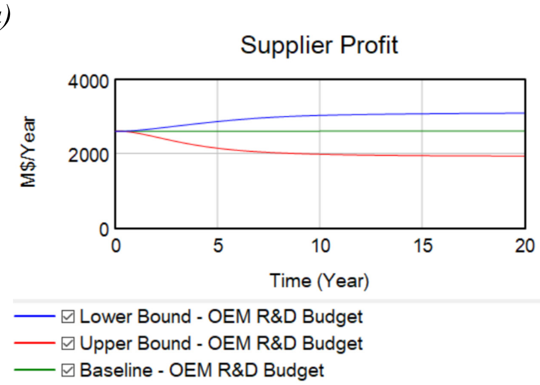


(c)

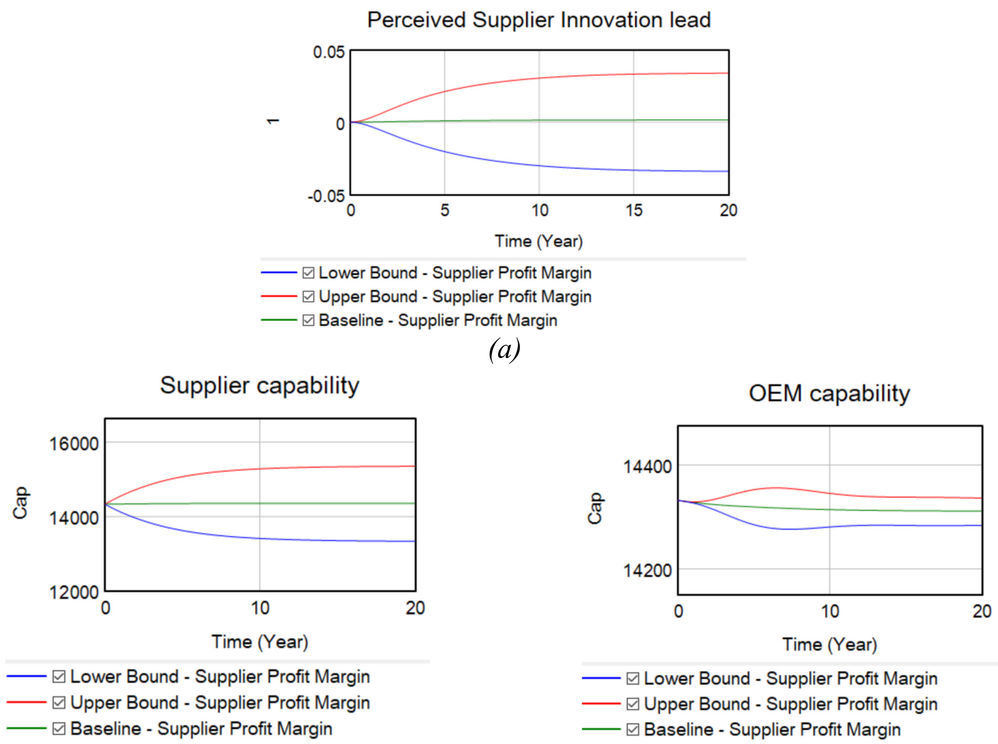
Figure 37 Sensitivity analysis for OEM R&D budget

In the model, capability development is positively related to the R&D budget. Therefore, a unilateral change in OEM's R&D investment will affect product attractiveness and the innovation lead in the relationship, as is shown in Figure 37(a) and (b). Note that balancing loops like complacency offsets the base R&D budget ratio changes, so the OEM does not gain the leadership numerically proportional to its base budgeting, as shown in Figure 37(b).

Since the scale of the OEM is several times greater than the supplier, this difference magnifies the impact of a shift in innovation lead on the supplier's profit, as is shown in Figure 37(c). In the worst-case scenario, when OEM cuts its R&D budget by half, the supplier enjoys an 18% increase in profit due to the innovation lead accumulated over the years. Note that the change in R&D ratio does not change time constants in the model. It takes the same duration for both scenarios to reach the new equilibrium.

6.5.4.2. Profit Margin

The profit margin has a similar but weaker effect on innovation capability since a higher profit incentivizes innovation through a higher R&D budgeting. The sensitivity analysis in this section focuses on the supplier profit margin and its impact on innovation lead and capability development. In the analysis, the base supplier profit margin for the baseline is 10%, and the best- and worst-case scenarios have 15% and 5%, respectively. The sensitivity analysis for the supplier's profit margin is shown in Figure 38.



(a)

(b) *(c)*

Figure 38 Sensitivity analysis for supplier's profit margin

Compared to the analysis from Figure 37, the same relative changes (+/- 50%) in profit margin have a smaller impact on the innovation lead, as is shown in Figure 37(a) and (b), where the big swing in profit margin only changes innovation lead and supplier capability by 5% relative to the baseline. A minor impact is expected because the profit-driven innovation loop is weaker than R&D-driven innovation.

Note that the change in supplier's profit has a subtle effect (less than 1%) on OEM's capability development, as shown in Figure 37(c). This behavior is expected due to the innovation lead "complacency" balancing loop (B3) described in Figure 24. When the supplier gains innovation lead through profit-driven innovation, boosted by a higher profit margin, the goal-seeking behavior of loop B3 will incentivize OEM to increase R&D expenses to catch up with the supplier.

6.5.4.3. Supplier Product Importance

The supplier product importance converts both OEM and supplier's innovation capability to product attractiveness. The sensitivity analysis changes supplier product importance from 50% (baseline) to 80% (best case, upper bound) and 20% (worst case, lower bound) to explore the impact of supplier product importance on model outputs. The results are shown in Figure 39.

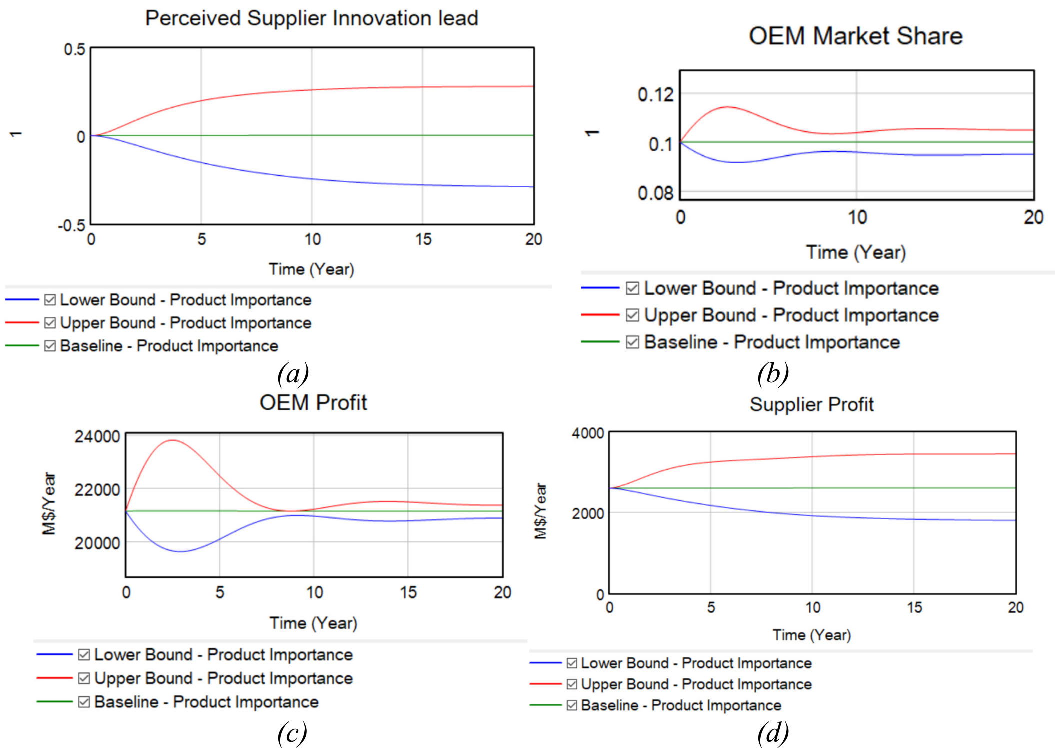


Figure 39 Sensitivity analysis for supplier product importance

Figure 39(a) shows that the 30% change in product importance shifts innovation in the same direction. Suppliers with a higher contribution to the subsystem are easier to lead the innovation in an OEM-supplier relationship. Innovation leadership magnifies supplier profit, as is shown in Figure 39(d).

However, since the OEM is several times bigger than the supplier, the profit loss due to the supplier's innovation lead is less than 0.5%, as shown in Figure 39(c). The OEM's profit is more relevant to market share (Figure 39(b)), which is influenced by the whole product attractiveness. Note that second-order transients could be observed in Figure 39(b) and (c). The transient is caused by the interactions between different first-order perception delays in loops B1, B3, and R4. For example, in the best-case scenario, the increasing supplier importance increases the OEM product attractiveness. This minor change in market competition boosts market share by 1% for the first 3 years. It takes the competitors 3 years to ramp up with the OEM-supplier ecosystem. The long-term equilibrium has less than 0.5% variance compared to the baseline, as is shown in Figure 39(b).

6.5.4.4. Perception Delay

The perception delay senses innovation leadership so the firms can react in time. This sensitivity analysis explores the impact of changes in delay on the model's numerical outputs and behavior modes. The results are presented in Figure 40. The model introduces disturbances by assigning 60% supplier product importance, and the baseline case sets delay as 1 year, with best case (lower bound) 0.1 year and worst case (upper bound) 3 years.

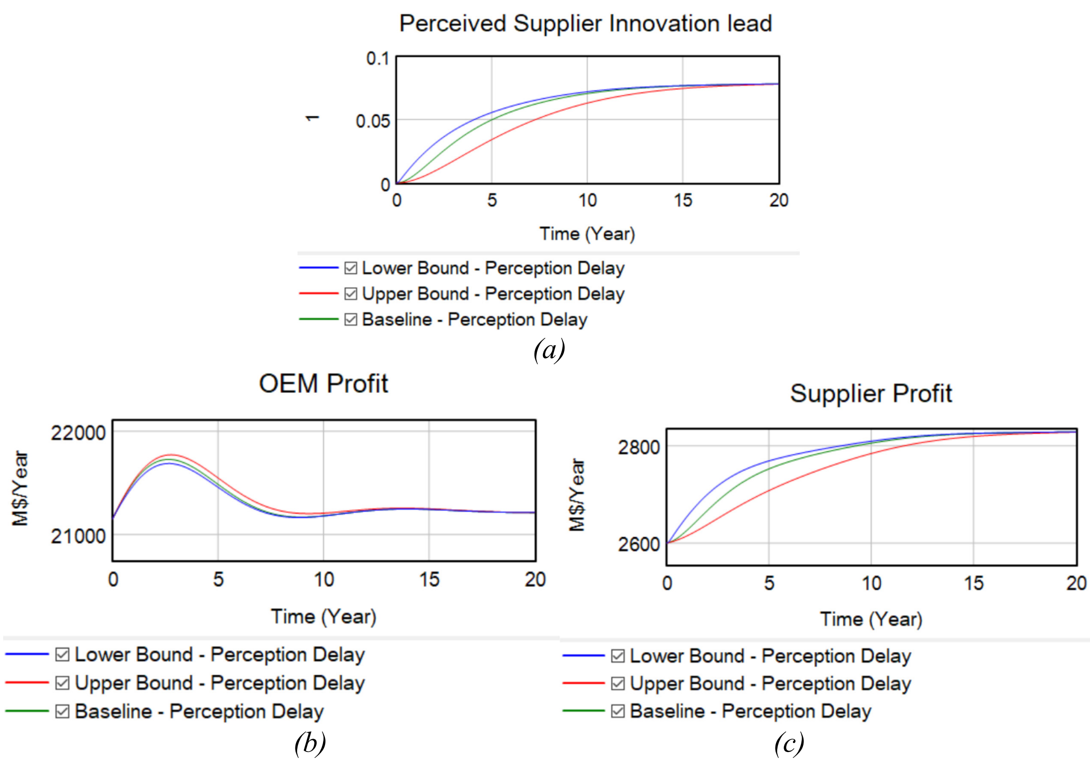


Figure 40 Sensitivity analysis for innovation leadership perception delay

The direct effect of the delay can be observed in Figure 40(a). A longer delay causes a longer ramp-up time for the supplier's innovation lead. This prolonged perception is beneficial to the OEM in the short term. In Figure 40(b), the magnitude of overshoots in OEM profit is higher with longer delays. In Figure 40(c), the supplier accumulates less profit before the system reaches equilibrium.

The numerical value of the perceived innovation lead remains the same regardless of perception delay. Therefore, the numerical value of OEM and supplier profit do not change at the equilibrium. In sum, the change in perception delay has an impact on behavior dynamics but does not change the numerical outputs at the equilibrium.

6.6. Hypothesis verification

This section verifies the hypothesis in Section 3.3 about the impact of competitive and collaborative behaviors on OEM and supplier performance. Based on the baseline model with parameters configured by section 6.4, the author creates multiple market scenarios to verify that the system's dynamic behavior conforms to the hypothesis.

6.6.1. Competitive outcomes in a stable market

In a stable and mature market with stagnant growth, where all OEMs quickly match each other's product attractiveness, it seems easier to compete with the supplier within one OEM-supplier ecosystem than win market share over other competitors in the whole product market.

The model configures the competitors with strong goal-seeking behaviors in the whole product market to keep their existing market shares. Strategic levers on both OEM and supplier sides are used to simulate the competitive behavior. A more competitive behavior has a higher investment in R&D, innovation vehicles, and culture to boost its capability development over the other party in one OEM-supplier relationship. Figure 41 shows the model's response to different competitive behaviors in a stable market. The changes in competitive behaviors are introduced in year 1 in the simulation.

As shown in Figure 41(a), the more competitive party in the relationship takes the superiority in innovation leadership. In Figure 41(c) and (d), the innovation leadership slowly translates into long-term profit gains. As the party (OEM or supplier) becomes strategically competitive at year 1, the innovation lead starts to ramp up around year 3 with a moderate increase in profit. The system reaches equilibrium after year 7.

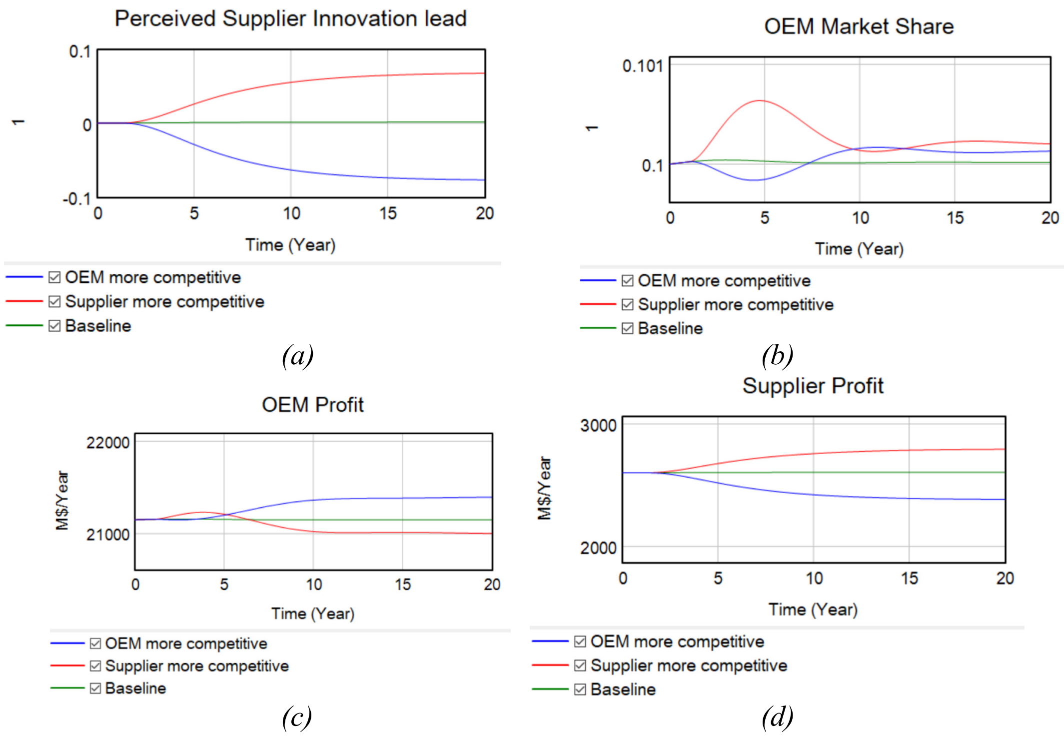


Figure 41 Model response over different competitive behaviors in a stable market

Though the competition hurts the party that loses the innovation lead with lower profit, the OEM product market share does not change much due to the stable market environment where competitors only aim at keeping the existing market share. In this model, since profit-driven innovation is weaker than R&D-driven innovation loops, the increase in product attractiveness from the leading innovation party outweighs the decrease from the lower profit from the loser in the relationship. The weak reinforcing loop increases product attractiveness with a negligible increase in market share in Figure 41(b).

