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Abstract — The literature on economic complexity has shown that the structure of the economy is a strong determinant of diversification, growth, innovation, inequality, and many other major socio-economic outcomes. Most of the empirical analyses, however, remain at a very macro level. It is not clear whether key features of the structure and dynamics of the macroeconomy also apply at a more meso, or micro-level. In this study, we deep dive into the automotive components industry in Japan and contribute to the literature by analyzing within-product category complexity and by taking a dynamic approach to the product space. To achieve this objective, we use unique survey data containing detailed information on each auto part supplier's product baskets to uncover the industry's productive structure and the process underlying structural change. We compute and visualize the auto parts product space and confirm properties found for international and domestic economies - suggesting the existence of fractals. These properties include power–laws, nestedness, and core-periphery structures. Moreover, this study develops exploratory and econometric approaches, unifying the measures of product relatedness and product complexity, explaining the productive structure's dynamic process due to capability accumulation. The empirical analyses reveal that the events of new product appearance are not random but are instead significantly contingent on the network topology of the product space, which in turn shapes its structure. In particular, the effects of the network topology have a significant impact on the development of more complex products with sophisticated capabilities.

Keywords — Product space, Relatedness, Economic complexity, Exploratory network analysis, Auto parts industry

JEL codes: L62, O31, O33

1. Introduction

Recent advances in economic complexity have shed new light on fundamental aspects of economic development that the conventional growth empirical literature has not fully explored. It has shown that the structure of the economy is a strong determinant of diversification, growth, innovation, inequality, and many other major socio-economic outcomes. In the related evolutionary framework, the process of knowledge production and technological change are key to understanding economic development and can be viewed as a cumulative, path-dependent, and interactive phenomenon (Arthur, 1989, 1999; Boschma, 2004; Frenken and Boschma, 2007; Hidalgo, 2021; Balland et al., 2022). Therefore, the development path of economies is highly associated with their pre-existing productive structures, which are defined as the links between products that economies can deliver rather than the products' aggregated monetary value (Hausmann *et al*., 2007; Hausmann and Hidalgo, 2011).

The entire economy can be represented by a bipartite network where links indicate that a country is a significant producer/exporter of a specific product. Hidalgo *et al.* (2007) used international trade data to first map this structure. This arrangement is further projected into a product-product network if two products then to be often simultaneously exported by the same countries. This network projection, referred to as *product space*, reflects the *relatedness* among products. Another piece of information extracted from the bipartite country-product network addresses the quality of capabilities available in a country and those required by a product. Hidalgo and Hausmann (2009) introduced a method to extract this hidden property of *complexity* by focusing on the diversity of a country, captured by the number of products exported by that country, and the ubiquity of a product captured by the number of countries exporting that product. The growing body of empirical studies using the measures of relatedness and complexity demonstrates the specific productive structures of countries or regions and their evolutionary process over the product space (Balland, 2016; Hidalgo *et al*., 2018; Hidalgo, 2021).

However, the empirical literature has not yet addressed some key issues. First, there is little information regarding the qualitative changes occurring with products the economy already has, presumably due to the unavailability of data. Within-category structural change can not be tracked. A 1987 Ford Escort, however, is very different from a 2022's Tesla S plaid. It is essential to uncover fine-grained structural change if we want to design a sound regional policy.

Second, from a methodological perspective, a framework that holds the productive structure as fixed would not be suitable to analyze the evolution of a network with more disaggregated products. Compare, for example, recent motor vehicles, such as electric or hybrid vehicles, with those featuring internal-combustion engines developed decades ago. It is easy to imagine that current technology-driven trends toward electrification and autonomous driving will dramatically reshape the industrial landscape through the co-evolution of the automotive and electronics sectors. Moreover, some auto part products with cutting-edge technologies have recently entered the market, while other products with obsolete technologies have disappeared. This contrast implies that an analytical framework explicitly incorporating a dynamic concept following technological progress is essential when analyzed at disaggregated product scales.

With a particular focus on the automotive components industry in Japan, this study aims to uncover the industry's productive structure and the process underlying its structural change by using unique survey data that contain detailed information on the product baskets of each auto part supplier. The automobile industry is highly complex and plays a vital role, along with related industries, in the Japanese economy (Hidalgo and Hausmann, 2009; Hausmann *et al*., 2014).[1] Following the Hidalgo *et al*. (2007) approach, the *auto parts product space* visually represents the productive structure of the Japanese automobile industry.

This study's contribution is four-fold. First, it complements the literature on relatedness and complexity by providing several stylized facts and empirical findings concerning the industry's productive structure, which has hitherto been vague at the meso- and micro-levels. Previous works have confirmed that common properties, such as the nested and the core-periphery structures, exist in the productive international structure, as reflected by the country-product network, and in the domestic structure, as reflected by the region-product network. This study shows that these properties also exist in the industry's structure as described by the firm-product network. The discovery of this fractal structure implies that, notwithstanding the differences in size, maturity, and industrial scope of economies, common principles and regularities would underlie the formation of productive structures.

Second, as a methodological contribution, this study develops a modeling approach that unifies the measures of product relatedness (capabilities overlap between products) and product complexity (quality of capabilities required for product manufacturing) and explains the productive structure's dynamic process as a result of capability accumulation. The exploratory and econometric analyses reveal that the events of a product's appearance are not random but are significantly contingent on the network topology of the product space, which in turn shapes the new structure of the product space.

Third, the analytical device used to describe the productive structure in a non-aggregative manner offers a new perspective on conventional studies of Japanese automobile industries. In management science, researchers have focused on the distinctive Japanese interfirm relationships between automobile manufacturers and auto part suppliers as a source of competitive advantage (Asanuma, 1989; Dyer, 1996; Dyer and Nobeoka, 2000; Ahmadjian and Lincoln, 2001). These relationships are referred to as *keiretsu* networks and are characterized by long-term purchasing relationships, intense collaboration, cross-shareholding, and frequent exchange of personnel and technology

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[1] Based on the 2015 input-output table categorized in the 37 sectors, Japan's exports of the transportation equipment industry amounted to 18.5 trillion JPY (21.3% of the total exports). Further, this export demand has a significant ripple effect on the economy, inducing domestic intermediate products by 13.0 trillion JPY.

(Dyer, 1996). The case study literature suggests that when transactions of customized components with low modularity, longstanding, tightly integrated relationships, rather than arm's-length relationships, contribute to the accumulation of shared human and physical assets by firms; as a result, a competitive advantage is built (Asanuma, 1989; Dyer, 1996; Hoetker *et al*., 2007). Only recently, Todo *et al*. (2016) and Bernard *et al*. (2019) used more comprehensive micro-level data and a systematic quantitative approach to investigate *how much* the supply chain structure affects aggregate levels of business productivity. However, these studies focused on inter-firm relationships and provided little insight into *what* products each firm develops. An analytical approach to estimating idiosyncratic capabilities hidden behind heterogeneous products offers further insight into the path-dependent development process and future potential of the Japanese automobile industry.

Finally, due to the Japanese automobile industry's significant presence and competitive advantages in domestic and global markets, explaining an underlying mechanism responsible for the advent of new technologies is of interest to academia and policymakers. The Ministry of Economy, Trade, and Industry (METI) faces drastic changes in the automotive business environment and is establishing strategies for the automobile industry to enhance competitiveness, lead global innovation, and confront global issues, including climate change (METI, 2018). Thus, systematic quantitative evidence will help focus on these policy issues. In addition, the evidence will be helpful in policy design in a regional context, such as the industrial cluster policies (METI, 2009), since the automotive industry is characterized by a remarkable agglomeration co-located with its associated industries (Klier and McMillen, 2008; Yamada and Kawakami, 2016).

The remainder of this paper is organized as follows. The following section summarizes this study's theoretical and methodological background. The subsequent section describes the data and establishes a collection of stylized facts regarding product portfolios from Japanese auto parts suppliers. The study implements these facts in an exploratory investigation of the auto parts industry's productive structure using the metrics of product relatedness and complexity. Then, an econometric analysis examines the role of product relatedness and complexity in the events of product appearance. The final section provides concluding remarks and discusses the remaining agenda for future research.