An interesting transient could be observed in Figure 41(c), where a more competitive supplier would initially increase OEM profit, but the equilibrium is lower than the baseline. The lower equilibrium is due to the difference in sensitivity on profit sharing between OEM and supplier. As mentioned in section 6.5.4 and shown in Figure 41(c) and (d), supplier profit (and the profit-driven innovation loop) is more sensitive to changes in innovation lead. In contrast, OEM profit is more sensitive to market share because the scale of OEM is several times bigger than the supplier. The different sources of sensitivity mean the supplier can quickly convert innovation leads to market leadership, which indirectly benefits OEM at the beginning of the strategic transition. However, as will be verified in the next section, this small win will diminish if the competitive behaviors persist.

In sum, the model demonstrates how competitive behaviors generate long-term benefit (profit) in a stable market to verify hypothesis H3.1.

6.6.2. Collaborative and competitive outcomes in a highly competitive market

The previous verification of competitive behavior appears trivial because competitors have little market pressure. Competition within the OEM-supplier relationship becomes the dominant factor affecting long-term performance. What should companies do when both collaboration and competition are viable options? This subsection verifies competitive and collaborative outcomes in a highly competitive market.

Figure 42 shows different model responses over a sudden drop in market share with collaborative and competitive behaviors. In the simulation, competitors increase their product attractiveness with disruptive innovations in year 1, causing the OEM's market share to drop. Though the goal-seeking behaviors in the balancing loops reactively boost innovation spending to regain the market share over time, both OEM and its supplier can adopt different innovation strategies to accelerate this process.

As shown in Figure 42(a), the baseline case or "doing nothing" has the slowest recovery performance, lagging the best case "more collaborative" by 4 years. The more collaborative the ecosystem is, the faster market share recovery. The timeliness of recovery also comes with a price tag – slower recovery causes the OEM-supplier ecosystem to lose more market share in the equilibrium by 0.2%.

The impact of collaboration and competition on innovation leadership in the relationship can be observed in Figure 42(b). The collaboration creates a subtle disturbance to the innovation lead in the relationship but is not significant enough to cause large swings in the supplier's profit. Therefore, compared to "doing nothing", collaborative behavior is beneficial for the OEM-supplier ecosystem in the long run. Note that in Figure 42(d), a collaborative relationship keeps the leadership balance around the index "0".

Instead of collaborating with the supplier to boost innovation development capability without enlarging the innovation gap within the ecosystem, the OEM could respond to the market dynamics by competing with the supplier. Since the OEM has better sensing of the whole product market's dynamics than the supplier, it can use information arbitrage to gain a competitive advantage.

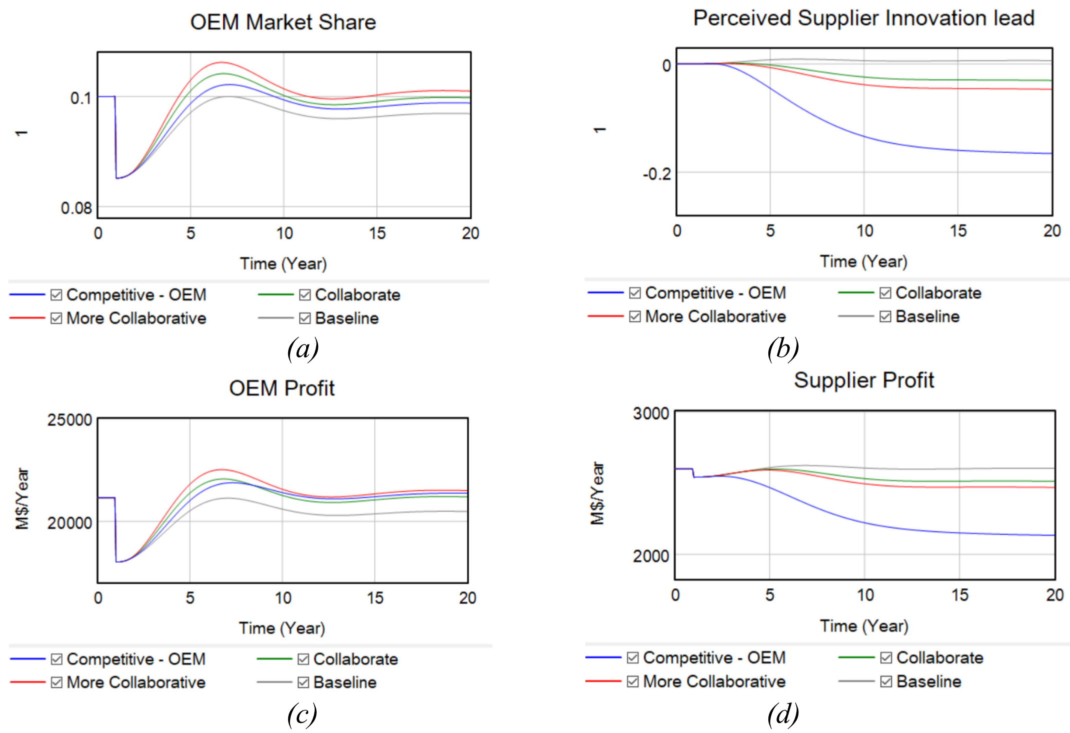


Figure 42 Model response over a sudden drop in market share

Even though it creates a noticeable innovation gap with the relationship, as shown in Figure 42(b), the OEM's competitive behavior could still accelerate the market share recovery but only better than the "doing nothing" option, as shown in Figure 42(a). The OEM's competitive behavior would benefit itself much more than the supplier. In Figure 42(c), competition helps OEM long-term profit estimation surpass the "collaborative" case. However, competition behavior drives OEM's market recovery at the cost of supplier's sustainable development. Figure 42(d) shows that the innovation gap causes the supplier to lose 20% profit over the recovery period. Though the model only describes innovation dynamics in the supplier and does not cover the operation of a company, it is reasonable to project that the competitive behavior of OEM accelerates the "death spiral" on the supplier side. The supplier's financial standing and innovation capability are likely to deteriorate further than stay at the new equilibrium for reasons not captured by this model.

Figure 43 shows different model responses in a highly competitive market with collaborative and competitive behaviors. The OEM-supplier ecosystem starts with a "losing battle" because competitors have faster innovation development (and product attractiveness) in the simulation. The declining market share causes OEM and its supplier to lose revenue, profit, R&D investment, and innovation capability over time, a typical death spiral. Both parties could adopt a new strategy (collaborate or compete) to get out of this death spiral at year 1 in the simulation.

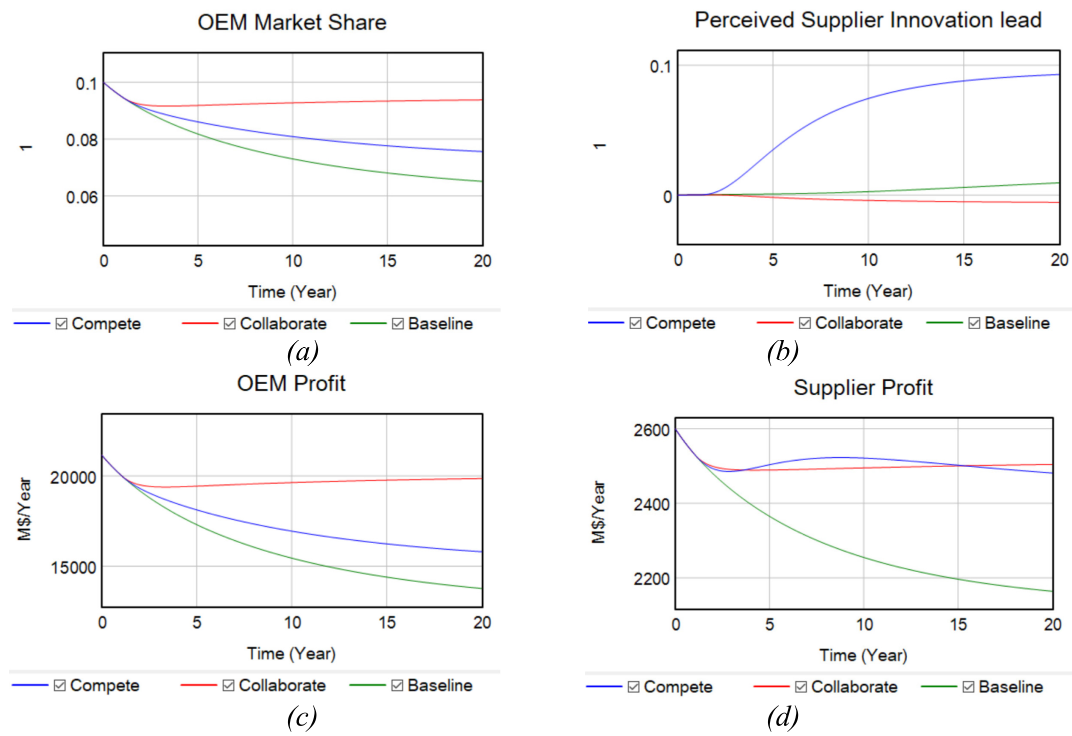


Figure 43 Model response in a highly competitive market

Though "doing nothing" is an option (baseline), the OEM-supplier ecosystem will lose more than a third of the market share over the simulation length, as shown in Figure 43(a). By collaborating to boost product attractiveness without creating a large innovation cap within the ecosystem, the agile response to the market pressure rewards the OEM and supplier with moderate recovery before year 5. As shown in Figure 43(c) and (d), though the ecosystem has not fully regained the lost market share within the simulation time frame, both parties are on track to full recovery.

Competitive behavior could also boost product attractiveness. As shown in Figure 43(d), a supplier's competitive behavior boosts its profit in the short- to medium-term and even causes a temporary year-over-year increase in profit (also known as a turnaround) before year 5. However, since the innovation development premium from the supplier’s competitiveness could not boost the product attractiveness fast enough to catch up with the competitors, the OEM-supplier ecosystem continues to lose market share at a slower rate, as shown in Figure 43(a). The losing market share hurts the supplier in the long run despite the short-term turnaround. In Figure 43(d), the supplier's profit decreases after year 8 and is lower than the “collaborate” case at the end of simulation time.

In sum, the model demonstrates how competitive and collaborative behaviors help a firm sustain system-level success in a highly competitive market to verify hypotheses H3.2 and H4. Both competition and collaboration help the OEM and supplier improve the ecosystem’s overall long-term performance, and collaboration is a more supplier-friendly option in a highly competitive market. Competitive behavior only temporarily boosts one party’s performance but hurts the ecosystem in the long run.

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Chapter 7

Model validation

This chapter compares empirical data and model simulation results to validate the model's ability to reproduce past events. The purpose of validation is to highlight the strength and weaknesses of this model using empirical data, evaluate its usefulness, and look for areas of improvement.

Two OEM-supplier relationships are presented for the validation process. The first validation case is about the decline of General Motors ("GM") and Delphi Corporation ("Delphi") from 1996-to 2009. The second validation case is the sustaining success of Stellantis and ZF Friedrichshafen AG ("ZF").

The general validation process configures the model's exogenous variables using empirical data, then tunes endogenous variables to make the firm's profit outputs fit the data. R^2 is used to evaluate behavior reproducibility and to support validation evaluation.

Note that the model's ability to fit the data is only one metric from the validation steps. The model's usefulness is evaluated on verification results from Chapter 6 reproducibility in this chapter.

7.1. Validation case 1: GM and Delphi

The first case is a typical situation described by the model developed in this thesis, focusing on a one-to-one relationship between the OEM and its supplier. The study period is between 1996, when Delphi's public financial record became available, to 2009, when Delphi exited bankruptcy while GM filed for bankruptcy.

The relationship between GM and Delphi is simple: Delphi became a GM spin-off in 1999 and depended heavily on GM throughout the case study period. According to Delphi's annual report in 2009, sales to Ford Motor Company and the Volkswagen Group were approximately 6% and 5% of total sales in 2008, respectively. The simple relationship between a dominating OEM and the captured Tier-1 supplier helps the validation focus on major loops covering innovation dynamics between the two parties without relying heavily on exogenous variables.

7.1.1. Overview of the empirical behavior

Figure 44 gives an overview of GM and Delphi's change in revenue and OEM's market share over the 1996-2009 study period. The US market size (purple dashed line) is the market reference. Figure 45 shows the changes in gross margin.

As shown in the figure, before 2004, GM's revenue reflects the whole market trend with moderate growth, though both GM's market share and gross margin are in steady decline. With the help of "turnaround" efforts in 2005-2006, GM saw an increase in revenue and profit, followed by plunging revenue and profit until it filed for bankruptcy in 2009.

Because GM is Delphi's biggest customer and source of revenue, the two figures show Delphi's revenue and gross profit changes are highly correlated to GM's performance. However, Delphi entered bankruptcy in 2005 and emerged from Chapter 11 in 2009.

This validation case tests model's ability to reproduce the innovation dynamics between a struggling OEM and a captured tier-1 supplier.

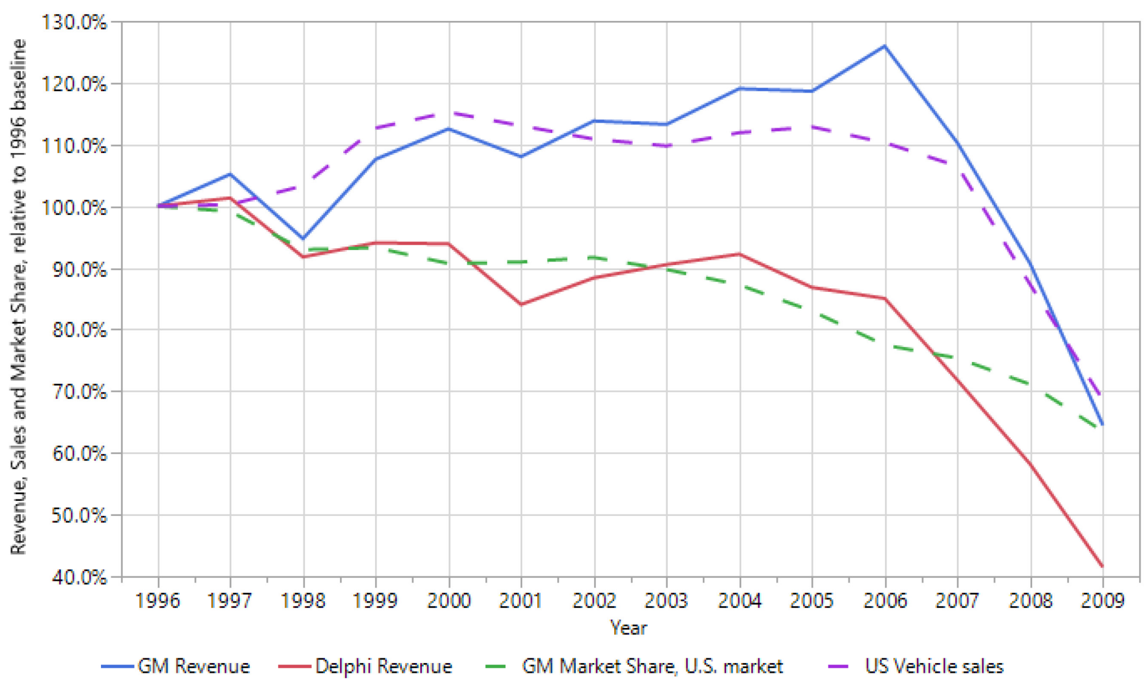


Figure 44 GM and Delphi's revenue, market share, and US market size, 1996-2009 % of 1996 baseline

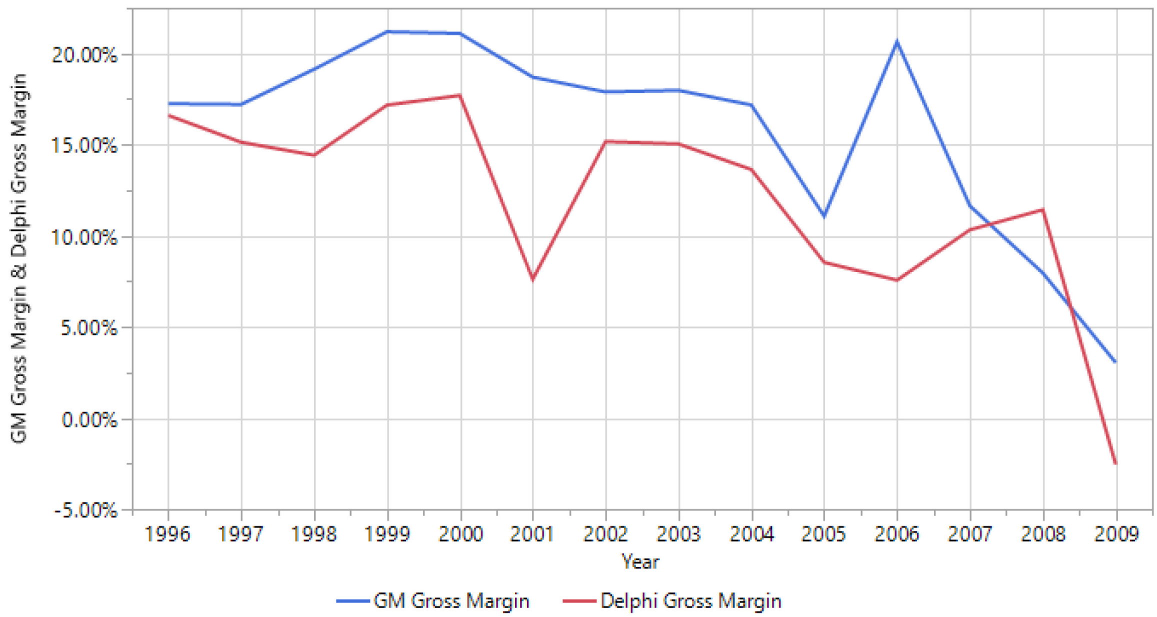
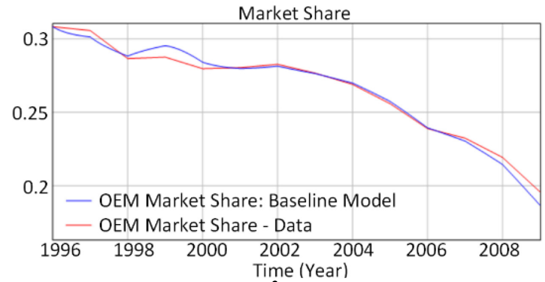


Figure 45 GM and Delphi's gross margin, 1996-2009

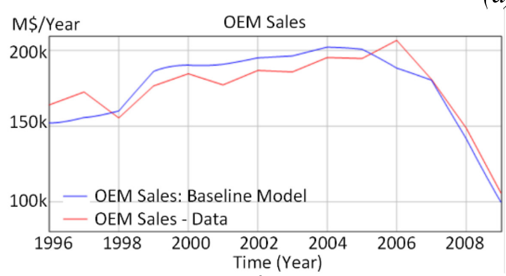
7.1.2. Validation Results

Validation starts with the baseline model proposed in Chapter 6, with additional exogenous data (market size, macroeconomic data, and homogenous competitor behaviors) applied to the baseline model. The comparison of performance outputs between the baseline model and the empirical data is shown in Figure 46.

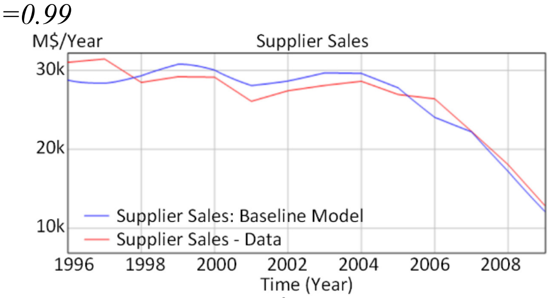
In the baseline model, the exogenous inputs help on a close track of market share and sales in Figure 46(a) to (c), but have poor results in profit (d)-(g). The endogenous variables are set to constants (indexed as "1") without further tuning. Figure 46(g) demonstrates the baseline model's underlying behavior: keeping a balanced relationship between the OEM and its supplier with indexed strategic and cultural variables and the resulted near-constant profit margin.



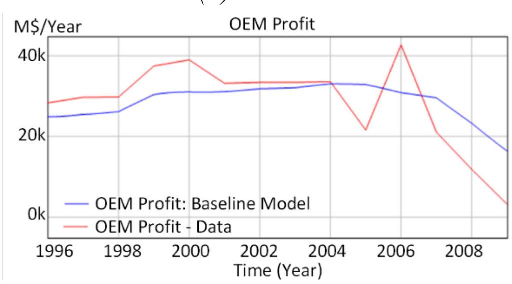
(a) R^2=0.99



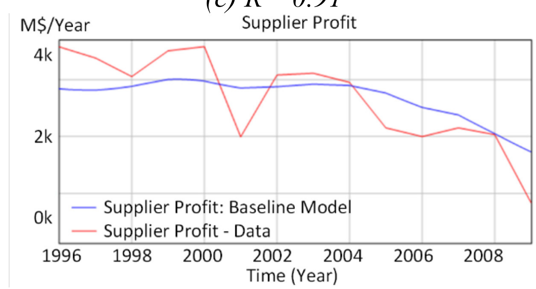
(b) R^2=0.87



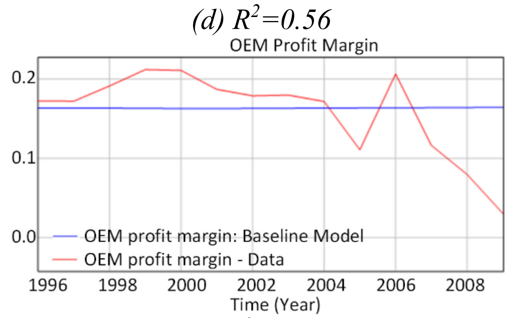
(c) R^2=0.91



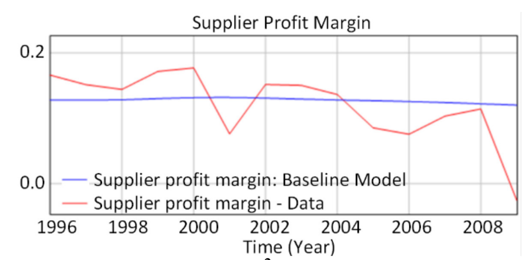
(d) R^2=0.56



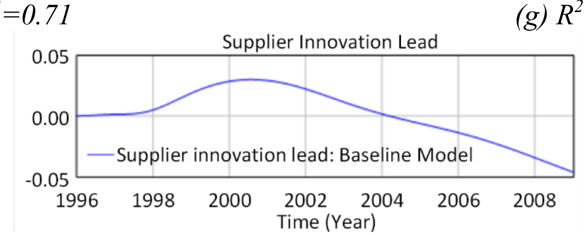
(e) R^2=0.70



(f) R^2=0.71

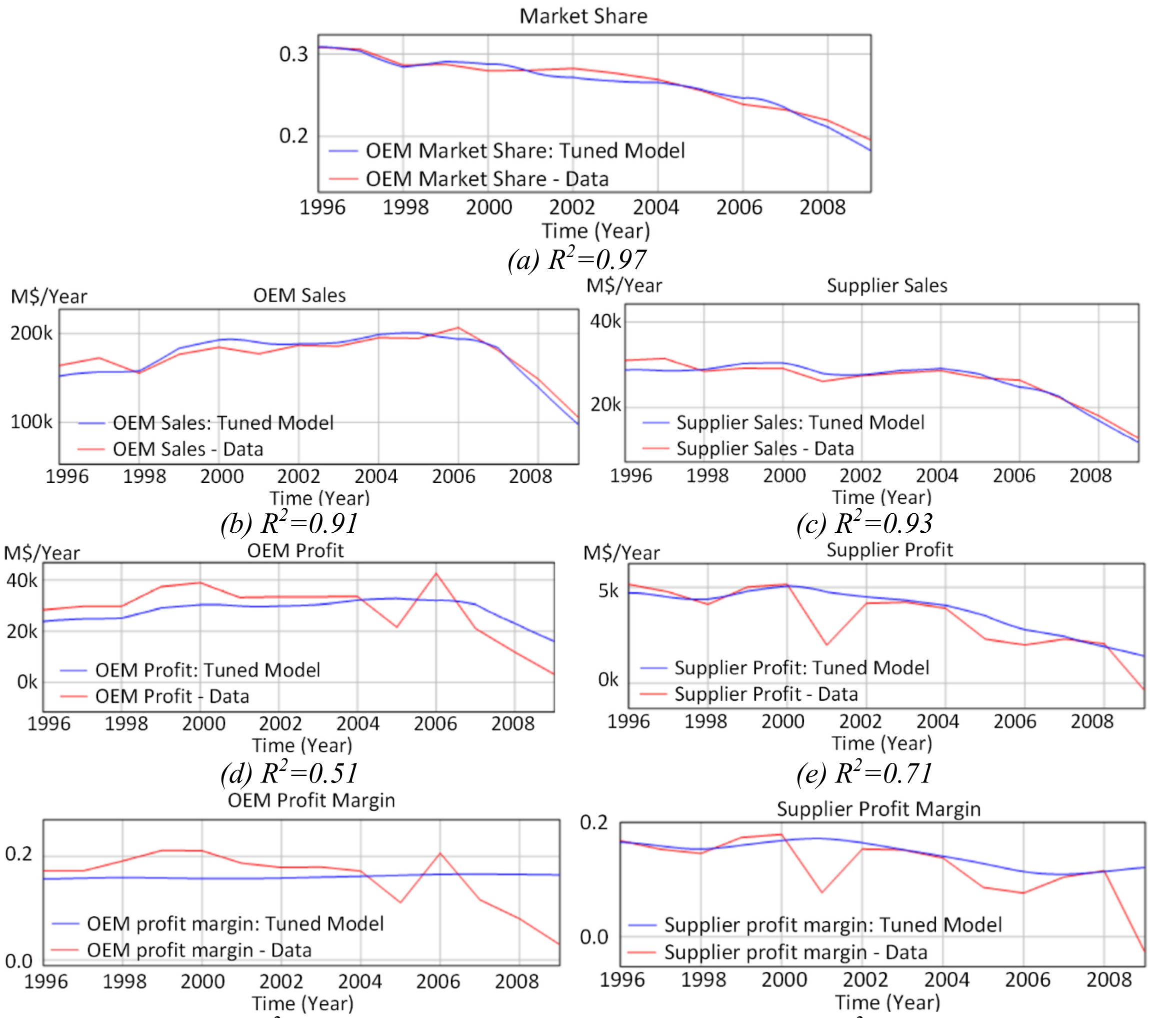


(g) R^2=0.45



(h)

Figure 46 GM-Delphi Baseline model validation results vs. empirical data, 1996-2009



(a) R^2=0.97

(b) R^2=0.91 *(c) R^2=0.93*

(d) R^2=0.51 *(e) R^2=0.71*

(f) R^2=0.42 *(g) R^2=0.35*

Figure 47 GM-Delphi tuned model validation results vs. empirical data, 1996-2009

The results from the tuned model, with soft data inferred from empirical study, are shown in Figure 47. On the market side, the tuned model has a similar R^2 compared to the baseline. There are minor changes to sales and negligible improvements to profit and profit margin on the OEM side. The supplier side has improvements: sales, profit, and profit margin receive a slight boost in R^2 but better fit at years except for 2001 and 2005-2006. In sum, the model does a better job reproducing supplier behavior than the OEM or market competitors.

Figure 48 helps explain the difference between the baseline and tuned model. The OEM and its supplier maintain a constant strategy and innovation culture to simulate the "do nothing" scenario in the baseline model. In the tuned model, variation of the key ratios interfacing different loops in the model illustrate how endogenous variables improve the behavior reproducibility of the model.