2. Theoretical and methodological background

Since the late 1980s, growth theories have introduced imperfect competition and emphasized the role of innovations in sustainable economic growth. These theories argue that structural transformations, via diversification of product variety (Dixit and Stiglitz, 1977; Romer, 1987, 1990) and product quality improvement (Aghion and Howitt, 1992, 1998), carry productivity growth to countries. Due to its nonrival nature, the freely available stock of knowledge or technology for R&D activities contributes to creating new products and driving turnovers. In parallel to the theoretical development of endogenous technological progress modeling, numerous empirical studies have explored how knowledge flows can be captured. In particular, implementing a wealth of patent data information has facilitated various approaches to measuring technological proximities between firms or industries (Scherer, 1984; Jaffe, 1986; Griliches, 1990; Jaffe *et al*., 1993; Bloom *et al*., 2013). These approaches have primarily focused on investigating R&D spillovers, that is, *how much* accessible knowledge can affect aggregate levels of firms' or industries' performance regarding patent numbers, stock value, and productivity.

Recent studies have examined the process underlying structural transformation regarding economic entities and their products at a disaggregated level. From complexity and evolutionary economics standpoints (Arthur, 1989, 1999; Boschma, 2004; Frenken and Boschma, 2007), the dynamics of knowledge production are cumulative, path-dependent, and interactive phenomena. These concepts describe the development process of economies by emphasizing *what* specific types of products are produced rather than *how much* value an economy derives from its products (Hausmann *et al*., 2007; Hausmann and Hidalgo, 2011). Despite its theoretical validity, it is difficult to develop quantitative methods to capture this qualitative aspect.

Two distinct but highly associated empirical methods that are theoretically grounded in complexity and evolutionary thinking use disaggregated information by applying network science techniques. They adopt an agnostic view to infer an internal set of complementary non-tradable inputs (or *capabilities*) accumulated in countries and embedded in products (Hidalgo *et al*., 2007; Hidalgo and Hausmann, 2009). Although it is difficult to draft genetic capabilities exhaustively, the method developed by Hidalgo *et al*. (2007) indirectly captures the *relatedness* of capabilities between products by observing which are often exported by countries in tandem; if two products are co-exported by many countries, they probably require the same capabilities (Hidalgo *et al*., 2007). Hausmann and Klinger (2006) and Hidalgo *et al*. (2007) introduced the *product space* framework—a network projection connecting products with links based on their degree of relatedness—to show that countries are more likely to diversify product export mixes related to existing export products. This path-dependent branching-out process of activities is observed for products and also for industries (Neffke *et al*., 2011), skills (Neffke, 2013), technologies (Boschma *et al*., 2014; Balland and Rigby, 2017), and research areas (Guevara *et al*., 2016); therefore, it can be generalized as the *principle of relatedness* (Hidalgo *et al*., 2018).

Another approach addresses capability quality referred to as *complexity*. Hidalgo and Hausmann (2009) introduced complexity metrics, which Hausmann *et al*. (2014) later referred to as the *economic complexity index* for countries and the *product complexity index* for products. Complexity indices are constructed by combining information on countries' product diversification and the ubiquity of the delivered products; capability-rich countries are expected to have more combinations of the capabilities that products require. Therefore, they have more diversified product compositions than countries with fewer capabilities. Focusing on product ubiquity means that countries with many and few capabilities will likely produce products that demand fewer capabilities; therefore, such products will be made in many countries. In the bipartite country-product network, diversity is captured by the number of products connecting to a country, and ubiquity is determined by the number of countries connected to a product. This way of indexation is justified because productive structures in international and domestic economies are characterized by *nestedness*, referring to a fundamental feature that the product mix present in a relatively nondiverse economy is likely to be a subset of that present in a relatively diverse economy (Hidalgo and Hausmann, 2009; Bustos *et al*., 2012).

The development of new products and resultant economic growth can also be understood as a path-dependent process combining the concepts of relatedness and complexity. A country manufacturing sophisticated products will likely have the knowledge to extract new combinations from a vast base of pre-existing capabilities and combine new capabilities with existing ones (Hidalgo and Hausmann 2009). Hausmann and Hidalgo (2011) and Cristelli *et al*. (2013) numerically show that a country's expected number of products follows exponentially increasing returns to the accumulation of the capabilities it already possesses. Hidalgo and Hausmann (2009) and Hausmann *et al*. (2014) provide empirical support by showing that the measure of available capabilities is significantly predictive of a country's future economic growth.

However, accumulating capabilities does not guarantee the immediate development of sophisticated products. Applying useful capabilities embedded in pre-existing sophisticated products can potentially lead to a product with complex technologies. The more capabilities required to develop a product, the harder it is to add new capabilities and recombine new and existing ones (Fleming and Solenson, 2001). One of the primary concerns in patent literature is the possibility of declining patents received per R&D investment, a feature confirmed in different industries and countries (Griliches, 1990; Kortum, 1993; Lanjouw and Schankerman, 2004). From a geographic perspective, Balland and Rigby (2017) found that technological complexity is unevenly distributed and that cities with more complex technological structures do not necessarily have the highest patenting rates. These empirical findings imply a complex combination of capabilities characterized by tacit knowledge that cannot simply be imitated and transferred without cost.

Based on these theories and methodologies, this study provides an in-depth investigation into the productive structure of the Japanese auto parts industry and the process underlying its structural transformation.

3. Data and stylized facts

3.1 Data description

This study used data extracted from published survey books assembled by Sogogiken, a management and technical consulting company. These books present annual domestic transactions between first-tier auto part suppliers and car manufacturers for each automotive component[2]. Sogogiken selects the products listed in the books as main components. Because some products are replaced with more advanced ones and embedded into modularized products, the list varies by year. Conversely, product delivery destinations remain the same and comprise 11 car manufacturers: Toyota, Nissan, Honda, Mazda, Mitsubishi, Isuzu, Suzuki, Daihatsu, Subaru (formerly Fuji Heavy Industries), Hino, and UD Trucks (formerly Nissan Diesel). All products are classified to belong to any *ex-ante* categories based on a bill of materials (Table 1). Since the volume of auto parts transactions is not displayed for many products (shown in a physical unit, if any), this study captures the transactions by (unweighted) occurrence.

One advantage of using this data is that products and firms listed in the books are not based on standard industrial classifications, which state that auto part products delivered from suppliers to car manufacturers are not limited to those classified as motor vehicle parts and accessories (JSIC code: 5422). These include a broader range of product classifications, such as chemical and carbon fibers, glass and rubber products, and electrical machinery. Disaggregating information on delivery to car manufacturers allows one to identify more realistic productive structures and their co-evolutionary process

[2] Car manufacturers that conduct in-house auto parts production are included as first-tier suppliers.

within the automobile industry. However, there are some issues when interpreting the analyses. First, these data do not provide any information on product transactions delivered by second-tier and lower-tier suppliers. Second, the data only record domestic product delivery, and third, product transaction information is limited to automotive manufacturing.

The following empirical analyses use data from four years: 1988, 1998, 2008, and 2016. Table 1 summarizes the numbers of auto part suppliers and primary products in total and by category for each year. The total number of products tends to increase over the analysis period. In particular, electrical parts increased by 52 from 1988 to 1998, showing significant progress in vehicle electrification during the 1990s. Auto parts for hybrid vehicles (HV) appeared in 2008, while those for electric and fuel cell vehicles (EV and FCV) appeared in 2016. Conversely, first-tier suppliers decreased by 14% from 1988 to 2016, partly due to the growing merger and acquisition activities trend.

(Table 1 around here)

3.2 Stylized facts

This study uses the Sogogiken data to establish the following three stylized facts about product portfolios of auto part suppliers, which motivated the exploratory and econometric analyses implemented in the later sections.

Fact 1: Very few suppliers deliver a wide range of products, whereas most suppliers specialize in a few products. Fig 1(a) presents the size of suppliers' product portfolios in descending order for 2016, spread out over a range from 1 to 73 auto parts. Denso is the supplier with the largest portfolio, followed by Toyota's in-house production, with 44 products, and Hitachi Automotive Systems, with 39 products. Of the 515 suppliers, only 36 (7%) have portfolios with more than 10 product types; conversely, 75% of suppliers specialize in 1 to 3 product types. Fig 1(b) shows that a power-law distribution approximates the cumulative distribution function for the suppliers' product portfolios in 2016.

Fact 2: Rare (ubiquitous) products delivered by a small (large) number of suppliers tend to be produced by diversified (specialized) suppliers. Fig 1(c) shows the inverse relationship between the number of suppliers for each product and the median of suppliers' portfolios that manufacture that product for 2016; the correlation coefficient is −0.27 ($P < 0.01$). Products plotted in the upper left side of the diagram, such as hybrid control computers and battery current sensors for HV, appear to have relatively complex structures. In contrast, products in the lower right, such as those manufactured by casting or forging molten metal, have simple structures. Care must be taken when interpreting the attributes of the products plotted in the lower left, which are produced only by limited suppliers with small portfolio sizes. These products are primarily auto parts for fuel cell vehicles and tend to be produced by suppliers who serve a vast range of customers and car manufacturers.