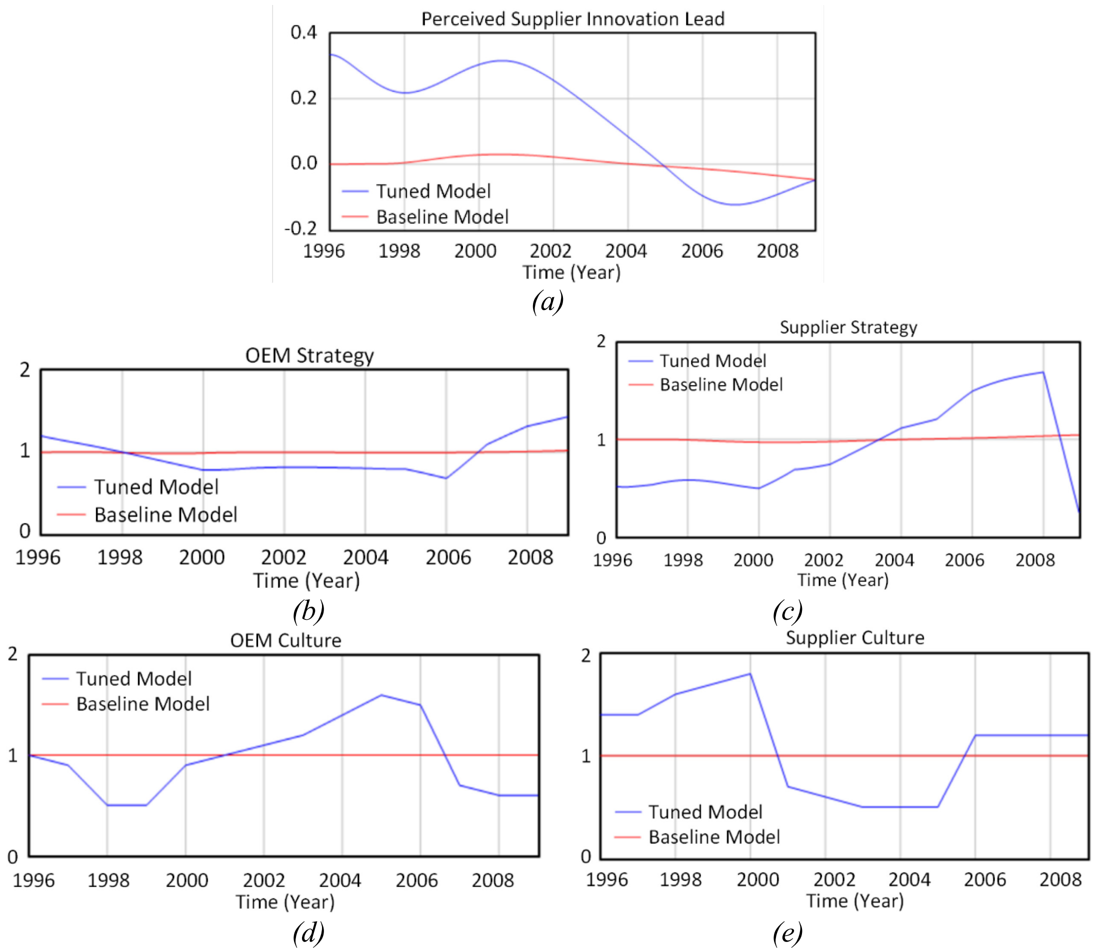


Figure 48 Comparison between Baseline and Tuned model

The tuned time-series data in Figure 48 (cultural and strategic ratios) reveal the innovation dynamics between GM and Delphi and the impact on the two firms' performance. At the beginning of the split, Delphi enjoyed an innovation lead shown in Figure 48(a) with steady sales with GM (Figure 47(c)), which boosted its profit margin between 1996-and 2002. As GM's market share growth started to slow down, the OEM ramped up capability development to narrow the innovation gap with the supplier, as shown in Figure 48(b) and (d). In response to the pressure, the supplier resorts to a more competitive innovation strategy in Figure 48(c) and (e). But the supplier's effort was offset by declining sales to the OEM, as shown in Figure 47(c). The competition between GM and its competitors and GM and Delphi accelerated the decline of the GM-Delphi ecosystem between 2003-and 2006. Eventually, the two parties collaborated with balanced innovation leadership in

2007-2009, as shown in Figure 48(a). But the effort could not invert the financial crisis of 2007-2008. Though a glimpse of Figure 48 illustrates how the tuned model elicits managerial implications, the validation with the GM-Delphi case points out the model's drawbacks and areas of improvement.

On the supplier side, the model could reproduce slow variances over the years via curve fitting but could not capture sharp drops in profit and profit margin in 2001 and 2005-2006, as shown in Figure 47(e) and (f). This validates the verification assessment in Section 6.5.1 about the model's limitation in cost structure modeling of this model. The assumption of the sales-to-profit ratio can capture dynamics at a time scale similar to innovations but not unexpected events or significant changes in the cost structure. On the OEM and market side, the dynamics have a negligible effect on OEM's profit margin, indicating that the source of changes is not covered by the model's exogenous and endogenous variables. The missing variables include other revenue sources, not from one supplier, heterogeneity of market competitors, and the interaction between cost structure and the market. The uncovered market dynamics limit the model's application to profit/loss within an OEM-supplier business relationship, not the whole OEM system described by the model.

7.2. Validation case 2: Stellantis and ZF

The second validation case focuses on two successful companies: Stellantis and ZF. The two firms' scale, product line, and relationship are more complex than the previous case.

Both Stellantis and ZF have a strong presence in the North American and European markets. Unlike Delphi relying heavily on GM, ZF has a diversified customer base in premium, mass-produced and commercial vehicle OEMs. Though the previous case reveals the model's weakness in the multi-to-multi OEM-supplier relationship, the Stellantis-ZF case further validates the model's performance in a weakly-coupled relationship.

The empirical study in Section 5.5 shows the success of the collaboration between Stellantis and ZF: diffusion of HST in the US mass-produced light-vehicle market. Stellantis first introduced ZF's 8-speed HST to its Chrysler 300 series in 2011, followed by ZF's 9-speed HST at the debut of Jeep Cherokee in the 2014 model year. The performance of the HST feature boosted Stellantis' strong recovery after the 2007-2008 financial crisis, despite the quality issues. The study period is 2005-2019, covering the whole diffusion cycle of HST.

7.2.1. Overview of empirical behavior

Figure 49 shows an overview of Stellantis and ZF's change in revenue and OEM's market share over the 2005-2019 study period. The US market size (purple dashed line) is the market reference. Figure 50 shows the changes in gross margin. Both firms were hit but avoided sustaining decline during the 2007-2008 financial crisis. Though the US sales of vehicles slowly recovered to the 2005 level in 2019, both firms demonstrated strong growth in revenue during the study period. Stellantis grew by more than twice, and ZF's revenue tripled over 15 years, as shown in Figure 49.

Figure 49 shows two rapid growths of ZF's revenue, between 2010-2013 and 2014-2018, to which HST partially contributed. As mentioned in the previous section, Stellantis led the diffusion of HST in the early 2010s with ZF's 8-speed products. And nearly all Stellantis models' HST feature was supplied by ZF even in 2021. ZF's innovation in HST attracted other mass-produced OEMs other than Stellantis. Honda introduced ZF's 9-speed HST in its 2014 CR-V model and remained heavily relying on ZF as its HST supplier, even after Honda's in-house 10-speed HST emerged in 2019.

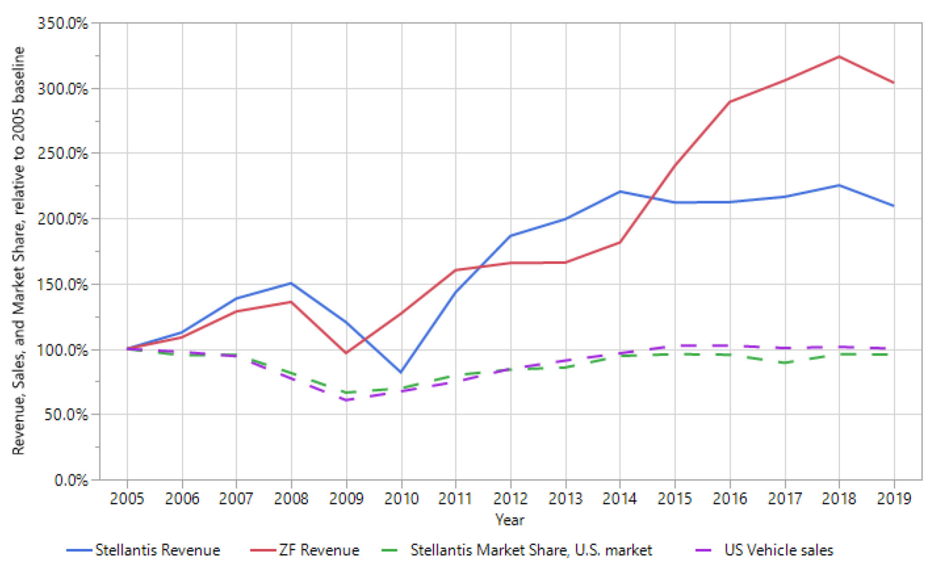


Figure 49 Stellantis and ZF's revenue, market share and US market size, 2005-2019 % of 2005 baseline

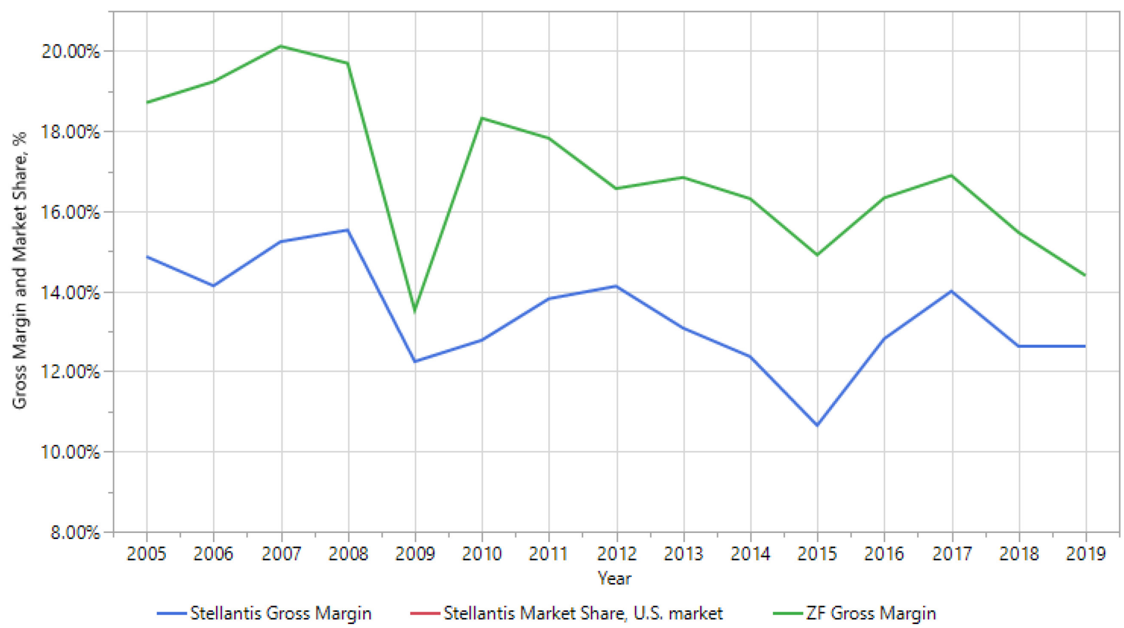
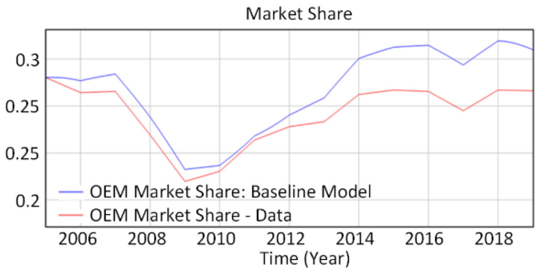


Figure 50 Stellantis and ZF's gross margin, 2005-2019

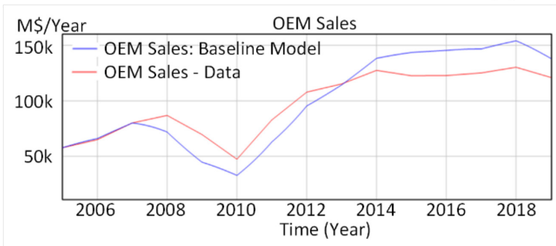
7.2.2. Validation Results

Following the same process mentioned in the GM-Delphi case, the comparison of performance outputs between the baseline model and the empirical data is shown in Figure 51. A similar model reproducibility level could be observed compared to Figure 46. Exogenous variables configured by empirical data with uncalibrated endogenous variables lead to a "doing nothing" behavior in the OEM-supplier relationship, as shown in the negligible changes in innovation leadership in Figure 51(h). Also, reproducibility for market and OEM sales is not as good as in previous cases.

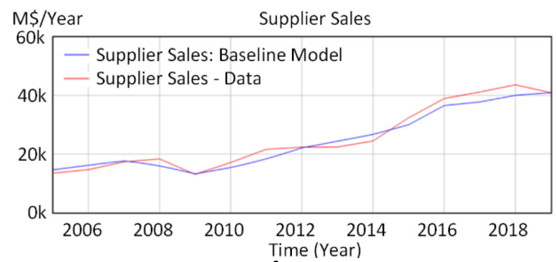
The results from the tuned model, with soft data inferred from empirical study, are shown in Figure 52. Similar behavior changes could be observed compared to the GM-Delphi case: improvements in reproducibility on the supplier side. However, the improvements via curve-fitting merely capture the long-term or slow dynamics in supplier profit margin, leaving large prediction errors in OEM performance and supplier sales unexplained by the model. The poor reproducibility exposes more modeling inadequacy when the business of OEM and supplier are weakly coupled.



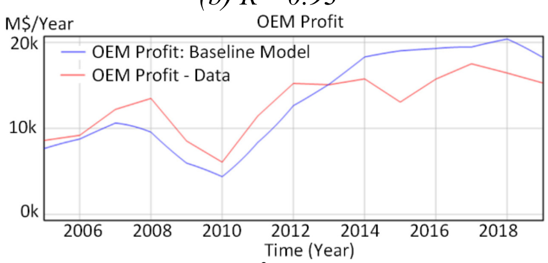
(a) R^2=0.87



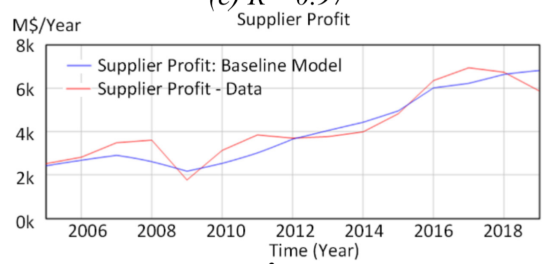
(b) R^2=0.93



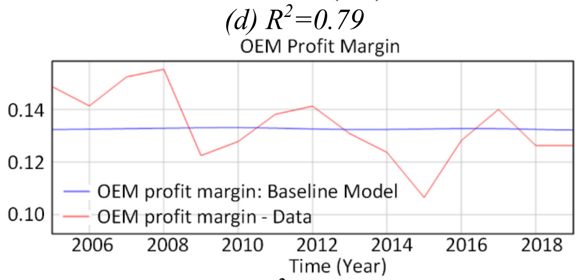
(c) R^2=0.97



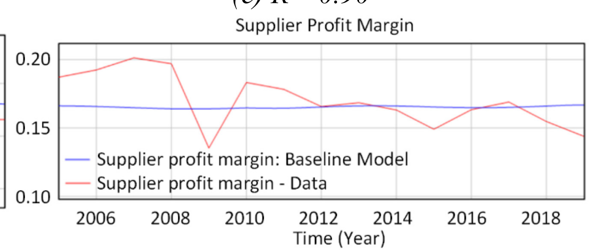
(d) R^2=0.79



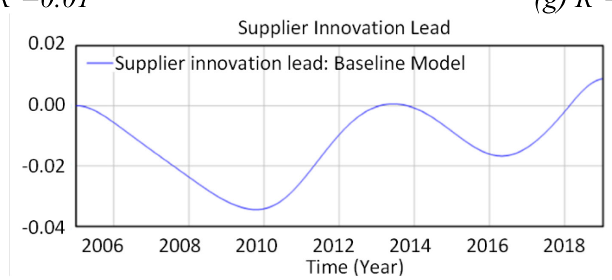
(e) R^2=0.90



(f) R^2=0.01

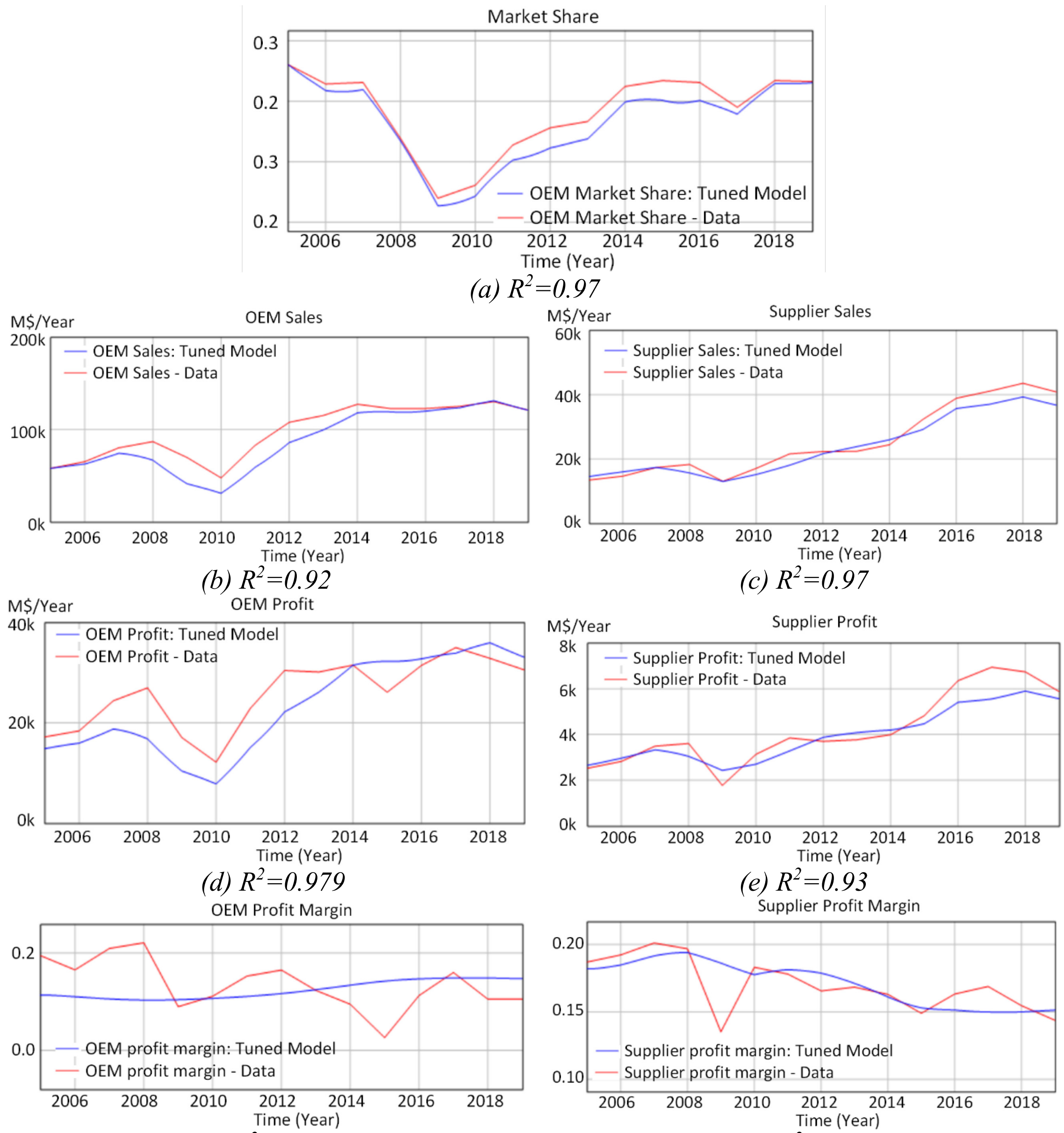


(g) R^2=0.05



(h)

Figure 51 Stellantis-ZF Baseline model validation results vs. empirical data, 2005-2019



(a) R^2=0.97

(b) R^2=0.92 *(c) R^2=0.97*

(d) R^2=0.979 *(e) R^2=0.93*

(f) R^2=0.28 *(g) R^2=0.38*

Figure 52 Stellantis-ZF tuned model validation results vs. empirical data, 2005-2019

Figure 53 shows the comparison of key strategic and cultural variables in both the baseline and tuned models to examine the quality of the reproduced behavior further. In contrast to Stellantis' heavy reliance on ZF for the HST feature in the empirical study, Figure 53(a) shows how innovation leadership shifted from the supplier to OEM. The fitted cultural and strategic variables in Figure 53(c) and (e) also show the simulated trends that are contradictory to the empirical data – ZFs' investment and morale are both low during its fastest revenue growth period over Stellantis.

It is possible that the OEM introduces an important feature like HST with a tier-1 supplier, learns from collaboration with the supplier, and eventually “captures” the supplier with more superior product knowledge in the corresponding subsystem. For example, GM installed Aisin’s 8-speed HST in its 2014 Cadillac models, starting the diffusion of HST in GM’s models. Later GM developed its in-house 8-speed HST and worked with Ford on the Ford-GM 10-speed HST. Honda shares a similar but more recent story with ZF mentioned at the beginning of this case study. On the contrary, Stellantis has the tradition of “outsourcing components as substantially as possible” mentioned by (Nishiguchi, 1987) and has not developed any in-house HST as of the model year 2021, even though the OEM leads other OEMs in HST diffusion. In sum, empirical study shows the supplier ZF captures its OEM Stellantis, not the other way around.

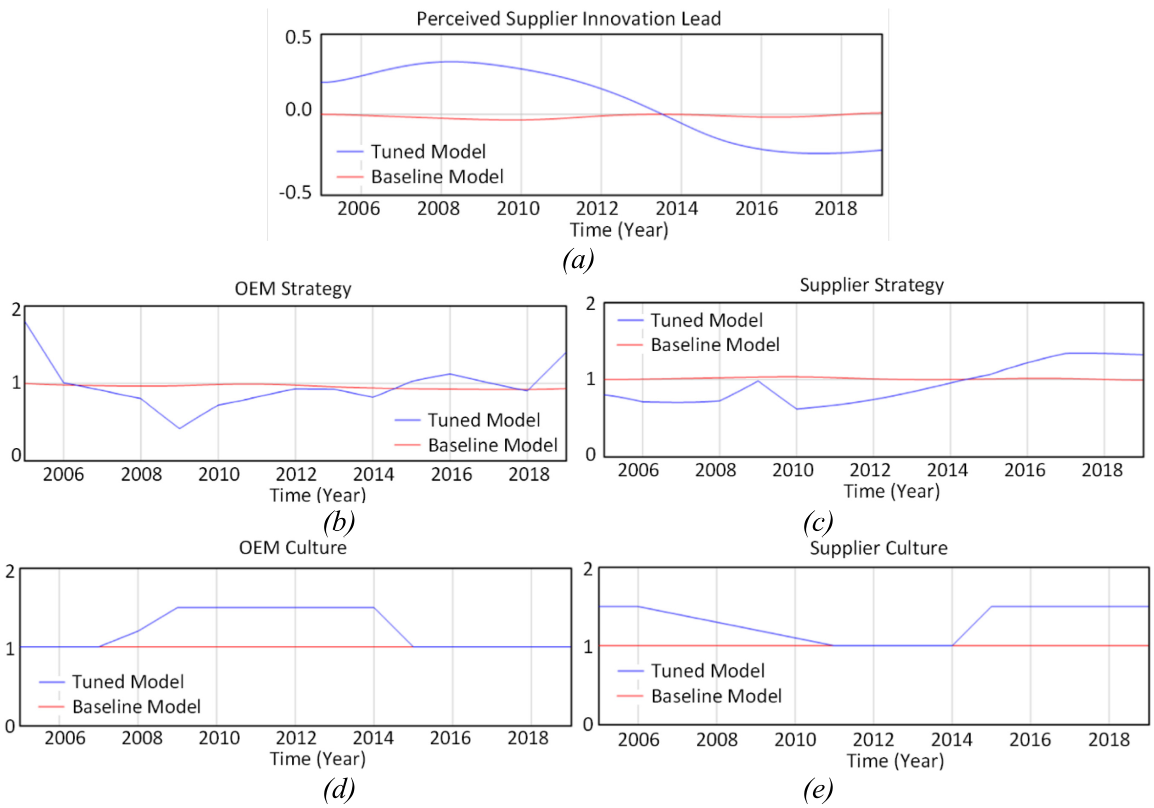


Figure 53 Comparison between Baseline and Tuned model

The contrast in storytelling between the tuned model and empirical study indicates that the model could numerically reproduce the empirical behavior with an inadequate structure. Without further information on sales and cost structure, the model naively attributes variations in sales and profit to the single relationship between Stellantis and ZF, leading to “good” curve fits but incorrect managerial implications. The validation of the Stellantis-

ZF case further highlights the model's weakness in the dynamics of a weakly-coupled relationship with diversified revenue sources.

7.3. Conclusion on model usefulness

Following the famous quotation, "All models are wrong, but some are useful" (Box, 1976), the validation process uses the GM-Delphi and Stellantis-ZF cases to illustrate the usefulness of this model. The outcome estimation is most accurate at the behavior level when predicting supplier revenue and profit dynamics related to innovation. At the firm level, the model performs best when the supplier has heavy dependence on the OEM.

Due to the structural inadequacy inherited from decisions in the level of aggregation when building the model, the prediction performance deteriorates when a firm's revenue source becomes more diversified. This leads to poor prediction on OEMs and suppliers who work with multiple tier-1 suppliers or other OEMs to build the whole product.

7.4. Summary of hypothesis testing

This section reviews the research question from Section 3.3 and the verification and validation results from Chapters 6 and 7. The model validates the hypotheses when the OEM's business is strongly coupled with the supplier. The model needs structural improvements to deliver validation results for relationships with weakly coupled parties.

7.4.1. A model with non-subjective data inputs

As discussed in Chapter 3, the key research question and prerequisite for the modeling effort is to validate if the model could deliver accurate predictions about innovation dynamics using non-subjective data. These publicly available data include financial data from public databases, supply chain data about trading between companies, and product data about feature diffusion and lifecycles.

As validated in Chapter 7, especially in the GM-Delphi case, the model and empirical data match each other in reproducing Delphi's revenue and profit outcome. However, the prediction accuracy is lower in market competition and OEM's revenue and profit due to inadequate model structure to capture firms' diversified revenue sources.

The model can offer more accurate predictions if the user enhances it with confidential data sources to improve structures of cost/profit, budgeting, and soft variables.

7.4.2. System thinking and model usefulness

Promoting "system thinking" is one of the key motivations driving the modeling process in this work. As explained in Sections 6.1 and 6.2, the supplier and OEM loops have equal weight in the modeling process to ensure the balance of modeling efforts. The verification and validation processes in Chapters 6 and 7 also address this balance.

Since the model offers an equally detailed description of dynamics inside and between OEM, supplier, and the whole product market, the model users (usually business managers of either the OEM or supplier) can see the "big picture" when designing strategic moves. SD's Stock-flow and causal loop diagrams enhance the model's readability and chances of management buying-ins.

Therefore, it is reasonable to believe the model has better usefulness via promoting system thinking to the model consumers than previous work using statistical methods.

7.4.3. Competitive and collaborative outcomes

Competition and collaboration help the OEM and supplier improve the ecosystem's overall long-term performance, but their effectiveness is different based on the market's competitiveness.

As verified in Section 6.6 and validated in Section 7.1.2 (GM-Delphi case), when market share is under pressure in a highly competitive environment, both parties improve performance through more collaborative behaviors to boost the whole product attractiveness to better compete in the market. Competitive behavior only temporarily boosts one party's performance but hurts the ecosystem in the long run.

Though verified in Section 6.6 but not fully validated in Section 7.2.2 (Stellantis-ZF case) due to the model's structural inadequacy, the more competitive firm has a better long-term performance in a relationship when the whole product market is stable.

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Chapter 8
Conclusion

8.1. Managerial implication

As explained in Sections 1.2 and 3.2, the motivation for this thesis work is to explore tools to provide managerial implications to help firms in an OEM-supplier relationship improve performance. Chapters 6 and 7 have detailed discussions on the innovation dynamics under various scenarios, and this section distills the findings into the following two subsections.

8.1.1. The balance between competition and collaboration

Both competitive and collaborative behaviors could increase a firm's innovative capability and financial performance in a relationship. The long-term impact of these behaviors on the whole product competitiveness depends on market competition. Therefore, OEMs and suppliers should keep the balance between competition and collaboration with each other over time to keep both satisfying short-term and long-term performance. When facing steep competition from other OEMs, the OEM and its supplier should prioritize collaboration over the competition to win over market share in the whole product market. In particular, OEMs should help their suppliers to develop a capability to become independent with diversified revenue sources. This helps build the resilience of the ecosystem during economic downturns.

8.1.2. Patience in innovation outcomes

While firms report their financial performance following the standard quarterly reporting cycles, innovation outcomes are not compatible with the financial reporting cycle. As validated by the empirical study, a new feature takes around 10 years to capture 50% of market diffusion, not to mention years of development before reaching a high enough TRL for production. Model simulation results also show that strategic changes in innovation take years to generate considerable financial rewards. Firms need to develop patience for their investments in innovation and offer continuous support to innovation for long-term growth.

8.2. Insights on modeling and data collection

One of the contributions of this thesis work is the synergy of SD modeling and empirical study during hypothesis verification and validation. This section contains the author's retrospective on modeling and data collection processes over this thesis journey.

8.2.1. Iterations in modeling and data collection

The research process from Section 4.4 and the data collection process in Section 5.5.3 are similar to a traditional "waterfall" in product development. One step builds upon the previous step, and everything proceeds as expected. The "go-back" paths in Figure 9 seem to be trivial and not needed.

In reality, the iterations play a vital role in model building and data collection. At the beginning of the modeling, the author faced a classic "chicken and egg problem" – without data, the model cannot be built and tested; Without a working model, there is no specification for data collection. Eventually, the author decomposed the big model, created prototypes for each sub-model, and used iterations to collect data and build the model. Iterations served as a time saver allowing the author to make mistakes and self-correction.

Iterations also worked well for "who supplies whom" data during the data collection process. Unlike financial data such as profit or P/E ratio, the supply chain data is considered business confidential, and no public databases offer the data with the granularity required by the model. Therefore, the author had to gather information from various data sources, convert non-standard data input to a local database, synthesize the information and enter each entry by hand. An incomplete specification in data collection means that the author has to repeat the collection process, which is time-consuming and discouraging. The iterations in modeling started with small batches of data that were easy to collect while validating the specifications for data collection for each iteration.

8.2.2. Importance of scientific research method

As an engineer and a student in an engineering school, the author always tends to "get hands dirty" by diving into the modeling before defining the research method. This thesis journey followed the scientific research method by clarifying the motivation and research question before moving forward. The clarification exercise helped the author define what to solve and ignore in the modeling stage.

Since the SD method makes assumptions on both the fundamental structure and model parameters, rigorous verification and validation steps are needed to ensure the model is useful. The author followed steps in (Sterman, 2000) to perform tests on system boundary, structure, extreme conditions, sensitivity analysis, and reproducibility to gain enough confidence in the model. Each step pointed out model drawbacks that were either fixed or noted as limitations.

The scientific process in this thesis journey seems tedious and slows down the whole process. Still, it helped the author avoid unnecessary iterations and eventually build a model with high confidence. As the authors mentioned in (Sterman, 2018), we should stick to the scientific method because it is the most efficient way to generate correct results.

8.3. Limitations of the Proposed Model

The current model has the following limitations, which lower the confidence of the model application:

- Inadequate modeling of exogenous sources that affect profit and revenue: the model can model innovation dynamics related to two parties inside the relationship (endogenous variable) with high confidence. This makes the model not work well when both parties' dominant source of disturbances is outside the relationship.
- Too simple cost structure: the current model assumes a conversion ratio between revenue, profit, and R&D budget. As validated by the empirical study, such a structure could accurately capture dynamics at a time scale that is similar to the innovation life cycle. However, this simple ratio-based structure could not capture disturbances from exogenous sources such as tactical moves from short-term "turnaround" efforts. The model should decompose the cost and profit structure to

enable exogenous inputs to improve the model performance. This improvement does not convert a problem-solving model into a model that attempts to model the whole system but adds interfaces to extra exogenous inputs to expand application and performance.

- Heavy reliance on empirical data on market dynamics: as verified in Section 6.4.2, the model uses a simple but accurate model to describe single feature diffusion in the whole product market. However, the actual competition contains a mixture of new and existing features, which lowers the confidence level of the model. This limitation comes from the assumption that the competitors in the rest of the product market can be treated as homogenous entities. An improved model should capture the heterogeneous nature of competitors to increase confidence levels.
- Lack of tools and standards to evaluate model accuracy and compare different modeling methods. Discussions in Chapters 6 and 7 benchmarks the model's accuracy against empirical data but cannot generate a quantitative horizontal comparison between different methods. Therefore, the tools and methods used in this work do not deliver a performance comparison between the proposed model and previous works with a high confidence level.