Fact 3: The supplier–product relationship exhibits a highly nested structure in both supplier diversity and product ubiquity. The nestedness feature can be represented by the binary supplier–product matrix $\mathbf{M}$, which summarizes the product portfolios of all suppliers and consists of an equivalent description of the bipartite supplier–product network. The generic element of the matrix $\mathbf{M}$ is defined as follows:

$$\begin{cases} M_{sp} = 1 & \text{if supplier } s \text{ delivers product } p, \\ M_{sp} = 0 & \text{otherwise.} \end{cases}$$

Fig 1(d) shows the matrix $\mathbf{M}$ for 2016, where entities equal to 1 are indicated in red. Suppliers represented in rows are sorted according to the number of different products each delivers (diversification); products in columns are arranged by the number of suppliers delivering each product (ubiquity). A substantially triangular matrix shape characterizes nestedness, as shown in Fig 1(d), indicating that, when viewed vertically, a relatively specialized supplier's product portfolio is likely to be a subset of a diverse supplier's portfolio. Viewed horizontally, suppliers that produce relatively rare products are likely to be a subset of those producing somewhat ubiquitous products.

(Fig 1 around here)

These stylized facts tend to remain stable over time (see sections 1 and 2 in S1 Materials) and have been confirmed in the structures of countries' and regions' product baskets (Hidalgo and Hausmann, 2009; Bustos *et al.*, 2012; Hausmann *et al.*, 2014). Therefore, arguments on the level of sophistication of economies and products, asserted in literature focusing on global and national economies, are expected to also hold at the industrial scales. First, in the automotive components industry, rare products manufactured by a few highly diversified suppliers require a specific combination of capabilities; thus, they are probably more sophisticated than ubiquitous products. Second, suppliers with large portfolios can practically relate their capabilities to manufacture a broader range of products; they should have more potential to develop new and sophisticated products than suppliers with small portfolios. The following sections further explore stylized facts using relatedness and complexity metrics and provide additional empirical evidence.

4. Exploratory network data analysis

4.1 Product relatedness

Measuring the degree to which products require similar capabilities (i.e., *product relatedness*) helps understand the path-dependent process of structural changes in industries. This study develops a co-occurrence-based measure to assess product relatedness, assuming that if auto part suppliers manufacture products in tandem, similar capabilities would be required (Hausmann and Klinger, 2006; Hidalgo *et al*., 2007). The co-occurrence product–product matrix $\mathbf{C}$ is obtained from the bipartite supplier–product relations, represented by the matrix $\mathbf{M}$ as:

$$\mathbf{C} = \mathbf{M}^{\mathbf{T}}\mathbf{M},$$

where the non-diagonal elements C_{ij} count the number of suppliers that deliver both auto parts i and j, and the diagonal elements C_{ii} calculate the number of suppliers that deliver auto part i.

Since the number of suppliers producing each auto part influences the probability of co-occurrence, regardless of capabilities' relatedness between products, the relative measure of relatedness controlling for such an effect should be determined. This study adopts the association strength measure, expressed by the ratio of the probability of the observed co-occurrence (P_{ij}^{A}) to that of a null model (P_{ij}^{0}) (Van Eck and Waltman, 2009; Hidalgo *et al*., 2009; Neffke *et al*., 2011). If production occurs independently, the probability of finding suppliers that produce both auto parts i and j is given by:

$$P_{ij}^{0} = \frac{C_i C_j}{N^2},$$

where N is the total number of suppliers in the total population and C_i is the number of suppliers producing auto part i. Hence, the relative estimate of the product relatedness between auto parts i and j is given by:

$$R_{ij} = k\frac{P_{ij}^{A}}{P_{ij}^{0}} = k\frac{C_{ij}/N}{C_i C_j/N^2} = k\frac{C_{ij}N}{C_i C_j},$$

where $k = 1/N$ is a normalizing factor used to express the measure that lies between 0 and 1.

The product relatedness matrix $\mathbf{R}$ with the elements of R_{ij} can be interpreted as the *auto parts product space*, defined as the set of all relatedness measures between all the auto part product pairs (Hidalgo *et al*., 2007). Fig 2(a) shows the number of pairs with relatedness values below a certain threshold for 2016. The product space represents a sparse structure as a whole; of all 37,675 possible product pairs of products, only 6,798 pairs (18.0%) have some relatedness values. Moreover, relatedness values are heterogeneously distributed, with 5,641 pairs (15.0%) between 0 and 0.1 and 1,157 pairs (3.1%) over 0.1, suggesting that weak ties connected many related pairs. Fig 2(b) shows the cumulative frequency of a product's connections related to other products for 2016. This figure corresponds to the cumulative degree distribution of the product–product network, connecting the nodes of distinct products if they are related. Plotting on a log-log scale illustrates that a handful of highly connected hubs coexist with numerous smaller-degree nodes.

(Fig 2 around here)

The auto parts product space structure (or the interconnectivity of products) can be explored through network visualization that connects related products. Following the procedure developed by Hidalgo *et al.* (2007), a maximum spanning tree (MST) is first built to draw the relevant, productive structure. The MST is constructed as a single tree with as many nodes as it could incorporate, maximizing the sum of the weight of links. The isolated nodes of products are delivered by specialized suppliers that manufacture only one product. Then, all links with significant weights over a certain threshold are superposed. The force-directed layout algorithm fixes the relative positions of nodes so that shorter links connect closely related pairs of nodes. Individual nodes are colored according to the product categories shown in Table 1.

Informative visualization of a network should not be too sparse or too dense. The present case achieves good visualization by using a proper threshold value so that the emerged network simultaneously contains highly connected dense cores and scarcely sparse peripheries. For 2016, this core-periphery network structure could be obtained by choosing the threshold value of 0.1, as shown in Fig 3(a). For comparison purposes, the same threshold value is also applied to visualize the productive structures for 2008, 1998, and 1988, as shown in Figs 3(b)–3(d).

(Fig 3 around here)

Examining Figs 3(a)–3(d) reveals some interesting qualitative properties. The literature suggests relatively stable productive structures of international and domestic economies (Hidalgo *et al*., 2007; Hidalgo, 2009; Neffke *et al*., 2011; Bustos *et al*., 2012); however, the more disaggregated productive structure within the industry differs. While these networks have roughly maintained the core-periphery structure over the four periods, a densely connected large core emerges over time. The degree of clustering for a whole network, captured by the average clustering coefficient, increases over time. The core in 1998 was initially composed of products classified into engine body parts (colored in red) and electrical parts (blue). During the 1990s, the core was remarkably enhanced by newly emerged electrical components rather than by the evolution of existing ones. Products for HV (green) appeared in the 2000s and tended to be at the core. Some smaller sub-clusters surrounding the larger core also appeared after 1998. Products forming the densely larger core tend to be manufactured by a few suppliers with large portfolios; therefore, they are considered highly sophisticated auto parts. Conversely, many products consistently fall on the periphery of networks. Some engine body parts and electrical components in or around the central cluster in 1988 retreated to the periphery in recent years. These peripheral products tend to be delivered by multiple suppliers with small portfolios, thus regarded as less sophisticated auto parts.

The indices that characterize the network's local attribute also capture this substantially heterogeneous structure of visualized networks. As measures of the influence of each product and its local link density, Fig 4 shows the respective distribution of (a) eigenvector centrality and (b) the local clustering coefficient for the classified products (see section 4 in S1 Materials for details on these indicators). Generally, the products located in the core (periphery) feature large (small) values of centrality and clustering coefficient.

(Fig 4 around here)

The visual representation shown in Figs 3(a)–3(d) suggests that auto parts classified into the same product category are not necessarily closely connected. Furthermore, as shown in Fig 4, the products' centrality values and clustering coefficient are broadly distributed within the product category, indicating that conventional *ex-ante* classification based on a bill of materials does not capture the whole range of factors influencing the relatedness among products. Therefore, a product-relatedness approach based on a co-occurrence measure is more relevant to deepen insights into the productive structure of the auto parts industry.

4.2 Product complexity

The method introduced by Hidalgo and Hausmann (2009) proposed a radical new way to capture the complexity of countries and products from the information contained in global export patterns. The key idea is those complex products are simultaneously rare (few countries significantly export them) and found only in places that produce many other products (they could make many). We follow this approach and derive complexity from the production patterns of the supplier-auto part network.

From the structure of the bipartite supplier–product network summarized in the matrix **M**, the diversity of supplier s (denoted by $k_s^{(0)}$) is given by the degree centrality of node s as:

$$k_s^{(0)} = \sum_p M_{sp},$$

where M_{sp} is defined above. Analogously, the ubiquity of product p ($k_p^{(0)}$) is given by the degree centrality of node p in the bipartite network as:

$$k_p^{(0)} = \sum_s M_{sp}.$$

The diversity $k_s^{(0)}$ and the ubiquity $k_p^{(0)}$ are understood as crude estimates of suppliers' ability and products' disvalue, respectively.

Complexity measures for both suppliers and products are calculated with an iterative linear algorithm, referred to as the *Method of Reflections* (Hidalgo and Hausmann, 2009); the information given by the initial quantities of diversity $k_s^{(0)}$ and ubiquity $k_p^{(0)}$ is refined at the higher n^{th} order of reflection:

$$k_s^{(n)} = \frac{1}{k_s^{(0)}} \sum_p M_{sp}\, k_p^{(n-1)},$$
$$k_p^{(n)} = \frac{1}{k_p^{(0)}} \sum_s M_{sp}\, k_s^{(n-1)}.$$

The economic meaning of $k_s^{(n)}$ and $k_p^{(n)}$ changes continuously with each iteration. For example, $k_p^{(0)}$ represents product ubiquity, whereas $k_p^{(1)}$ captures the average diversity of suppliers that deliver product p. Then, $k_p^{(2)}$ refines the measure of ubiquity $k_p^{(0)}$ via the average ubiquity of the products delivered by supplier s ($k_s^{(1)}$).

The seminal contribution by Hidalgo and Hausmann (2009) has inspired several other approaches, which have in turn generated a substantial conversation in the literature (Balland et al., 2022). Given the structure of the supplier-product matrix, we use the variation proposed by Tacchella *et al.* (2012) to limit the weight of overspecialized suppliers. The modified non-linear metrics using the binary supplier–product matrix **M,** which relate to the degree of suppliers' fitness (i.e., competitiveness) F_s to the degree of products' quality Q_p. In the formulas, while the complexity of suppliers is defined by the sum of the complexity of the delivered products, the complexity of products decreases significantly if poorly diversified suppliers manufacture the products. This plays a role for our data structure, since we have an important amount of low ubiquity products. This idea is reflected by the following non-linear relation between the complexity of suppliers and the products they deliver. With the initial conditions $F_s^{(0)} = 1\ \forall s$ and $Q_p^{(0)} = 1\ \forall p$, the respective complexity metrics for suppliers and products are intermediately calculated by:

$$\begin{cases} \tilde{F}_s^{(n)} = \sum_p M_{sp} Q_p^{(n-1)}, \\ \tilde{Q}_p^{(n)} = \dfrac{1}{\sum_s M_{sp} \dfrac{1}{F_s^{(n-1)}}}, \end{cases}$$

and then normalized by using the averages of the intermediate values as:

$$
\begin{cases}
F_s^{(n)} = \dfrac{\tilde{F}_s^{(n)}}{\left\langle \tilde{F}_s^{(n)} \right\rangle_s}, \\
Q_p^{(n)} = \dfrac{\tilde{Q}_p^{(n)}}{\left\langle \tilde{Q}_p^{(n)} \right\rangle_p}.
\end{cases}
$$

Cristelli *et al*. (2013) numerically show that these coupled metrics have a unique asymptotic solution for each supplier and product, independent of the initial condition. The fixed points of F_s^* and Q_p^* provide a clear ranking of suppliers and products in terms of complexity.

Employing the non-linear metrics on complexity, Tables 2(a) and 2(b) list the 20 highest- and lowest-ranked auto part products for each year, respectively.[3] In 1988, the top-ranked auto parts were related to engine body parts (colored in red) and electrical parts (blue), although most engine body parts lost their position over time. Newly emerged hybrid and fuel cell vehicle parts (green and orange, respectively), which tend to be produced by suppliers with large portfolios, assumed high ranks in 2008 and 2016. Although electrical parts always made the top 20, their contents were largely replaced with new products, including various sensors. Conversely, the least complex auto parts belong to engine body parts and vehicle interior and exterior parts (pink). Unlike high-ranked products, low-ranked products experienced little change during the study period (Fig 5).

(Table 2 around here)

(Fig 5 around here)

4.3 A unified exploratory network data analysis

Since the concepts of product relatedness and complexity capture the different but closely associated features of capability arguments, a unified approach using relatedness and complexity information is useful for exploring the productive structure and its dynamic process in more detail. First, it is visually studied where sophisticated (unsophisticated)

[3] This study aims to investigate the productive structure of the auto parts industry from a technological perspective, and it only focuses on the complexity of auto part products. The authors can provide the results of the complexity of suppliers upon request.

products with large (small) complexity values tend to be located in the auto parts product space. Figs 6(a) and 6(b) show the location of the top 20% and bottom 20% of products, respectively, in terms of complexity for 2016. Fig 6(a) suggests that the core of the product space primarily comprises sophisticated products classified into electrical parts and hybrid vehicle parts. Sophisticated fuel cell vehicle parts and driving parts are not in the core but act as network hubs. Conversely, Fig 6(b) shows that the network's periphery contains unsophisticated products classified into engine body parts, driving parts, and vehicle body parts.

(Fig 6 around here)

Second, to explore the path-dependent accumulation of capabilities and the resulting development of products, this study investigates the location of newly emerged products in the auto parts product space. Fig 6(c) shows the location of products found in 2016 that were not produced in 1988. Although new products tend to be in the core and the smaller clusters surrounding them, some are also found in the periphery. It is noteworthy that not all new products during these three decades were sophisticated. Among the new products, Fig 6(d) shows the location of sophisticated products in the top 20%, in terms of complexity, for 2016. The new sophisticated products emerge from the densely connected core or the hubs connecting peripheral products to the core (see section 3 in S1 Materials). This implies that, since capabilities are supposed to accumulate heavily in the dense clusters of the product space, the path-dependent accumulation of capabilities is significant for developing sophisticated products.

5. Econometric analysis

This section applies econometric models to examine the extent to which the product space's topology (i.e., the degree of capabilities overlaps between products) and product complexity (i.e., the degree of capabilities accumulation) contribute to diversifying into new products. Using the measure of product relatedness, the binary dependent variable $Related_{i,j,t}$ is defined as:

$$\begin{cases} Related_{i,j,t} = 1 \text{ if new product } i \text{ not present in year } t-1 \text{ but emerges by year } t \\ \quad \text{is related to pre-existing product } j \text{ present in year } t-1, \\ Related_{i,j,t} = 0 \text{ otherwise.} \end{cases}$$

The dependent variable assumes the value of 1, representing that a newly emerged product is developed based on specific capabilities embedded in the existing connected products. Among the independent variables, the following three measures characterizing the local topology of product j in year $t-1$ are introduced: (1) the eigenvector centrality $Cent_{j,t-1}$, measuring how closely product j is located to the core of the product space; (2) the local clustering coefficient $Clust_{j,t-1}$, measuring how densely neighbors of product j are connected; (3) the Burt's constraint measure $Burt_{j,t-1}$, measuring the extent to which product j, directly and indirectly, bridges various products belonging to different communities (see section 4 in S1 Materials). Another independent focal variable is the product j's complexity $Comp_{j,t-1}$. The logit function of the probability that diversifies into new product i is estimated based on the following linear predictor:

$$\text{logit}\left(Related_{i,j,t}\right) = \beta_0 + \beta_1 Cent_{j,t-1} + \beta_2 Clust_{j,t-1} + \beta_3 Burt_{j,t-1} + \beta_4 Comp_{j,t-1}.$$

The model is first estimated using the pooled data for all three periods (1988–1998, 1998–2008, and 2008–2016) and then estimated using the data from each separate period. The pooled data model includes period-specific fixed effects. Section 5 in S1 Materials provides a summary of descriptive statistics for the variables. All results presented in Tables 3 and 4 are based on the logistic regression with random effects on newly emerged product i to deal with a suspected overdispersion problem in the error term.

The first column of Table 3 presents the result using the pooled data, and the second to fourth columns show the results for each separate period. Among the local topology measures, the coefficient of centrality is significantly positive in the pooled data model, suggesting that capabilities overlap with many other products is essential for product development. Although the centrality effect is significantly negative in the 1988–1998 period, the importance of sharing many capabilities has increased in recent years. In general, the densely shared capabilities also significantly positively affect the development of related new products except in 1998–2008, when non-incumbent suppliers developed some auto parts for HV. Since Burt's constraint measure is small when the product bridges a variety of other products, the negative sign for this coefficient means that various capabilities significantly contributed to product development. The insignificant coefficient of this constraint measure in the 2008–2016 period resulted from the size of the product space shrinking, in terms of the average path length, forming one massive core component, as suggested in Fig 3.