8.4. Future Work: Hybrid ABM and SD Modeling

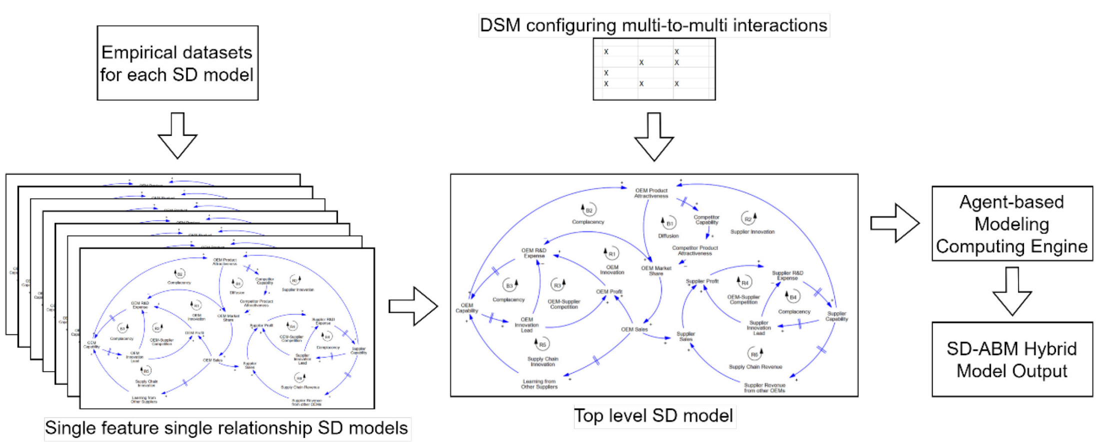

Figure 54 A hybrid SD-ABM model for the multi-to-multi relationship

The model proposed by this thesis has good performance explaining innovation dynamics with endogenous variables when focusing on a single feature and one-to-one relationship but does not perform as great when more complex relationships or exogenous variables are present. If the structural improvements mentioned in the previous section are made, the improved model could serve as a basic building block to describe a more complex system, as shown in Figure 54.

In the figure, the single-feature-single-relationship SD models ("building blocks") offer high-quality predictions with empirical data. The outputs of one building block serve as inputs of exogenous variables in other building blocks. And a top-level SD model uses a DSM to manage the interactions between subsystem-level interactions, integrating building blocks to the complete model. The ABM engine could simulate the whole model with its distributed and heterogeneous nature, generating the final output.

This hybrid SD-ABM model combines the good performance of the SD model on a single feature in a single relationship with ABM's capability to capture the heterogeneous nature between different relationships/markets.

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Appendix A: Market Data

Table 6 U.S. Light-vehicle market share %, 8 major OEMs, 2001-2021

Year	Ford	GM	Honda	Hyundai	Kia	Nissan	Stellantis	Toyota	Other
2001	21.6	28.04	6.91	1.98	1.28	4.03	13.01	9.97	13.18
2002	19.9	28.27	7.28	2.19	1.38	4.31	12.87	10.25	13.55
2003	19.19	27.67	7.96	2.36	1.4	4.68	12.54	11	13.2
2004	17.99	26.9	8.06	2.42	1.56	5.7	12.75	11.91	12.71
2005	17.01	25.59	8.38	2.61	1.58	6.17	13.21	12.96	12.49
2006	16.04	23.89	8.85	2.67	1.73	5.98	12.57	14.91	13.36
2007	14.59	23.24	9.43	2.84	1.86	6.49	12.62	15.92	13.01
2008	14.19	21.93	10.59	2.98	2.03	7.05	10.77	16.44	14.02
2009	15.29	19.58	10.85	4.1	2.83	7.26	8.79	16.7	14.6
2010	16.44	18.81	10.45	4.57	3.03	7.72	9.22	14.98	14.78
2011	16.47	19.19	8.79	4.95	3.72	7.99	10.55	12.6	15.74
2012	15.22	17.56	9.63	4.76	3.77	7.72	11.12	14.09	16.13
2013	15.7	17.54	9.6	4.54	3.37	7.86	11.33	14.08	15.98
2014	14.72	17.41	9.14	4.3	3.44	8.23	12.49	14.08	16.19
2015	14.63	17.26	8.88	4.27	3.5	8.32	12.68	14	16.46
2016	14.62	17.02	9.16	4.33	3.62	8.75	12.62	13.7	16.18
2017	14.73	17.09	9.34	3.9	3.36	9.07	11.8	13.86	16.85
2018	14.1	16.68	9.06	3.83	3.33	8.43	12.68	13.7	18.19
2019	13.85	16.51	9.2	4.06	3.52	7.69	12.65	13.63	18.89
2020	13.74	17.12	9.05	4.29	3.94	6.04	12.27	14.2	19.35
2021	12.37	14.4	9.52	5.11	4.55	6.34	11.58	15.14	20.99

Table 7 U.S. Light vehicle sales, number of vehicles, 1970-2021

Year	Sales	Year	Sales	Year	Sales	Year	Sales
1970	10,194,446	1983	12,311,516	1996	15,456,112	2009	10,602,043
1971	12,314,912	1984	14,483,141	1997	15,497,860	2010	11,772,526
1972	13,555,502	1985	15,725,291	1998	15,967,287	2011	13,048,386
1973	14,555,675	1986	16,322,894	1999	17,414,728	2012	14,779,484
1974	11,534,001	1987	15,188,525	2000	17,811,673	2013	15,882,712
1975	11,099,138	1988	15,788,353	2001	17,472,378	2014	16,859,843
1976	13,288,454	1989	14,842,647	2002	17,138,652	2015	17,857,324
1977	14,851,334	1990	14,147,369	2003	16,967,442	2016	17,878,307
1978	15,419,077	1991	12,549,523	2004	17,298,573	2017	17,565,127
1979	14,140,178	1992	13,117,444	2005	17,444,329	2018	17,712,804
1980	11,459,187	1993	14,198,854	2006	17,048,981	2019	17,488,154
1981	10,777,206	1994	15,411,374	2007	16,460,315	2020	14,881,356
1982	10,538,362	1995	15,116,325	2008	13,493,192	2021	15,408,565

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Appendix B: Financial Data

Table 8 Revenue of selected OEMs in Millions U.S. Dollar, 2006-2019

Year	Ford	GM	Honda	Nissan	Toyota
2019	155,900	137,237	143,277	104,372	272,551
2018	160,338	147,049	138,598	107,831	265,122
2017	156,776	145,588	129,278	108,231	255,078
2016	151,800	166,380	121,591	101,508	236,533
2015	149,558	152,356	121,323	103,546	247,980
2014	144,077	155,929	118,222	104,646	256,480
2013	146,917	155,427	119,145	116,149	266,131
2012	134,252	152,256	100,658	119,160	235,351
2011	136,264	150,276	104,357	102,445	221,792
2010	128,954	135,592	92,382	80,947	204,067
2009	118,308	105,810	99,536	83,884	204,114
2008	146,371	148,781	105,022	94,709	230,024
2007	172,654	180,897	94,834	89,543	204,841
2006	160,123	206,656	87,535	83,297	185,856

Table 9 Gross margin (%) of selected OEMs, 2006-2019

Year	Ford	GM	Honda	Nissan	Toyota
2019	18.005	20.297	19.635	12.663	17.757
2018	10.001	16.796	19.710	13.876	17.784
2017	12.258	15.456	19.886	15.958	17.954
2016	14.193	14.890	20.875	17.422	18.533
2015	15.234	18.471	21.293	19.154	17.905
2014	15.201	17.756	21.512	19.216	20.053
2013	20.060	17.317	21.559	18.349	19.917
2012	17.133	13.924	26.020	17.182	18.955
2011	17.300	15.985	25.641	16.137	15.917
2010	18.355	14.592	25.521	16.816	11.727
2009	18.268	17.720	27.303	17.729	11.289
2008	19.584	17.533	25.229	17.287	12.614
2007	15.209	3.043	25.887	14.544	8.623
2006	17.569	7.963	28.824	21.558	18.399

Table 10 R&D budgeting of selected OEMs, % of revenue, 2006-2019

Year	Ford	GM	Honda	Nissan	Toyota
2019	4.747	4.955	4.146	4.520	3.470
2018	5.114	5.304	3.893	4.149	3.622
2017	5.103	5.014	3.849	4.184	3.756
2016	4.809	4.868	3.622	4.363	3.717
2015	4.480	4.923	3.618	4.450	3.687
2014	4.789	4.746	5.355	4.776	3.544
2013	4.356	4.632	5.672	4.880	3.660
2012	4.097	4.839	6.540	4.549	4.196
2011	3.890	5.406	5.456	4.551	3.845
2010	3.877	5.135	5.401	4.512	3.827
2009	4.142	5.719	5.626	5.399	4.404
2008	4.987	5.377	4.899	4.226	3.647
2007	4.344	4.478	4.977	4.440	3.720
2006	4.497	3.194	5.151	4.747	3.863

Table 11 Revenue of selected Tier-1 Suppliers in Millions U.S. Dollar, 2012-2019

Year	2019	2018	2017	2016	2015	2014	2013	2012
Aisin	36,459	35,269	32,900	27,008	26,980	28,174	30,516	29,181
AAM	6,530.9	7,270.4	6,266.0	3,948.0	3,903.1	3,696.0	3,207.3	2,930.9
Aptiv	14,357	14,435	12,884	16,661	15,165	17,023	16,463	15,519
Borgwarner	10,173	10,532	9,796	9,071	8,025	8,304	7,435	7,178
Continental	44,478	44,404	44,010	40,550	39,232	34,506	33,331	32,736
Denso	48,359	46,090	41,807	37,678	39,231	40,889	43,192	39,951
Faurecia	17,768	17,525	20,182	18,711	18,770	18,829	18,029	17,365
Hyundai Mobis	32,627	31,939	31,087	32,979	31,825	34,375	31,238	27,328
Lear	19,814	21,151	20,469	18,562	18,208	17,726	16,230	14,566
Magna	52,371	52,926	50,591	48,402	41,221	40,499	35,891	30,826
Mahle	12,049	12,581	12,788	12,322	11,486	9,942	6,941	6,159
Bosch	77,721	78,465	78,066	73,129	70,607	48,951	46,068	52,464
Tenneco	17,450	11,763	9,274	8,599	8,209	8,420	7,964	7,363
ZF	36,518	36,929	36,444	35,166	29,154	18,415	16,837	17,366

Table 12 Gross margin (%) of selected Tier-1 suppliers, 2012-2019

Year	2019	2018	2017	2016	2015	2014	2013	2012
Aisin	11.996	13.398	14.174	14.346	14.036	14.530	13.718	13.210
AAM	12.263	14.335	16.687	18.804	16.661	14.121	14.838	14.678
Aptiv	25.646	26.076	26.351	28.666	28.032	25.789	24.850	24.357
Borgwarner	20.692	21.202	21.604	21.315	21.152	21.149	21.113	20.314
Continental	23.631	24.856	25.699	26.415	25.805	24.936	23.120	21.215
Denso	24.245	24.965	16.285	25.543	26.344	26.994	24.984	22.824
Faurecia	13.688	13.221	10.477	9.014	8.189	7.336	6.773	6.705
Hyundai Mobis	13.743	12.567	12.253	13.412	13.911	13.967	13.742	14.453
Lear	9.783	11.598	11.370	11.808	10.304	8.687	7.922	8.465
Magna	10.309	11.003	11.800	12.154	12.117	11.287	9.945	9.813
Mahle	15.881	17.780	16.697	18.892	18.729	19.167	20.322	21.266
Bosch	31.504	34.116	35.439	5.240	5.046	3.397	33.880	30.819
Tenneco	11.032	11.936	13.748	13.443	13.412	13.052	12.657	13.663
ZF	14.393	15.473	16.894	16.334	14.910	16.313	16.844	16.567

Table 13 R&D budgeting of selected Tier-1 suppliers, % of revenue, 2012-2019

Year	2019	2018	2017	2016	2015	2014	2013	2012
Aisin	5.001	4.679	4.708	5.015	5.031	5.116	5.339	5.271
AAM	2.216	2.011	2.577	3.541	2.918	2.811	3.224	4.210
Aptiv	8.115	8.001	6.846	7.202	7.913	7.637	7.896	7.732
Borgwarner	4.060	4.179	4.160	3.783	3.831	4.049	4.078	3.704
Continental	10.054	9.639	7.052	6.934	6.244	6.195	5.636	5.395
Denso	9.275	8.758	9.039	8.824	9.199	9.002	9.368	9.458
Faurecia	2.341	1.624	1.319	0.240	0.355	0.304	0.459	0.465
Hyundai Mobis	2.537	2.146	1.956	1.628	1.586	1.343	1.150	1.128
Lear	1.598	1.402	0.723	0.774	0.696	0.575	0.668	0.716
Magna	1.622	1.440	1.339	N/A	N/A	N/A	N/A	N/A
mahle	6.231	5.968	5.850	6.114	5.720	5.555	4.844	4.699
Bosch	7.715	7.505	8.992	9.139	9.033	10.131	9.862	9.124
Tenneco	1.857	1.700	1.704	0.291	0.426	0.523	0.540	1.711
ZF	5.825	5.562	5.856	5.360	4.593	4.665	4.805	4.687

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Appendix C: Patent Data

Table 14 Number of U.S. Patents issued, selected OEMs, 2010-2019

Year	Ford	GM	Honda	Nissan	Toyota
2019	2636	1542	1726	403	3013
2018	2971	1598	1208	525	2360
2017	2529	1388	1220	371	2071
2016	1949	1126	1034	486	2742
2015	1970	1258	1041	614	2062
2014	1441	1327	1136	438	1795
2013	1087	1506	1034	464	1602
2012	765	1542	1162	271	1534
2011	817	1399	1160	225	1257
2010	711	1112	1153	224	1945

Table 15 Number of U.S. Patents issued selected Suppliers, 2010-2019

Year	2019	2018	2017	2016	2015	2014	2013	2012
Aisin	335	342	332	374	325	314	342	360
AAM	26	34	28	45	30	28	15	12
Aptiv	138	70	20	3	N/A	N/A	N/A	N/A
Borgwarner	195	251	291	299	332	220	199	160
Continentak	481	485	492	531	572	398	408	282
Denso	1598	1246	1139	1115	1137	879	847	985
Faurecia	151	99	87	101	86	105	117	71
Hyundai Mobis	127	81	82	215	222	68	33	16
Lear	106	96	69	62	71	90	97	108
Magna	334	262	290	252	208	220	180	121
mahle	132	150	135	163	176	147	104	75
Bosch	1153	1122	1209	1238	1465	1693	1499	1145
Tenneco	63	63	57	55	54	62	33	29
ZF	243	167	184	208	219	155	160	185

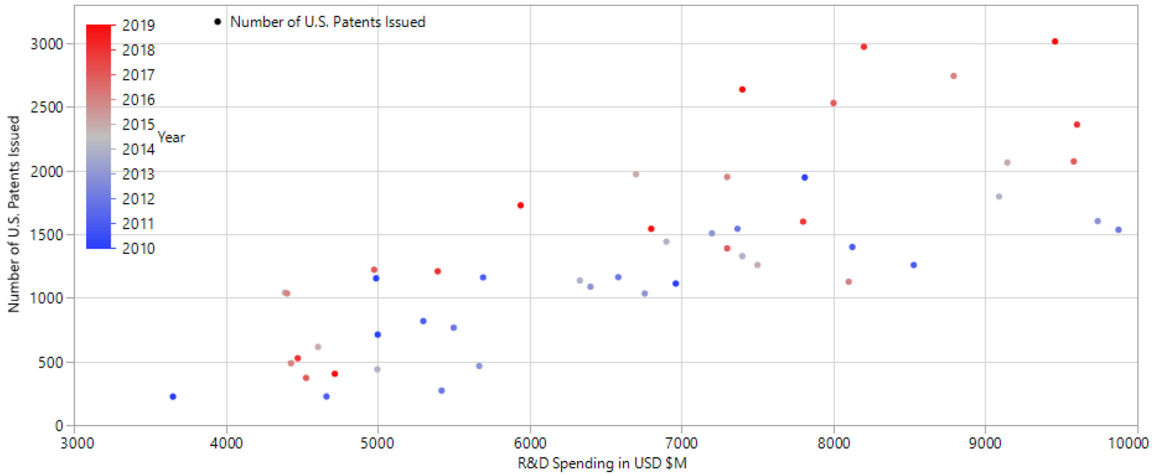

Figure 55 OEM patents vs R&D Spending, 2010-2019

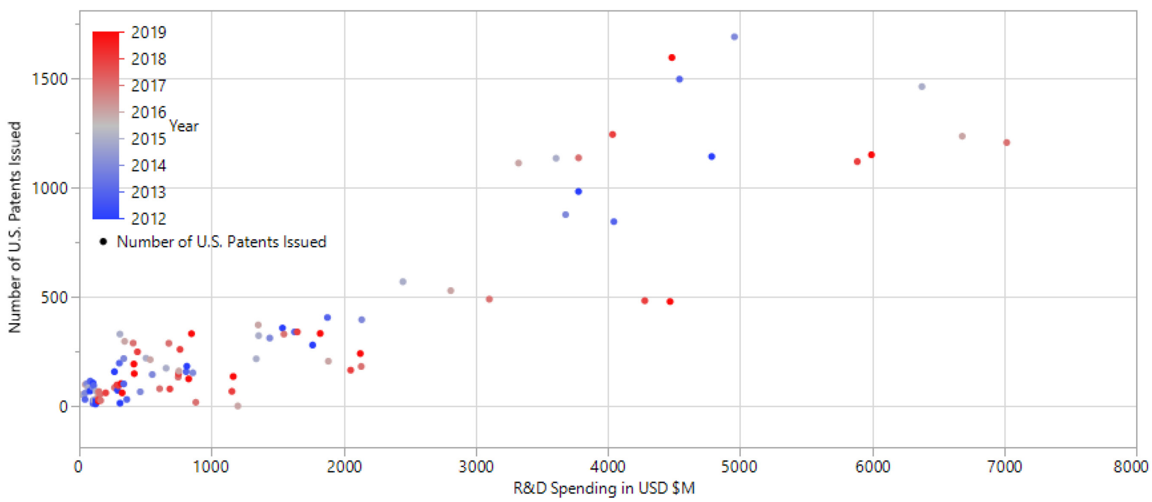

Figure 56 Suppliers patents vs R&D Spending, 2010-2019

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Appendix D: Diffusion Data – PKE

Table 16 Summary of empirical study for PKE diffusion, N.A. light-vehicle market, 2004-2020

Year	Available models	Models with PKE	Models with PKE as standard	Models with RKE (Remote Keyless Entry)	Total shipments	Shipments, PKE, standard or optional, estimated	Shipments PKE, standard
2004	46	1	1	45	6108986	3665	3665
2005	54	3	3	51	6111164	69716	69716
2006	52	3	3	49	5612878	65397	65397
2007	53	3	3	50	5130572	56308	56308
2008	49	3	3	46	4261549	43011	43011
2009	50	4	3	47	3402592	29345	20758
2010	48	7	4	44	4007041	147853	75626
2011	50	12	7	43	4502876	345704	121714
2012	44	15	6	38	4656371	654673	139803
2013	48	24	9	39	5091064	1206113	241120
2014	50	28	12	38	5215798	1412557.5	383125
2015	52	35	17	35	5426314	1774817	831957
2016	54	40	20	34	5416545	1887516.5	919625
2017	54	44	25	29	5408499	2758013	1626852
2018	53	47	28	25	5292317	3188794.5	2070842
2019	53	50	30	23	5033158	3452977	2062911
2020	46	44	31	15	4298720	2910088	1688730

Table 17 PKE diffusion in Ford, N.A. light-vehicle market, 2004-2020

Year	Available models	Models with PKE	Models with PKE as standard	Models RKE	Total shipments	Shipments, PKE, standard or optional, estimated	Shipments PKE, standard
2004	21	0	0	21	2926611	0	0
2005	23	0	0	23	2772352	0	0
2006	23	0	0	23	2534007	0	0
2007	23	0	0	23	2228370	0	0
2008	22	0	0	22	1799455	0	0
2009	23	1	0	23	1527486	8587	0
2010	22	3	1	21	1795908	49073	7435
2011	22	7	3	19	1994313	235389	40636
2012	17	8	3	14	2085370	379349	44725
2013	18	14	4	14	2320177	757160	73081
2014	18	14	4	14	2304394	740581.5	70964
2015	19	17	8	11	2382586	1066195	530158
2016	19	17	8	11	2358490	1025947	519464
2017	19	18	9	10	2359974	1535306	710791
2018	20	19	9	11	2267443	1446350	625257
2019	18	18	9	9	2075859	1319411	583803
2020	15	15	10	5	1826257	1190972	564218

Table 18 PKE diffusion in GM, N.A. light-vehicle market, 2004-2020

Year	Available models	Models with PKE	Models with PKE as standard	Models with RKE	Total shipments	Shipments, PKE, standard or optional, estimated	Shipments PKE, standard
2004	25	1	1	24	3182375	3665	3665
2005	31	3	3	28	3338812	69716	69716
2006	29	3	3	26	3078871	65397	65397
2007	30	3	3	27	2902202	56308	56308
2008	27	3	3	24	2462094	43011	43011
2009	27	3	3	24	1875106	20758	20758
2010	26	4	3	23	2211133	98780	68191
2011	28	5	4	24	2508563	110315	81078
2012	27	7	3	24	2571001	275324	95078
2013	30	10	5	25	2770887	448953	168039
2014	32	14	8	24	2911404	671976	312161
2015	33	18	9	24	3043728	708622	301799
2016	35	23	12	23	3058055	861569.5	400161
2017	35	26	16	19	3048525	1222707	916061
2018	33	28	19	14	3024874	1742444.5	1445585
2019	35	32	21	14	2957299	2133566.5	1479108
2020	31	29	21	10	2472463	1719116	1124512

Table 19 OEM-Supplier "Who supplies whom" relationship for years 2004, 2010, 2014, 2017, 2019 and 2020, PKE subsystem

Year	OEM	Number of models	PKE supplier	Year	OEM	Number of models	PKE supplier
2004	GM	1	Siemens VDO/Continental	2017	GM	21	Denso
2010	Ford	3	Continental	2017	GM	1	Hella
2010	GM	2	Continental	2017	GM	4	Strattec
2010	GM	1	Strattec	2019	Ford	18	Continental
2014	Ford	14	Continental	2019	GM	30	Denso
2014	GM	3	Continental	2019	GM	1	Hella
2014	GM	1	Denso	2019	GM	1	Strattec
2014	GM	5	Hella	2020	Ford	15	Continental
2014	GM	8	Strattec	2020	GM	23	Denso
2017	Ford	18	Continental	2020	GM	2	Huf
2017	GM	2	Continental	2020	GM	1	Strattec

Figure 57 visualizes data in Table 19 in a Sankey chart:

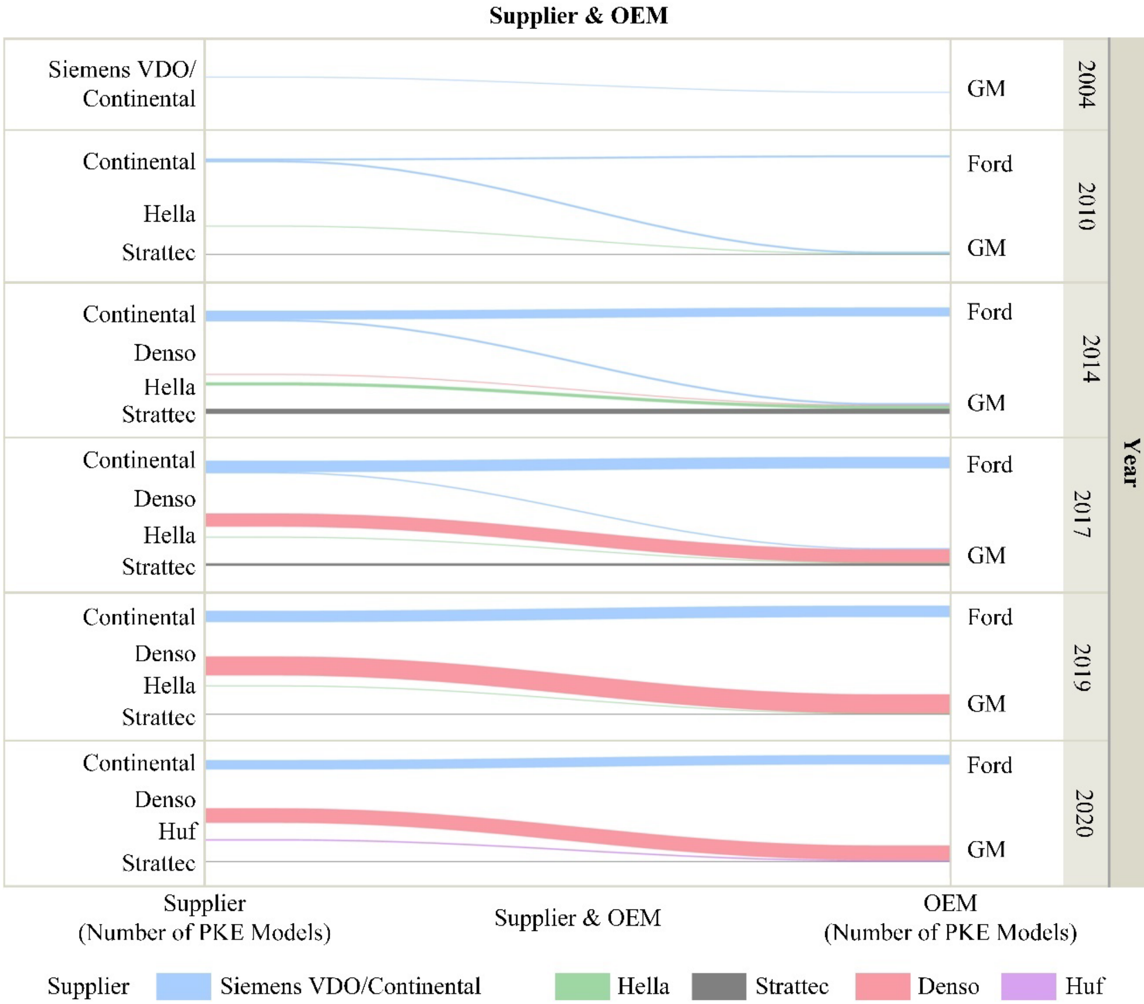

Figure 57 Diffusion from Tier 1 Supplier to OEM for PKE, 2004 -2020, adapted from (Moser et al., 2021)

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Appendix E: Diffusion Data – HST

Table 20 Summary of empirical study for HST diffusion, U.S. light-vehicle market, 2011-2021

Year	Available models	Models with HST	Models with HST as standard	Total shipments	Shipments, HST, standard or optional, estimated
2011	155	2	0	10601629	19739
2012	151	4	1	11953902	97628
2013	154	5	2	12853047	299021
2014	156	10	6	13613488	961119
2015	157	16	10	14265529	1375431
2016	162	29	17	14243769	2093379
2017	157	39	23	13851211	2977020
2018	153	54	30	13820481	4327724
2019	160	73	42	13446138	5646098
2020	158	91	65	11397707	6203193
2021	149	87	62	11411203	6256238

Table 21 HST diffusion in Ford, U.S. light-vehicle market, 2011-2021

Year	Available models	Models with HST, standard or optional
2011	23	0
2012	21	0
2013	20	0
2014	20	0
2015	21	0
2016	22	0
2017	22	1
2018	23	3
2019	23	8
2020	19	15
2021	19	16

Table 22 HST diffusion in GM, U.S. light-vehicle market, 2011-2021

Year	Available models	Models with HST, standard or optional
2011	40	0
2012	38	0
2013	39	0
2014	39	1
2015	41	2
2016	44	11
2017	42	15
2018	41	24
2019	41	31
2020	38	32
2021	34	29

Table 23 HST diffusion in Stellantis, U.S. light-vehicle market, 2011-2021

Year	Available models	Models with HST, standard or optional
2011	21	1
2012	20	2
2013	21	3
2014	22	6
2015	22	10
2016	23	11
2017	22	13
2018	19	13
2019	21	13
2020	20	15
2021	19	15

Table 24 HST diffusion in Nissan, U.S. light-vehicle market, 2011-2021

Year	Available models	Models with HST, standard or optional
2011	17	0
2012	18	0
2013	19	0
2014	19	0
2015	17	0
2016	16	0
2017	17	0
2018	17	0
2019	17	0
2020	17	2
2021	16	2

Table 25 HST diffusion in Toyota, U.S. light-vehicle market, 2011-2021

Year	Available models	Models with HST, standard or optional
2011	19	0
2012	21	0
2013	21	0
2014	21	0
2015	22	0
2016	22	0
2017	18	3
2018	19	4
2019	18	5
2020	19	7
2021	18	7

Table 26 HST diffusion in Kia, U.S. light-vehicle market, 2011-2021

Year	Available models	Models with HST, standard or optional
2011	9	0
2012	7	0
2013	8	0
2014	9	1
2015	9	1
2016	9	1
2017	11	2
2018	10	2
2019	11	4
2020	13	6
2021	12	5

Table 27 HST diffusion in Hyundai, U.S. light-vehicle market, 2011-2021

Year	Available models	Models with HST, standard or optional
2011	10	1
2012	10	2
2013	9	2
2014	9	2
2015	9	2
2016	11	2
2017	10	0
2018	10	1
2019	12	2
2020	15	3
2021	17	4

Table 28 HST diffusion in Honda, U.S. light-vehicle market, 2011-2021

Year	Available models	Models with HST, standard or optional
2011	16	0
2012	16	0
2013	17	0
2014	17	0
2015	16	1
2016	15	4
2017	15	5
2018	16	7
2019	17	10
2020	17	11
2021	14	9