While the effect of product complexity on the development of related products is significantly positive in the pooled data and the 1988–1998 period data models, the magnitude is too small. For the 1998–2008 and 2008–2016 models, the coefficients of product complexity are statistically insignificant. These results suggest that while capabilities accumulation was conducive to diversifying into new products, more complex capabilities create more difficulty in developing sophisticated products. The period-specific fixed effects are significantly negative for 1998–2008 and 2008–2016, making it harder to introduce new products to the market over time.

(Table 3 around here)

As studied in the previous section, not all new products are sophisticated. Following the path-dependent development arguments, it is difficult to add new capabilities or recombine new and existing ones to develop new products; however, new sophisticated products can only be developed by relating the capabilities used in a wide range of pre-existing products. Furthermore, the earlier exploratory network analyses show that newly sophisticated products typically appear from the densely connected core or the network hubs in the product space. The interaction terms, which represent the effect of the product space topology of pre-existing products conditional on the complexity of newly developed products, are additionally introduced into the previous baseline specification to investigate this phenomenon statistically.

Based on the pooled data model shown in the first to third columns of Table 4, all the estimates of the interaction terms emphasize the contribution of the product space's local attributes to bringing sophisticated new products to the market. The results for each of the three periods (the fourth to twelfth columns of Table 4) show that every local topology measure significantly contributes to developing new sophisticated products, particularly in the later periods. These results imply that when existing related products widely, densely, and diversely share capabilities with other products, developing more complex products with sophisticated capabilities will likely be promoted. Overall, these empirical findings provide significant insight into the nature of the path-dependent development process and the consequent evolution of the productive structure in the automotive industry.

(Table 4 around here)

Conclusion

Recent research efforts applying a network science approach have explained the path-dependent accumulation of capabilities and resulting international and domestic economic development. However, the feature of structural change focusing on specific industries has not yet been addressed. Clarifying the industries' productive structure is of interest to academia and policymakers, particularly when focal industries have a significant presence and play a key role in economies. This study investigates the industry's productive structure and its structural change process, focusing on Japan's automotive components industry.

Using unique survey data that contain detailed information on each auto part supplier's product basket, this study establishes a collection of stylized facts about product portfolios from auto part suppliers. (1) Very few suppliers deliver a wide range of products, and most suppliers specialize in a few products. (2) Rare (ubiquitous) products delivered by a small (large) number of suppliers tend to be produced by diversified (specialized) suppliers. (3) The supplier–product relationship, represented by the binary supplier–product matrix, exhibits a highly nested structure, both in supplier diversity and product ubiquity.

Motivated by these facts, this study clarifies the productive structure of the auto parts industry. More specifically, the capabilities similarity between all the auto product pairs (product relatedness) is measured and then visually represented as the auto parts product space. The visual network representation allows the identification of the core-periphery structure. These structural properties in the industry include the power-law structure of the cumulative frequency of the suppliers' product portfolio, the inverse relationship between the number of each product's suppliers and the portfolio size of suppliers that deliver related products, the nestedness of the supplier–product network, and the core-periphery structure of the product space. These properties are all in common with those in the international and domestic economies, meaning that, notwithstanding the differences in size, maturity, and industrial scope of economies, common principles and regularities underlie the formation of productive structures.

Although the core-periphery structure can be confirmed in 1988, newly emerged products, such as recent electric and hybrid vehicle parts, remarkably enhance the core. Some smaller clusters surrounding the larger core also appeared after 1998. These findings suggest that an analytical framework incorporating a dynamic concept following technological progress would be indispensable, unlike the global and national economies.

As another line of network analysis, the degree of product sophistication (product complexity) can be measured by combining information on countries' product diversification and the ubiquity of the delivered products. An unambiguous ranking of products is provided based on the complexity measure, calculated by a non-linear iterative algorithm. The result shows that most top-ranked engine body and electrical parts in 1988 lost their position over time. Moreover, some newly emerged electric, hybrid vehicle, and fuel cell vehicle parts, which tend to be produced by suppliers with large portfolios, were highly ranked in 2008 and 2016. Conversely, the least complex auto parts, i.e., engine body parts and vehicle interior and exterior parts, experienced little change in position during the study period.

Finally, the study examines how much the topology of the product space and product complexity contribute to diversifying into new products by applying econometric models. The results show that, in general, high network centrality, local density, and local brokerage in the product space contribute to diversifying into new products. Focusing on developing products with sophisticated capabilities further emphasizes the role of these local attributes of the product space. These results reveal that the emergence of products, especially sophisticated products, is not random but rather significantly contingent on the network topology of the product space, which in turn shapes the new structure of the product space.

The study opens several avenues for future research. The first is related to the studied industrial scope. The empirical analyses are implemented based on the detailed information on auto parts transactions between suppliers and car manufacturers; however, auto parts suppliers also transact with firms in other industries, such as electrical machinery and aircraft parts manufacturers. From a perspective of inter-sectoral co-evolution, determining the capabilities required to produce auto parts related to products from other industries is of much interest if any available data allows such analyses.

Second, the features of productive structure and its evolution of the automobile industry would be heterogeneous in some countries. Different historical trajectories and institutions may lead to varying configurations of the industrial landscape (Neffke *et al*., 2011). An international comparison could potentially explore the generality and specificity of the arguments.

Finally, and more importantly, the analytical approach must incorporate a geographical context as another dimension to affect capabilities sharing and diffusion. A growing body of literature on the geography of innovation has shown the geographical concentration patterns of innovation activities and emphasized the role of the geographically proximate knowledge base on the underlying process of innovation (Balland, 2016). Clarifying what kinds of technological capabilities and associated knowledge bases are deeply rooted in regions and to what extent areas can develop their technical capabilities would be highly informative and help establish a sound regional policy framework.

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Table 1. Number of suppliers and auto-parts.

	Year	1988	1998	2008	2016
	Suppliers	596	584	567	514
	Auto parts	197	249	254	275
1	Engine body parts	71	79	75	72
2	Electrical parts	33	67	68	68
3	Drivivng parts	36	40	41	42
4	Suspension and brake parts	19	22	24	21
5	Body parts	38	41	40	35
6	HV parts			6	14
7	EV parts				4
8	FCV parts				19

Table 2. The most and least complex auto-part products. a Top 20 auto-parts. **b** Bottom 20 auto-parts. The colors in the table represent the product categories shown in Table 1.

a

1988		1998		2008		2016	
1	supply pump	1	oil nozzle	3	hybrid control computer_HEV	3	hybrid control computer_HEV
1	injection system	1	supply pump	1	supply pump	3	battery cooling system
1	oil nozzle	1	injection system	1	injection system	3	battery current sensor
1	pressure regulator	2	engine control unit_deisel	2	engine control unit_deisel	5	fuel cell stack
1	ACV	2	electronically controlled carburetor	2	A/F sensor	5	high-pressure hydrogen tank
1	HAC	2	spark plug	2	air quality sensor	2	ECU_ suspension
1	ISC	1	ACV	2	ECU_4WS	1	injection system
1	electric fuel pump	2	O2 sensor	2	O2 sensor	1	supply pump
2	spark plug	1	pressure regulator	2	air-flow meter	2	engine control unit_deisel
1	injector	1	ISC	2	accelerator pedal position sensor	2	ECU_4WS
2	distributor	2	air-flow meter	2	crank position sensor	6	4WD_electric
2	igniter	1	HAC	1	pulsation damper	2	A/F sensor
2	air-flow meter	2	engine control temperature senseor	1	pressure regulator	2	air quality sensor
2	wiper	2	knock sensor	1	electric fuel pump	2	O2 sensor
2	window washer	2	ultrasonic sensor	2	automatic light control sensor	2	air-flow meter
2	alternator	2	sonar	2	knock sensor	2	ECU_power steering
2	starter	1	pulsation damper	2	ultrasonic sensor	2	yaw rate sensor
2	flasher unit	1	carburetor	2	sonar	2	ETC
2	headlamp	1	throttle body	6	4WD_electric	2	knock sensor
2	high-mounted stop lamp	2	automatic air conditioner sensor	2	yaw rate sensor	5	hydrogen injector_FCV

b

1988		1998		2008		2016	
1	pulley	1	cylinder head gasket	1	cylinder head gasket	1	cylinder head gasket
1	cylinder head gasket	1	fuel tank	1	fuel tank	1	fuel tank
1	fuel tank	8	sealant	1	connecting rod	1	air intake hose
8	seat	8	paint	1	air intake hose	1	connecting rod
8	bumper_steel	8	door trim	2	wire harness	1	crankshaft_forging
1	oil pan	8	seat	3	battery_HEV	1	oil pan
8	door trim	8	head lining	1	oil pan	8	mark
8	headrest	8	floor carpet	1	intake manifold	7	suspension ball joint
1	flywheel	1	intake manifold	8	door trim	8	window glass
1	rocker arm	1	air intake hose	8	seat	8	door trim
8	door hinge	8	headrest	8	power seat	8	seat
1	crankshaft_forging	1	oil pan	8	headrest	8	headrest
1	cylinder headcover	1	timing belt cover	8	floor carpet	8	power seat
6	clutch housing	2	battery	8	head lining	6	differential gear
1	timing gear	1	rocker arm	6	aluminum wheel	6	steering column
1	timing gear cover	1	accelerator pedal	7	lower control arm	8	head lining
6	differential gear	6	MT lever	1	engine assy	8	floor carpet
1	intake manifold	1	cylinder headcover	7	upper arm	2	horn
8	spare tire carrier	7	brake pedal	8	window glass	2	battery
1	exhaust pipe	6	clutch pedal	2	car audio	1	accelerator pedal

Product category

1	Engine body parts
2	Electrical parts
3	Driving parts
4	Suspension and brake parts
5	Body parts
6	HV parts
7	EV parts
8	FCV parts

Table 3. Econometric analysis of product development (baseline model).

Independent variables	Baseline model			
	Pooled	1988–1998	1998–2008	2008–2016
$Cent_{j,t-1}$	0.724 ***	-1.310 ***	3.017 ***	3.543 ***
	(0.076)	(0.114)	(0.142)	(0.195)
$Clust_{j,t-1}$	0.696 ***	1.906 ***	-0.186	1.069 ***
	(0.109)	(0.163)	(0.177)	(0.262)
$Burt_{j,t-1}$	-9.348 ***	-27.185 ***	-1.721 ***	0.523
	(0.667)	(1.549)	(0.667)	(0.460)
$Comp_{j,t-1}$	0.007 ***	0.006 **	-0.002	0.002
	(0.002)	(0.002)	(0.003)	(0.004)
Period 1998–2008	-0.552 ***			
	(0.196)			
Period 2008–2016	-1.474 ***			
	(0.209)			
Constant	-1.365 ***	-0.201	-2.815 ***	-4.980 ***
	(0.156)	(0.190)	(0.230)	(0.317)
# of Obs.	30,796	11,773	10,168	8,855
AIC	26,102	11,696	8,698	4,768
Log likelihood	-13,043	-5,842	-4,343	-2,378
Pseudo R^2	0.052	0.132	0.153	0.190

Standard errors in parentheses

* Significant at the 10 % level; ** at the 5 % level; *** at the 1 % level

Table 4. Econometric analysis of product development (models with the interaction terms).

Independent	Models with the interaction terms											
variables	Pooled	Pooled	Pooled	1988–1998	1988–1998	1988–1998	1998–2008	1998–2008	1998–2008	2008–2016	2008–2016	2008–2016
$Cent_{j,t-1}$	0.589 ***	0.716 ***	0.720 ***	-1.217 ***	-1.312 ***	-1.310 ***	2.894 ***	3.016 ***	3.023 ***	3.039 ***	3.415 ***	3.538 ***
	(0.077)	(0.076)	(0.076)	(0.115)	(0.114)	(0.114)	(0.144)	(0.142)	(0.142)	(0.200)	(0.199)	(0.195)
$Clust_{j,t-1}$	0.706 ***	0.698 ***	0.585 ***	1.921 ***	1.906 ***	1.865 ***	-0.184	-0.185 ***	-0.311 ***	1.030 ***	1.133 ***	0.574 **
	(0.110)	(0.109)	(0.110)	(0.163)	(0.163)	(0.164)	(0.177)	(0.177)	(0.179)	(0.264)	(0.263)	(0.276)
$Burt_{j,t-1}$	-9.480 ***	-9.164 ***	-9.380 ***	-27.484 ***	-27.422 ***	-27.184 ***	-1.796 ***	-1.810 ***	-1.770 ***	0.421	0.818 *	0.338
	(0.671)	(0.666)	(0.667)	(1.558)	(1.564)	(1.549)	(0.676)	(0.691)	(0.667)	(0.463)	(0.456)	(0.466)
$Comp_{j,t-1}$	0.007 ***	0.007 ***	0.007 ***	0.006 **	0.006 **	0.006 **	-0.002	-0.002	-0.002	0.003	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)		(0.004)	(0.004)	(0.004)
$Cent_{j,t-1}$*$Comp_{i,t}$	0.064 ***			-0.446 ***			0.044 ***			0.067 ***		
	(0.006)			(0.072)			(0.009)			(0.009)		
$Clust_{j,t-1}$*$Comp_{i,t}$		0.032 ***			0.126 *			0.030 ***			0.045 ***	
		(0.005)			(0.066)			(0.007)			(0.008)	
$Burt_{j,t-1}$*$Comp_{i,t}$			-0.119 ***			0.637			0.014			-0.252 ***
			(0.046)			(0.461)			(0.020)			(0.095)
Period 1998–2008	-0.665 ***	-0.534 ***	-0.627 ***									
	(0.207)	(0.201)	(0.198)									
Period 2008–2016	-1.645 ***	-1.446 ***	-1.595 ***									
	(0.220)	(0.214)	(0.212)									
Constant	-1.317 ***	-1.377 ***	-1.294 ***	-0.182	-0.200	-0.205	-2.836 ***	-2.812 ***	-2.808 ***	-4.866 ***	-4.923 ***	-4.793 ***
	(0.161)	(0.159)	(0.157)	(0.193)	(0.190)	(0.192)	(0.230)	(0.230)	(0.236)	(0.311)	(0.330)	(0.313)
# of Obs.	30,796	30,796	30,796	11,773	11,773	11,773	10,168	10,168	10,168	8,855	8,855	8,855
AIC	25,920	26,095	26,059	11,638	11,696	11,694	8,668	8,700	8,682	4,685	4,753	4,731
Log likelihood	-12,951	-13,038	-13,020	-5,812	-5,841	-5,840	-4,327	-4,343	-4,334	-2,336	-2,370	-2,359
Pseudo R^2	0.059	0.052	0.054	0.136	0.132	0.132	0.156	0.153	0.154	0.205	0.193	0.197

Standard errors in parentheses

* Significant at the 10 % level; ** at the 5 % level; *** at the 1 % level

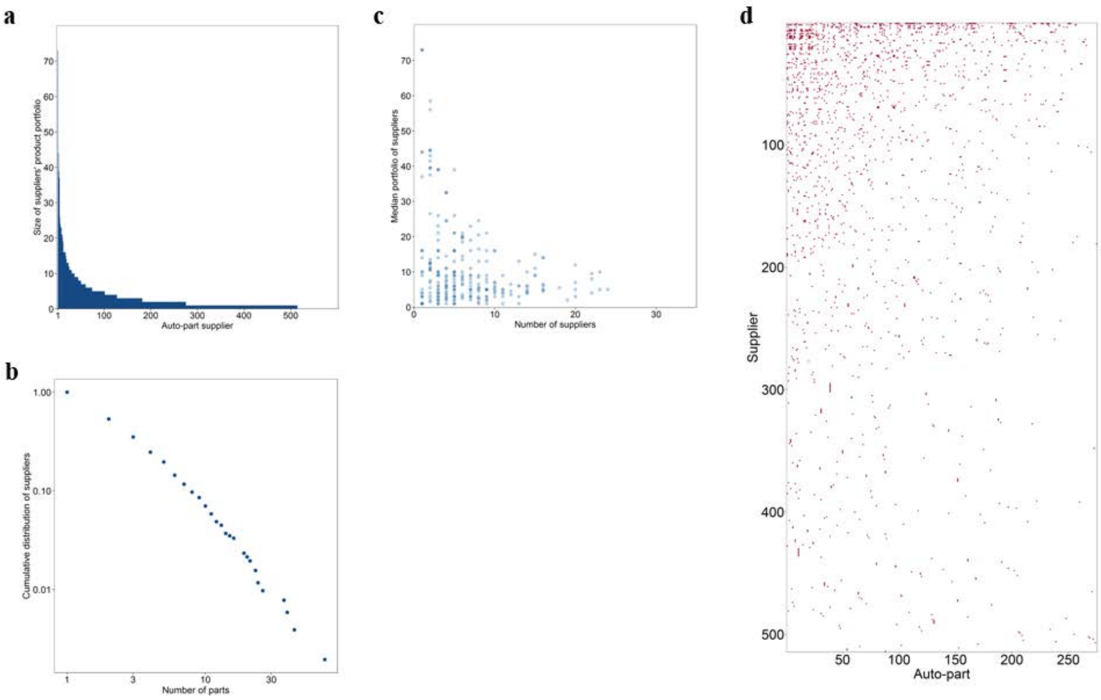


Fig 1. Stylized facts for the year 2016. a) Distribution of the number of auto part suppliers' portfolios. **b)** Cumulative distribution function for the number of suppliers' product portfolios. **c)** Inverse relationship between the number of suppliers for each product and the average median portfolio of suppliers that deliver the corresponding products. The points corresponding to two or more products are colored in darker blue. **d)** Nestedenss of the supplier–product relationship.