Table 29 OEM-Supplier "Who supplies whom" relationship 2011-2021, HST subsystem

Year	OEM	Number of models	HST supplier	Year	OEM	Number of models	HST supplier
2011	Stellantis	1	ZF	2018	Honda	3	in-house
2011	Hyundai	1	in-house	2018	Ford	1	in-house
2012	Stellantis	2	ZF	2019	Stellantis	7	ZF
2012	Hyundai	2	in-house	2019	GM	3	Aisin
2013	Stellantis	3	ZF	2019	GM	2	in-house
2013	Hyundai	2	in-house	2019	GM	11	in-house
2014	Stellantis	4	ZF	2019	Kia	3	in-house
2014	Hyundai	2	in-house	2019	Honda	1	ZF
2014	GM	1	Aisin	2019	Honda	4	in-house
2014	Kia	1	in-house	2019	Ford	1	in-house
2015	Stellantis	7	ZF	2019	Ford	4	in-house
2015	Hyundai	2	in-house	2019	Toyota	5	Aisin
2015	GM	2	Aisin	2019	Hyundai	2	in-house
2015	Kia	1	in-house	2020	Stellantis	8	ZF
2015	Honda	1	ZF	2020	GM	8	in-house
2016	Stellantis	7	ZF	2020	GM	4	in-house
2016	Hyundai	2	in-house	2020	GM	1	Aisin
2016	GM	9	in-house	2020	Kia	6	in-house
2016	GM	2	Aisin	2020	Honda	1	ZF
2016	Kia	1	in-house	2020	Honda	5	in-house
2016	Honda	1	in-house	2020	Ford	5	in-house
2016	Honda	1	ZF	2020	Ford	1	in-house
2017	Stellantis	7	ZF	2020	Toyota	1	ZF
2017	GM	12	in-house	2020	Toyota	6	Aisin
2017	GM	1	Aisin	2020	Hyundai	3	in-house
2017	GM	1	in-house	2021	Stellantis	8	ZF
2017	Kia	2	in-house	2021	GM	7	in-house
2017	Honda	2	in-house	2021	GM	3	in-house
2017	Honda	1	ZF	2021	Kia	5	in-house
2018	Stellantis	7	ZF	2021	Honda	3	in-house
2018	GM	11	in-house	2021	Ford	6	in-house
2018	GM	3	Aisin	2021	Ford	1	in-house
2018	GM	1	in-house	2021	Toyota	1	ZF
2018	Kia	2	in-house	2021	Toyota	5	Aisin
2018	Honda	1	ZF	2021	Hyundai	4	in-house

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Appendix F: Model equations and baseline model parameters

All models presented in this thesis are modeled and simulated in Vensim DSS Version 9.1.1 x64. The following model equations and parameter configurations are outputs from VenSim's Document Tool:

1) Base Capability Development Rate=5727; Units: Cap/Year
2) Base Competitor Strategy=1; Units: 1
3) Base OEM customer sales=26000; Units: M$/Year
4) base OEM sales target=Market size*OEM Base market share; Units: M$/Year
5) "Base profit R&D ratio"=0.1; Units: 1
6) Base supplier market=1; Units: 1
7) Comp market share=1-OEM Market Share; Units: 1
8) Comp Target Market share=1-OEM Base market share; Units: 1
9) Competitor Capability Development=Base Capability Development Rate + SMOOTH (Competitor Innovation Strategy * OEM attractiveness lead*(Competitor Product Attractiveness + OEM Product Attractiveness), Market Perception Delay; Units: Cap/Year
10) competitor decay=Competitor Product Attractiveness/Competitor innovation lifetime; Units: Cap/Year
11) Competitor innovation lifetime=5; Units: Year
12) Competitor Innovation Strategy=Base Competitor Strategy*Comp Target Market share/Comp market share; Units: 1
13) Competitor Product Attractiveness= INTEG (Competitor Capability Development-competitor decay,26000); Units: Cap
14) Innovation lifetime=5; Units: Year
15) M$ to Cap unit=1; Units: Cap/M$
16) BD unit=1; Units: 1/Year
17) Market Perception Delay=3; Units: Year
18) Market size= 1.41e+06; Units: M$/Year
19) OEM attractiveness lead=(OEM Product Attractiveness-Competitor Product Attractiveness)/(OEM Product Attractiveness+Competitor Product Attractiveness); Units:1
20) OEM base margin=0.15; Units: 1
21) OEM Base market share=0.1; Units: 1
22) "OEM Base R&D Ratio"=0.044; Units: 1
23) OEM base strategy=1; Units: 1
24) OEM Business Development= BD unit*(OEM Sales/base OEM sales target)*(1-Supplier Trading/OEM market saturation); Units: 1/Year
25) OEM cap decay= OEM capability/Innovation lifetime; Units: Cap/Year
26) OEM capability= INTEG (OEM capability development-OEM cap decay,13000); Units: Cap
27) OEM capability development=OEM innovation; Units: Cap/Year
28) OEM Culture=1; Units: 1
29) OEM Customer Trading= INTEG (Supplier Business Development, Supplier market saturation); Units: 1
30) OEM innovation= OEM Culture*OEM innovation vehicle*(OEM Patents + Supplier Trading*Supplier trading to Cap ratio); Units: Cap/Year
31) OEM innovation vehicle=1; Units: 1
32) OEM market saturation= 20; Units: 1

33) OEM Market Share=OEM Base market share*OEM Product Attractiveness/Competitor Product Attractiveness; Units: 1
34) OEM Patents= M$ to Cap unit*SMOOTH("OEM R&D Expense"*0.32, 1); Units: Cap/Year
35) OEM Product Attractiveness= Supplier capability+OEM capability; Units: Cap
36) OEM Profit=OEM Sales*(OEM base margin-OEM Sales to Profit incentive Factor*Perceived Supplier Innovation lead); Units: M$/Year
37) "OEM R&D Expense"=OEM Strategy* (OEM Sales*"OEM Base R&D Ratio"+ OEM Profit* "Base profit R&D ratio"); Units: M$/Year
38) OEM revenue mix= 0.1844; Units: 1
39) OEM Sales= OEM Market Share*Market size; Units: M$/Year
40) OEM Sales to Profit incentive Factor=0.02; Units: 1
41) OEM Strategy=OEM base strategy-OEM attractiveness lead; Units: 1
42) Perceived Supplier Innovation lead=SMOOTH((Supplier capability - OEM capability) / (OEM capability + Supplier capability), Perception Delay); Units: 1
43) Perception Delay=1; Units: Year
44) Supplier base margin= 0.1;Units: 1
45) "Supplier base R&D Ratio"=0.052; Units: 1
46) Supplier base strategy=0; Units: 1
47) Supplier Business Development=BD unit*Perceived Supplier Innovation lead * (1-OEM Customer Trading/Supplier market saturation)*Time Factor; Units: 1/Year
48) Time Factor=1; Units: 1
49) Supplier cap decay=Supplier capability/Innovation lifetime; Units: Cap/Year
50) Supplier capability= INTEG (Supplier capability development-Supplier cap decay,13000); Units: Cap
51) Supplier capability development=Supplier Innovation*Supplier innovation share ratio; Units: Cap/Year
52) Supplier Culture=1; Units: 1
53) Supplier Innovation=Supplier Culture*Supplier Patents*Supplier Innovation Vehicle; Units: Cap/Year
54) Supplier innovation share ratio= 4.05; Units: 1
55) Supplier Innovation Vehicle=1; Units: 1
56) Supplier market saturation= Base supplier market * (1-Supplier revenue mix); Units: 1
57) Supplier Patents=M$ to Cap unit*SMOOTH("Supplier R&D Expense"*0.22, 1); Units: Cap/Year
58) Supplier Profit=Supplier Sales*Supplier base margin + OEM Sales * Perceived Supplier Innovation lead * Supplier Sales to Profit Incentive Factor; Units: M$/Year
59) "Supplier R&D Expense"=OEM Strategy* (OEM Sales*"OEM Base R&D Ratio"+ OEM Profit* "Base profit R&D ratio"); Units: M$/Year
60) Supplier revenue mix=0.15; Units: 1
61) Supplier Sales= OEM Sales*OEM revenue mix*Supplier revenue mix + OEM Customer Trading*Base OEM customer sales; Units: M$/Year
62) Supplier Sales to Profit Incentive Factor= 0.02; Units: 1
63) Supplier Strategy=Supplier base strategy + Trading strength*Supplier Trading/OEM market saturation-Perceived Supplier Innovation lead; Units: 1
64) Supplier Trading= INTEG (OEM Business Development,OEM market saturation); Units: 1
65) Supplier trading to Cap ratio= 10; Units: Cap/Year
66) Trading strength=1; Units: 1

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Appendix G: Tuned model parameters for GM-Delphi case

The empirical reference data and numerical changes over baseline model parameters shown in Appendix F are documented as follows:

Table 30 Reference empirical data for GM-Delphi case, 1996-2009

Year	U.S. market share	OEM revenue (M$ USD)	Supplier revenue (M$ USD)	OEM profit (M$ USD)	Supplier profit (M$ USD)	OEM margin	Supplier margin
1996	0.3083	164069	31032	28307	5154	0.172531	0.166087
1997	0.3057	172580	31447	29709	4760	0.172146	0.151366
1998	0.2866	155445	28479	29756	4108	0.191425	0.144247
1999	0.2876	176558	29192	37431	5014	0.212004	0.171759
2000	0.2797	184632	29139	38968	5159	0.211058	0.177048
2001	0.2804	177260	26088	33167	1988	0.187109	0.076204
2002	0.2827	186763	27427	33419	4162	0.178938	0.151748
2003	0.2767	185837	28096	33418	4226	0.179824	0.150413
2004	0.269	195351	28622	33560	3904	0.171793	0.136399
2005	0.2559	194655	26947	21571	2302	0.110817	0.085427
2006	0.2389	206655.9	26392	42667	1997	0.206464	0.075667
2007	0.2324	180897	22283	21057	2303	0.116403	0.103352
2008	0.2193	148781	18060	11848	2065	0.079634	0.114341
2009	0.1958	105810	12874	3220	-327	0.030432	-0.0254

Table 31 Parameter changes compared to the baseline model

Parameter	Value (Baseline)	Value (Tuned model)
OEM base margin	0.15	0.163
Supplier base margin	0.1	0.128
OEM base R&D Ratio	0.044	0.039
Supplier base R&D Ratio	0.052	0.065
Supplier revenue mix	0.15	1
Base OEM customer sales	26000	0
OEM base market share	0.1	Time-series in Table 32
U.S. Market size	1.41e6	
Supplier innovation share ratio	4.05	
OEM base strategy	1	
OEM base culture	1	
Supplier base Strategy	0	
Supplier base Culture	1	
Base Capacbility Development Rate	5727	
OEM revenue mix	0.184	

Table 32 Time-series data input of the tuned model

Year	OEM base market share	U.S. market size (M$ in USD)	Supplier innov. share ratio	OEM base strategy	OEM base culture	Supplier base strategy	Supplier base culture	Base cap. dev. rate	OEM revenue mix
1996	0.308	493428	10	1.2	1	-0.15	1.4	7000	0.189
1997	0.306	516793	10	1.1	0.9	-0.2	1.4	7000	0.182
1998	0.287	555146	10	1	0.5	-0.2	1.6	6000	0.183
1999	0.288	630228	10	0.9	0.5	-0.2	1.7	6000	0.165
2000	0.280	669915	10	0.8	0.9	-0.2	1.8	7000	0.158
2001	0.280	681993	9	0.8	1	0	0.7	6000	0.147
2002	0.283	693332	9	0.8	1.1	0	0.6	6000	0.147
2003	0.277	710527	9	0.8	1.2	0.1	0.5	6000	0.151
2004	0.269	748986	8	0.8	1.4	0.2	0.5	6000	0.147
2005	0.256	780097	5	0.8	1.6	0.2	0.5	6000	0.138
2006	0.239	786654	5	0.7	1.5	0.4	1.2	6000	0.128
2007	0.232	782893	5	1.1	0.7	0.5	1.2	7000	0.123
2008	0.219	660952	5	1.3	0.6	0.6	1.2	7000	0.121
2009	0.196	534404	5	1.4	0.6	-0.8	1.2	7000	0.122

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Appendix H: Tuned model parameters for Stellantis-ZF case

The empirical reference data and numerical changes over baseline model parameters shown in Appendix F are documented as follows:

Table 33 Reference empirical data for Stellantis-ZF case, 2005-2019

Year	U.S. market share	OEM revenue	Supplier revenue	OEM profit (M$ USD)	Supplier profit	OEM margin	Supplier margin
2005	0.1321	57813.72	13456	8595.542	2517.798	0.148677	0.187113
2006	0.1257	65059.55	14634.38	9198.109	2815.414	0.14138	0.192384
2007	0.1262	80115.46	17314.16	12209.84	3483.638	0.152403	0.201202
2008	0.1077	86886.65	18291.85	13493.92	3602.474	0.155305	0.196944
2009	0.0879	69664.47	13029.93	8531.819	1763.094	0.12247	0.135311
2010	0.0922	47479.18	17079.54	6068.548	3129.55	0.127815	0.183234
2011	0.1055	82830.25	21568.77	11444.28	3843.967	0.138166	0.178219
2012	0.1112	107840.2	22306.1	15236.38	3695.418	0.141287	0.165669
2013	0.1133	115258.5	22353.11	15080.41	3765.125	0.13084	0.168439
2014	0.1249	127458.1	24426.48	15767.45	3984.641	0.123707	0.163128
2015	0.1268	122641.1	32329.48	13064.2	4820.479	0.106524	0.149105
2016	0.1262	122807.8	38900.53	15742.29	6353.997	0.128186	0.16334
2017	0.118	125126.3	41106.45	17522.46	6944.693	0.140038	0.168944
2018	0.1268	130258.5	43566.98	16451.61	6741.09	0.1263	0.154729
2019	0.1265	121088.2	40872.72	15294.53	5882.771	0.126309	0.143929

Table 34 Parameter changes compared to the baseline model

<table>
<tr><th>Parameter</th><th>Value (Baseline)</th><th>Value (Tuned model)</th></tr>
<tr><td>OEM base margin</td><td>0.15</td><td>0.132</td></tr>
<tr><td>Supplier base margin</td><td>0.1</td><td>0.166</td></tr>
<tr><td>OEM base R&D Ratio</td><td>0.044</td><td>0.016</td></tr>
<tr><td>Supplier revenue mix</td><td>0.15</td><td>0.1</td></tr>
<tr><td>OEM revenue mix</td><td>0.184</td><td>0.267</td></tr>
<tr><td>Time Factor</td><td>1</td><td>0.2</td></tr>
<tr><td>OEM base market share</td><td>0.1</td><td rowspan="9">Time-series in Table 35</td></tr>
<tr><td>U.S. Market size</td><td>1.41e6</td></tr>
<tr><td>Supplier innovation share ratio</td><td>4.05</td></tr>
<tr><td>OEM base strategy</td><td>1</td></tr>
<tr><td>OEM base culture</td><td>1</td></tr>
<tr><td>Supplier base Strategy</td><td>0</td></tr>
<tr><td>Supplier base Culture</td><td>1</td></tr>
<tr><td>Base OEM customer sales</td><td>26000</td></tr>
<tr><td>Base Capacbility Development Rate</td><td>5727</td></tr>
</table>

Table 35 Time-series data input of the tuned model

Year	OEM base market share	U.S. market size (M$ in USD)	Supplier innov. share ratio	OEM base strategy	OEM base culture	Supplier base strategy	Supplier base culture	Base cap. dev. rate	Base OEM customer sales
2005	0.132	437651	10	1.8	1	0	1.5	4,000	13000
2006	0.126	505848	10	1	1	-0.05	1.5	4,000	15000
2007	0.126	599019	8	0.9	1	0	1.4	3,000	17000
2008	0.108	624019	6	0.8	1.2	0.05	1.3	2,500	19000
2009	0.088	481679	4	0.4	1.5	0.3	1.2	2,500	21000
2010	0.092	347526	2	0.7	1.5	-0.1	1.1	1,500	23000
2011	0.106	587272	1	0.8	1.5	-0.1	1	1,800	24000
2012	0.111	821639	1	0.9	1.5	-0.1	1	2,000	25000
2013	0.113	926218	1	0.9	1.5	-0.1	1	2,300	25500
2014	0.125	986289	1	0.8	1.5	-0.1	1	2,400	26000
2015	0.127	990100	1	1	1	-0.1	1.5	2,600	28000
2016	0.126	997330	1	1.1	1	0	1.5	2,600	35000
2017	0.118	1067740	1	1	1	0.1	1.5	2,600	37000
2018	0.127	1043090	1	0.9	1	0.1	1.5	2,600	39000
2019	0.127	959623	1	1.4	1	0.1	1.5	2,600	37000

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