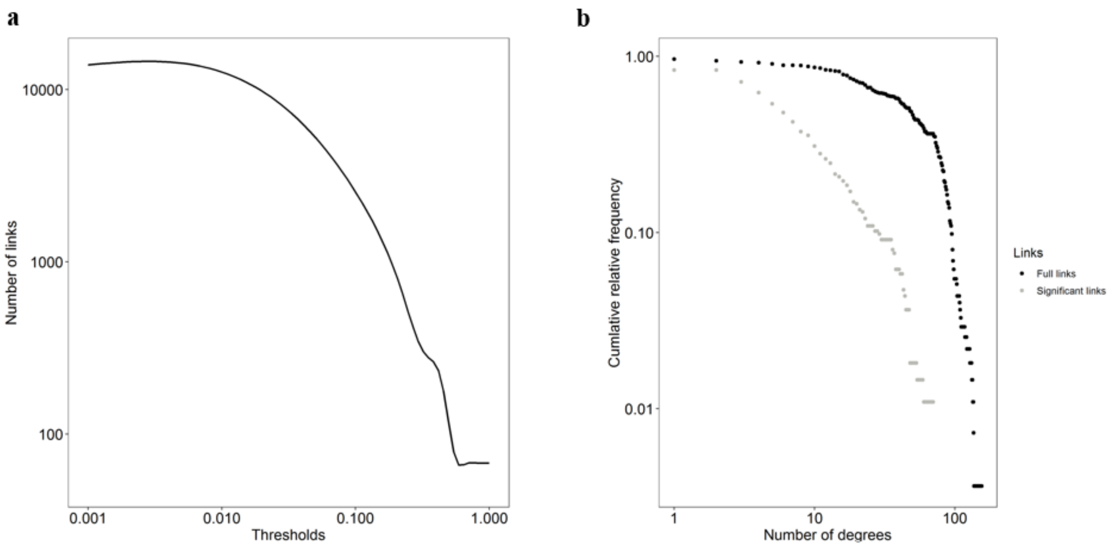
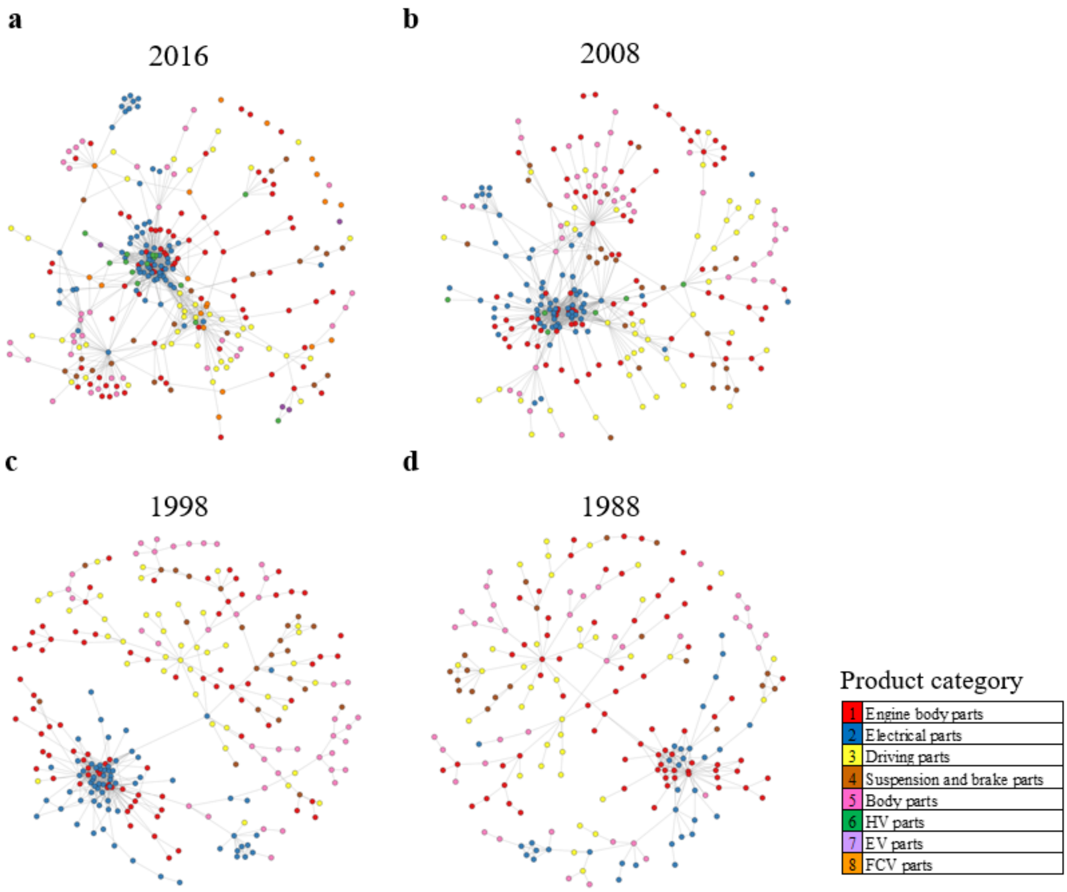


Fig 2. Distribution of relatedness for the year 2016. a) Cumulative distribution of the number of links under certain thresholds. **b)** Cumulative degree distribution of the product–product network. For the network including all relatedness links, the median of the number of links each node has is 47, whereas the maximum is 153. For the network with significant links having a proximity value of 0.1 or larger, the median is 6, whereas the maximum is 67.



Year	# of nodes	Ave. path length	Ave. culstering coefficient
1988	197	7.11	0.32
1998	249	7.28	0.38
2008	254	4.80	0.50
2016	275	4.60	0.58

Fig 3. Visualization of the auto parts product space for the years (a) 2016, (b) 2008, (c) 1998, and (d) 1989. The average path length and the average clustering coefficient are calculated based on the networks of the MST superposed by all links with a proximity value of 0.1 or larger. Care must be taken when interpreting the nodes isolated from network structures. It is possible that suppliers that deliver only one (isolated) auto part product to car manufacturers also deliver their products to other industries, such as electrical machinery and aircraft manufacturing.

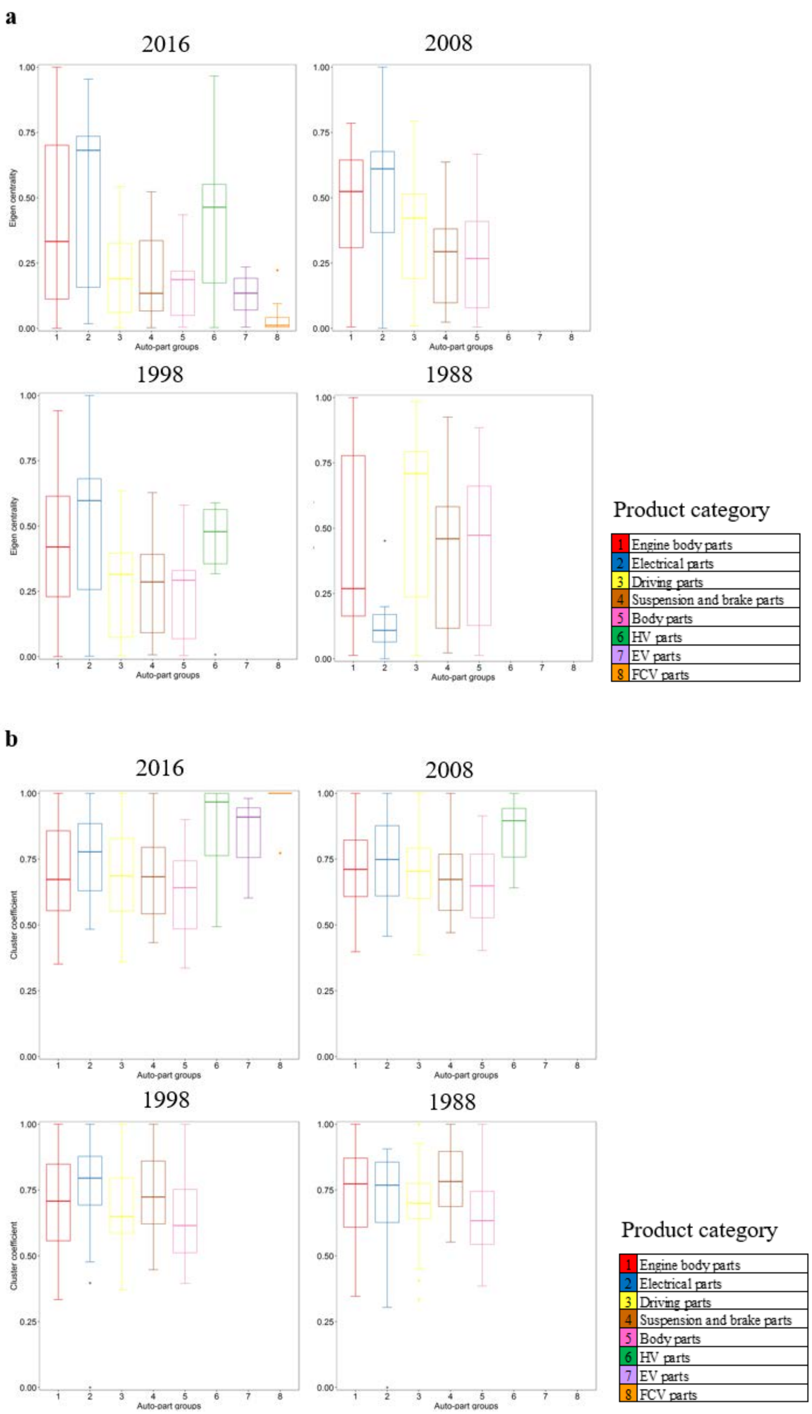


Fig 4. Local attributes of the auto parts product space. a) Distribution of the eigenvector centrality. **b)** Distribution of the local clustering coefficient. The eigenvector centrality and the local clustering coefficient indices are calculated based on the full networks without imposing any thresholds.

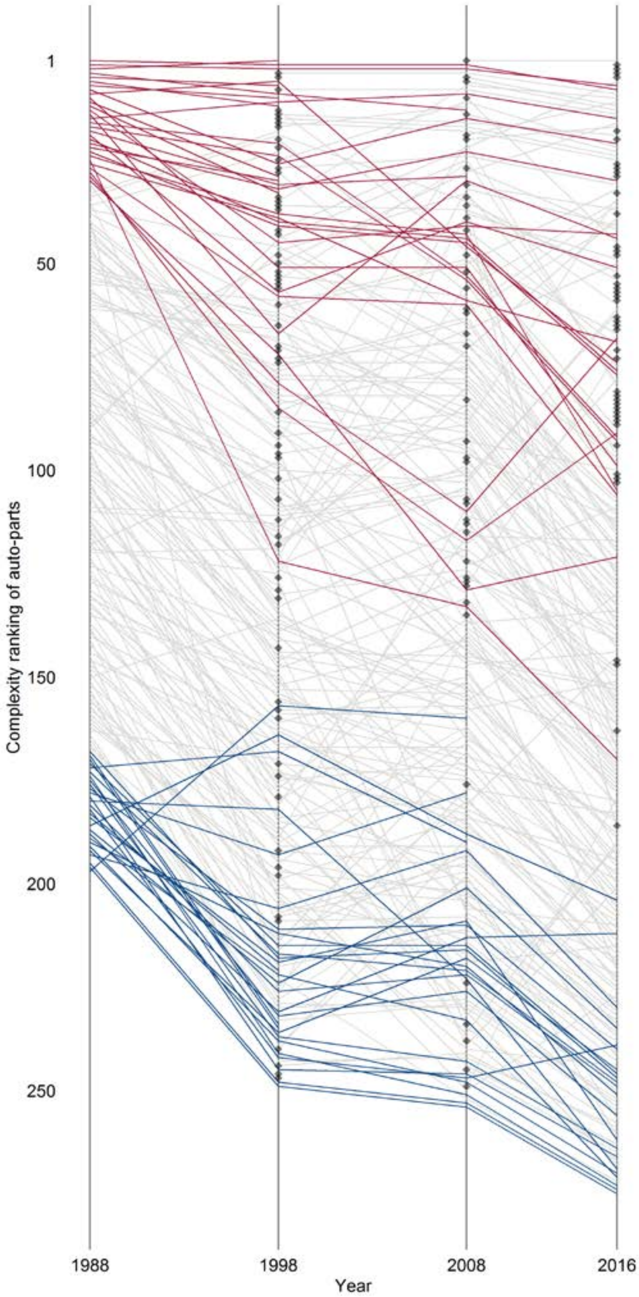


Fig 5. Changes in the ranking of auto parts. Auto parts are ranked according to the product complexity for 1988, 1998, 2008, and 2016. Each line represents the movement of the auto part product in the ranking. Lines colored in red (blue) are the top (bottom) 30 products in the initial year (1988). Many top-ranked auto parts lost their position, while low-ranked products experienced little change in position during the study period. The dots plotted in 1998, 2008, and 2016 represent new products first found in each year. While the new products tend to be evaluated as relatively sophisticated, not all newly emerged products are sophisticated.

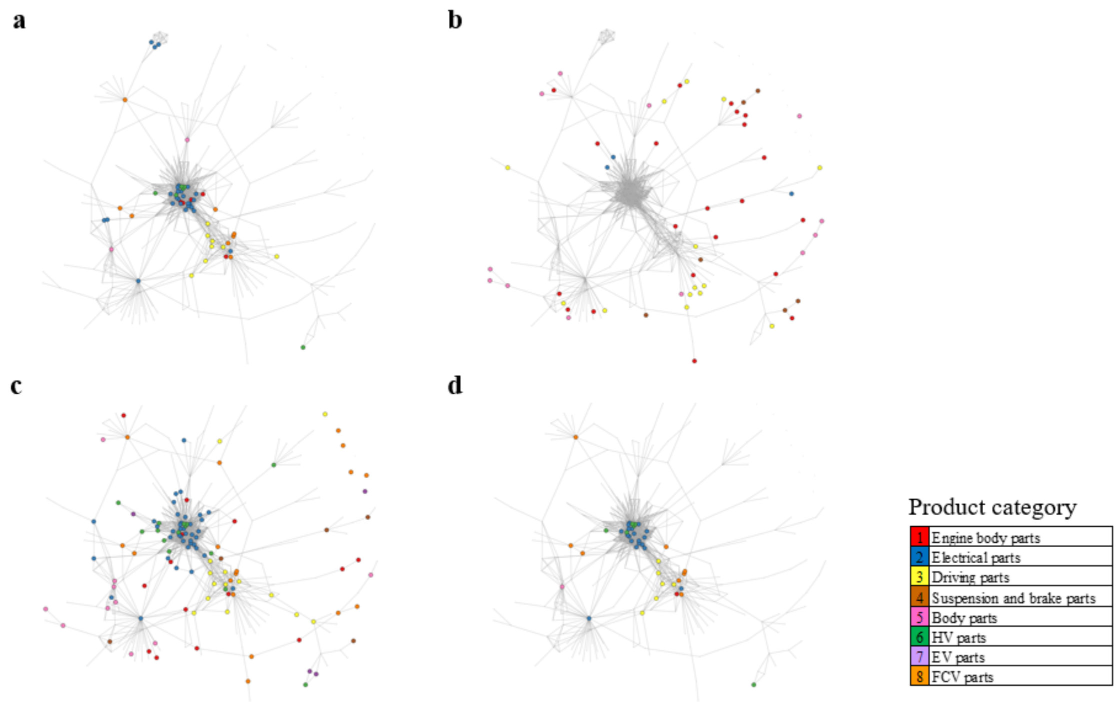


Fig 6. Location of sophisticated and unsophisticated products in the auto parts product space. a) Location of the top 20% of complex products for 2016. **b)** Location of the bottom 20% of less complex products for 2016. **c)** Location of the newly appeared products found in 2016 but not in 1988. **d)** Location of the newly appeared products ranked in the top 20% of complex products for 2016. Figs 6(a)–6(d) are depicted based on the 2016 product space.